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Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection

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ABSTRACT

The increasing frequency and complexity of web application attacks necessitate more advanced detection methods. This research explores integrating Transformer models and Natural Language Processing (NLP) techniques to enhance network intrusion detection systems (NIDS). Traditional NIDS often rely on predefined signatures and rules, limiting their effectiveness against new attacks. By leveraging the Transformer's ability to capture long-term dependencies and the contextual richness of NLP, this study aims to develop a more adaptive and intelligent intrusion detection framework. Utilizing the CSIC 2010 dataset, comprehensive preprocessing steps such as tokenization, stemming, lemmatization, and normalization were applied. Techniques like Word2Vec, BERT, and TF-IDF were used for text representation, followed by the application of the Transformer architecture. Performance evaluation using accuracy, precision, recall, F1 score, and AUC demonstrated the superiority of the Transformer-NLP model over traditional machine learning methods. Statistical validation through Friedman and T-tests confirmed the model's robustness and practical significance. Despite promising results, limitations include the dataset's scope, computational complexity, and the need for further research to generalize the model to other types of network attacks. This study indicates significant improvements in detecting complex web application attacks, reducing false positives, and enhancing overall security, making it a viable solution for addressing increasingly sophisticated cybersecurity threats

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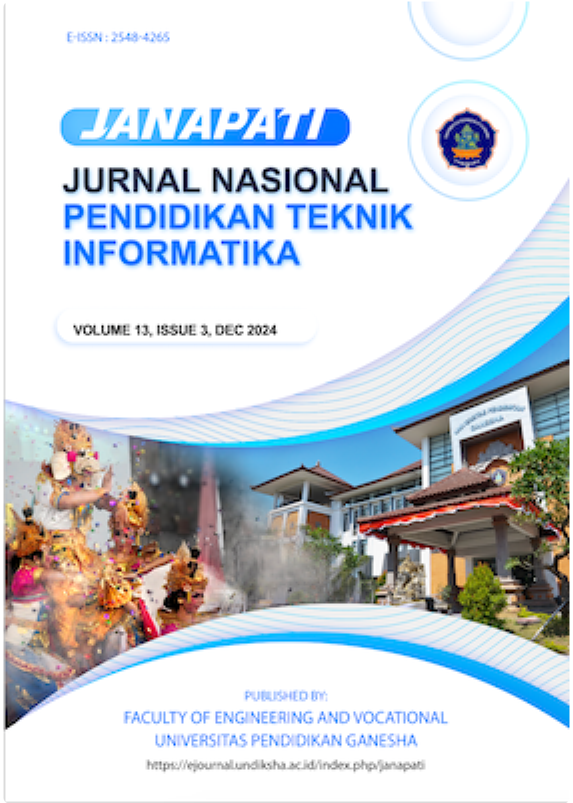
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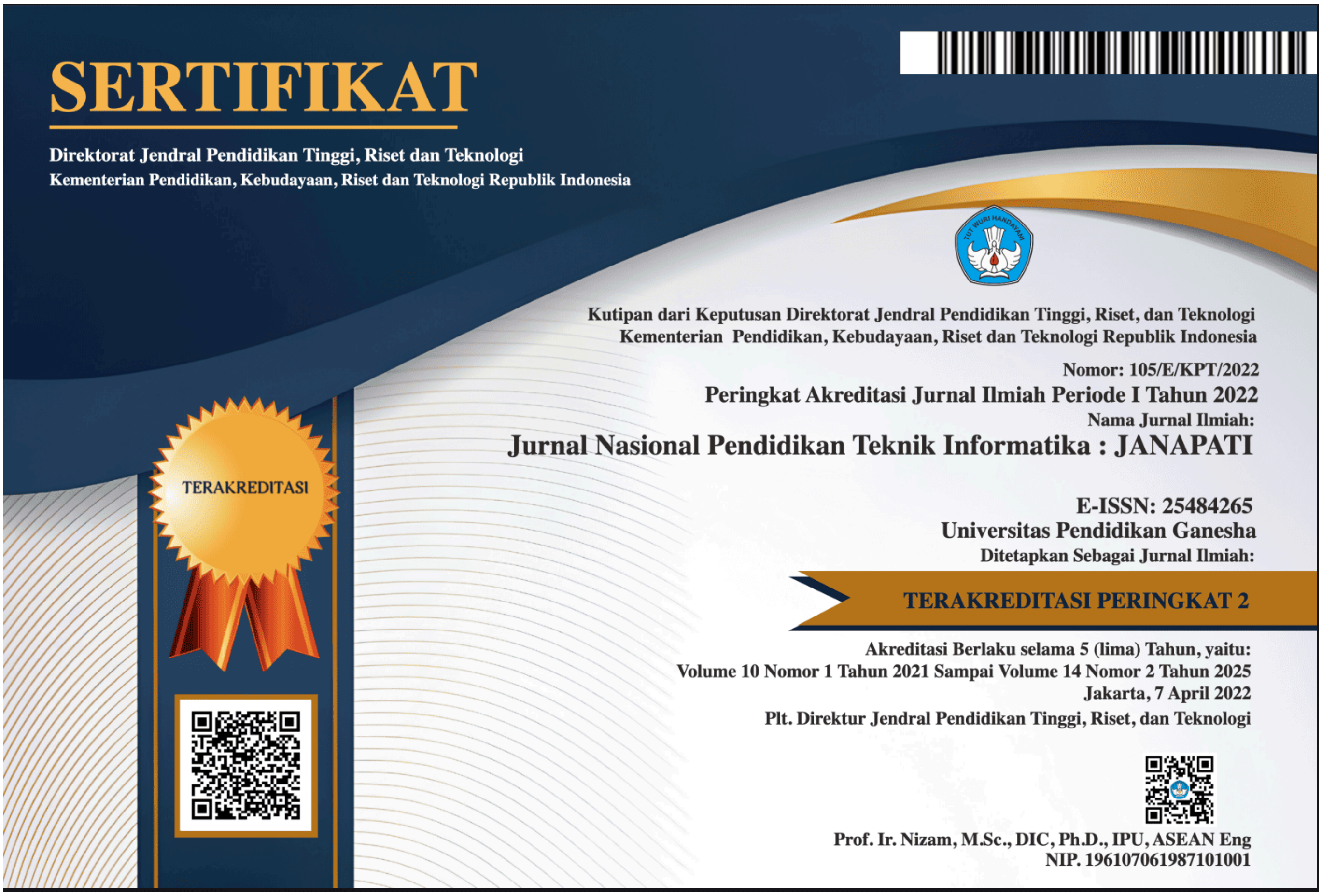

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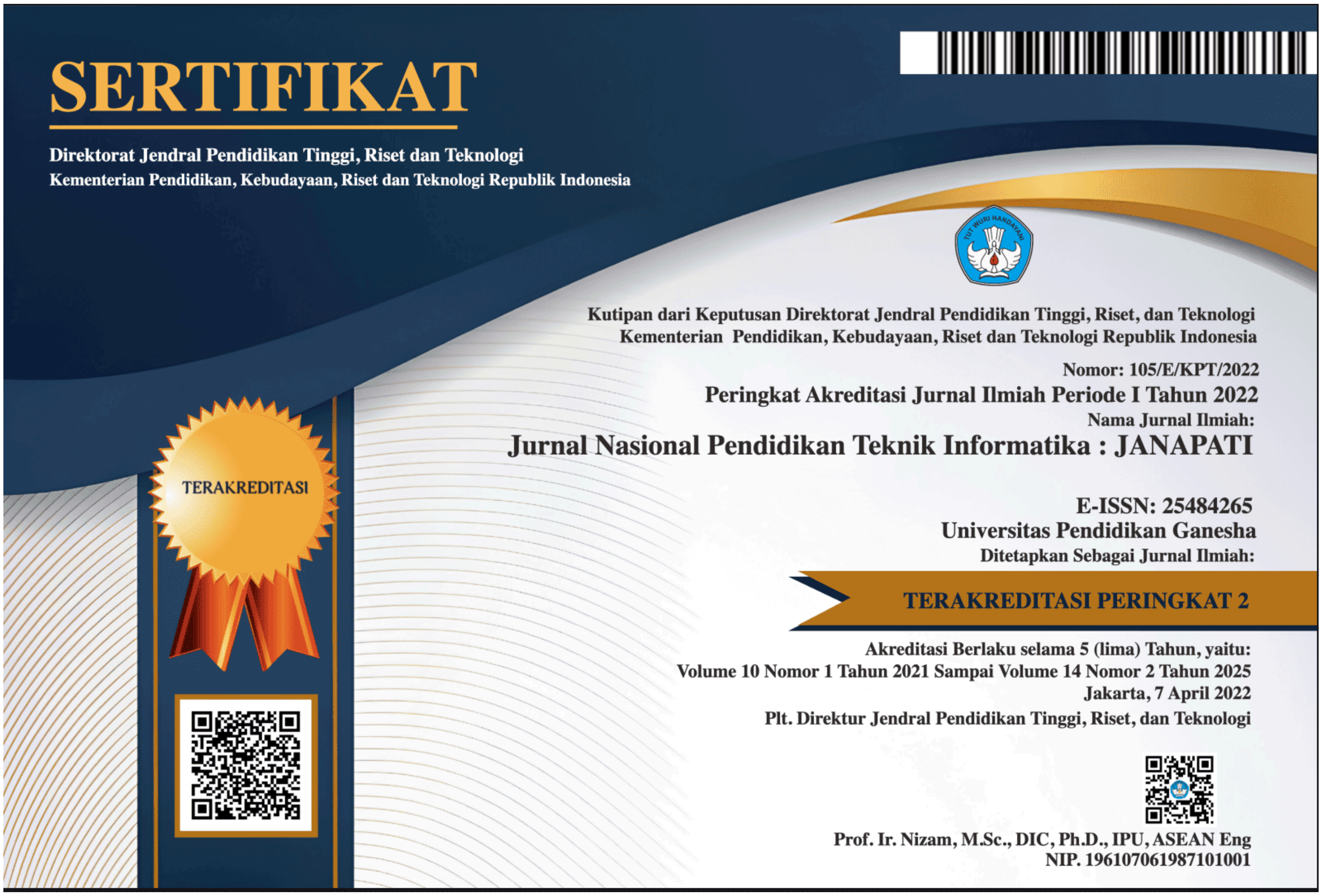

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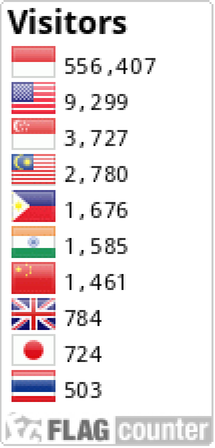

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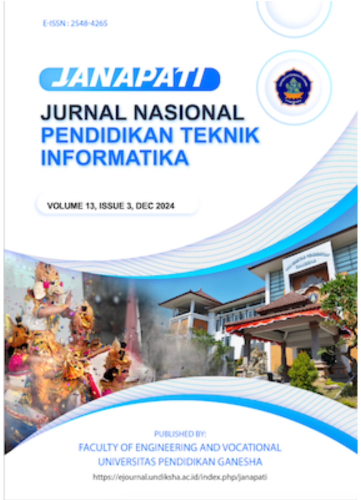
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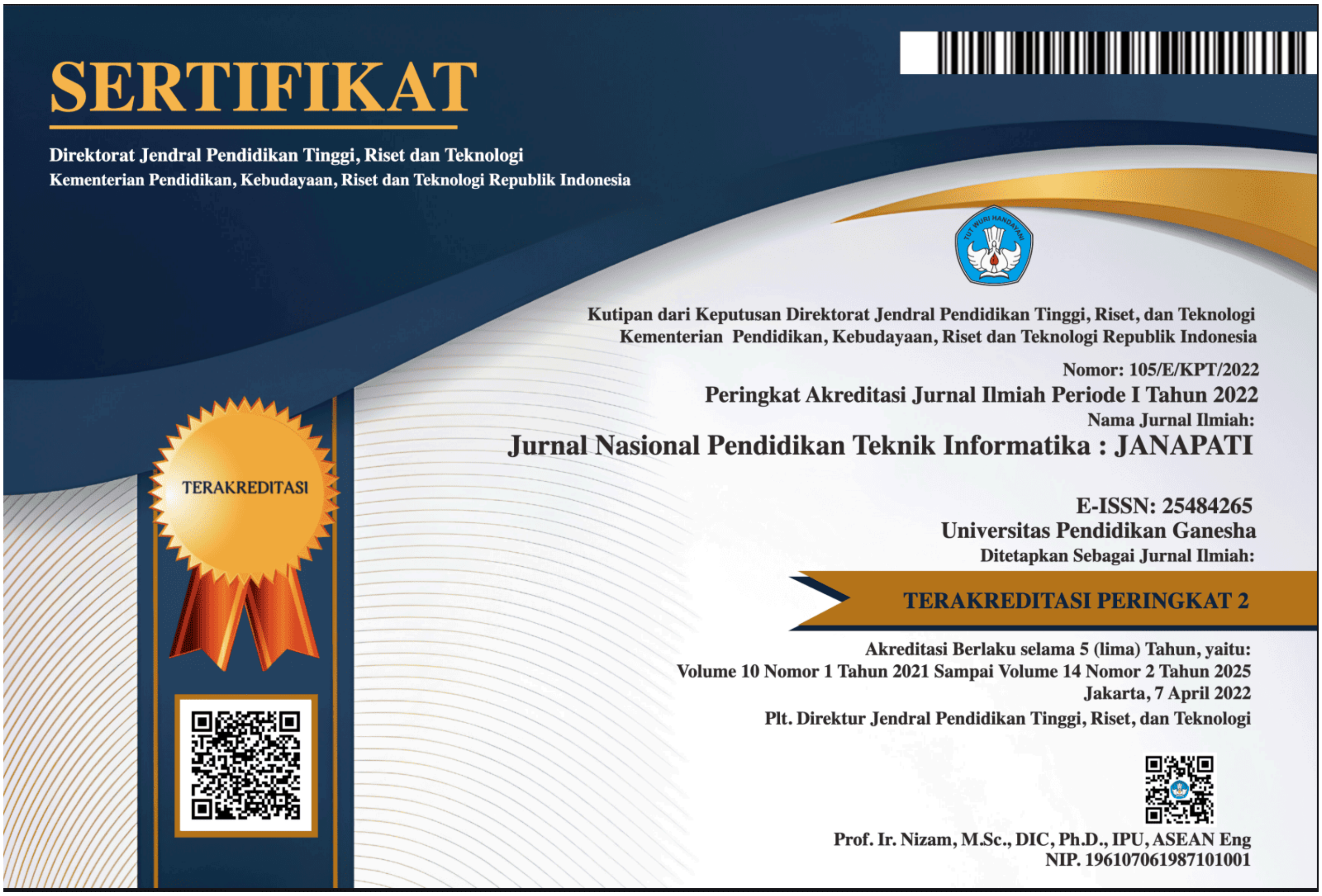

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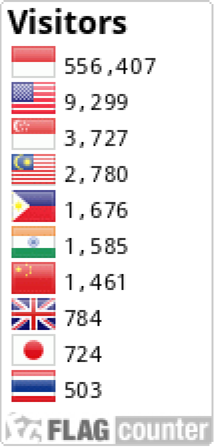

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Wowon Priatna[1], Irwan Sembiring[2], Adi Setiawan[3], Iwan Setyawan[4],
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Abstract

The increasing complexity and frequency of web application attacks demand more advanced detection methods than traditional network intrusion detection systems (NIDS), which rely heavily on predefined signatures and rules, limiting their effectiveness against novel threats. This study proposes a novel approach by integrating Transformer models with Natural Language Processing (NLP) techniques to develop an adaptive and intelligent intrusion detection framework. Leveraging the Transformer's capacity to capture long-term dependencies and NLP's ability to process contextual information, the model effectively addresses the dynamic and diverse nature of web application traffic. Using the CSIC 2010 dataset, this study applied comprehensive preprocessing, including tokenization, stemming, lemmatization, and normalization, followed by text representation techniques such as Word2Vec, BERT, and TF-IDF. The Transformer-NLP architecture significantly improved detection performance, achieving 85% accuracy, 95% precision, 83% recall, 84% F1 score, and an AUC of 0.95. Friedman and t-test validations confirmed the robustness and practical significance of the model. Despite these promising results, challenges related to computational complexity, dataset scope, and generalizability to broader network attacks remain. Future research should focus on expanding the dataset, optimizing the model, and exploring broader cybersecurity applications. This study demonstrates a significant advancement in detecting complex web application attacks, reducing false positives, and improving overall security, offering a viable solution to growing cybersecurity challenges.

Keywords: NLP, Intrusion Detection, Transformer, Web Application Attack, Machine Learning

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INTRODUCTION

The security of web applications has become a paramount concern in the current digital era, especially with the rise of attacks targeting vulnerabilities in web applications[1].As technology evolves and internet usage grows, web applications become more vulnerable to attacks like SQL injection, Cross-Site Scripting (XSS), and Denial of Service (DoS). These attacks compromise data integrity, confidentiality, and service availability, with rising frequency and complexity over time [2].

Web applications are often the first point of entry for attackers, exploiting vulnerabilities like SQL injection and Cross-Site Scripting (XSS) to gain unauthorized access or inject malicious scripts. These vulnerabilities highlight the need for robust detection mechanisms specifically tailored to web applications. Therefore, this study focuses on detecting attacks targeting web applications, recognizing this as a critical aspect of maintaining overall network security[3]. Research on network intrusion detection systems (NIDS) has explored various methodologies to counteract these threats[4]. For instance, Research [5] provides a comprehensive overview of existing detection systems specifically designed to monitor web traffic, comparing the capabilities of systems like AppSensor, PHPIDS, ModSecurity, Shadow Daemon, and AQTRONIX WebKnight. Other studies have focused on input validation techniques to prevent intrusions, such as the approach detailed in Research [6], which emphasizes input validation against web application attacks. Additionally, Research [7] has developed an intrusion detection model to mitigate cyber-attacks, data breaches, and identity theft, aiding in effective risk management.

Traditional approaches to network intrusion detection rely heavily on predefined signatures and rules, which limits their effectiveness in detecting new or unknown variants of attacks[8]. This rigidity necessitates more adaptive solutions. A popular approach to overcoming these limitations involves the use of machine learning (ML) and artificial intelligence (AI) to create more intelligent and flexible intrusion detection systems [9]. Machine learning models, such as Random Forest and Support Vector Machines, have been successfully employed to detect anomalies in network traffic[10]. Some studies have advanced this further by combining ensemble learning with NLP-based methods, as indicated in Research [11], to enhance the detection models' effectiveness. However, even these sophisticated methods face challenges in handling the highly dynamic and diverse data generated by web applications. The complexity of web application traffic stems from frequent updates, varying user inputs, and increasingly sophisticated attack vectors, making it difficult for traditional models to adapt in real time[12]. For example, studies have shown that vulnerabilities such as SQL injection and Cross-Site Scripting (XSS) are among the most common attack types, with SQL injection accounting for approximately 65% of web application attacks in 2022, according to OWASP reports[13]. The evolving nature of these vulnerabilities, along with their high frequency, underscores the critical need for more adaptive detection systems capable of handling the sheer volume and variety of data produced by modern web applications.

For instance, research [14] utilizing traditional ML models demonstrated moderate success in detecting known intrusions, but performance degraded significantly when applied to unknown or zero-day attacks. Moreover, approaches based on signature detection or anomaly detection often suffer from high false positive rates, making them impractical for real-world applications. To address these challenges, this study proposes a novel approach that integrates advanced Transformer models with NLP techniques to better capture the complex patterns and contextual information inherent in web application data[15]. While NLP techniques have been widely adopted, the deep integration of NLP with Transformer architectures for web application intrusion detection is a relatively unexplored area, offering a more nuanced detection of web attacks. This combination allows for the detection of complex[16], evolving web threats that are often missed by traditional machine-learning models.

Recent advancements in deep learning, particularly the development of the Transformer model by Vaswani et al., offer a promising solution[17]. The Transformer's ability to capture long-range dependencies in sequential data and process this information efficiently through an attention-based architecture provides a robust framework for addressing the complexities of web application data. The application of Transformer models in network intrusion detection presents new opportunities for developing more adaptive and sophisticated systems capable of identifying a wide range of web attacks[18]. Research has shown that Transformers are particularly effective in analyzing patterns and anomalies within network data, leading to improved detection rates of complex attacks that are often missed by conventional methods[19].

Unlike previous models that focus on static or homogeneous data sets, the proposed research utilizes both Transformer models and NLP techniques to handle the diverse and ever-evolving nature of web application data. This approach differs significantly from existing studies, which often rely on traditional machine learning models or shallow integration of NLP techniques. Our research leverages the Transformer's ability to handle intricate patterns within the data, providing a significant advancement over existing methods. By combining the strengths of NLP in text representation and the deep learning capabilities of Transformers, this study introduces a unique framework that significantly enhances detection performance, particularly for sophisticated web attacks. While earlier studies [11][20][21] employed NLP for enhancing feature extraction in intrusion detection, this research integrates these methods more deeply within a Transformer-based architecture, representing a novel approach to the field.

The novelty of this study lies in its dual integration of NLP techniques and Transformer models for web application intrusion detection, which has not been fully explored in prior research. This combination not only provides a more nuanced approach to understanding the data but also significantly enhances the model's ability to detect sophisticated web attacks. This research contributes to the field by presenting a novel framework that leverages advanced NLP and deep learning techniques to build more resilient intrusion detection systems, potentially reducing false positives and improving overall security[22]. The findings from this study are expected to offer valuable insights and practical implications for future research in cybersecurity, particularly in applying NLP and deep learning to enhance network security.

METHOD

This study aims to develop and analyze a network intrusion detection model based on Transformer methods and Natural Language Processing (NLP) techniques to enhance the security of web applications.

Dataset

The CSIC 2010 dataset, developed by the Spanish Research National Council, contains 61,065 records with 17 attributes, including both normal and malicious web traffic such as SQL injection, Cross-Site Scripting (XSS), and Path Traversal attacks. This dataset's diversity is crucial for training models to recognize both attack patterns and normal behaviors in web traffic, ensuring a robust evaluation of the model's ability to handle real-world scenarios[17]. The dataset's size is sufficient for training deep learning models like Transformers, which require large and diverse datasets to capture complex relationships and generalize well without overfitting. NLP techniques are essential for analyzing the textual nature of web-based attacks. Many attacks, such as SQL injection and XSS, exploit text-based inputs within HTTP requests, making them difficult to detect using traditional methods. NLP allows for deeper analysis of textual data, such as URL parameters and HTTP headers, enabling the model to identify subtle anomalies. The Transformer architecture excels at capturing long-range dependencies, making it adaptable to both known and evolving attack patterns, which is vital for detecting emerging threats in web applications.

Algorithm Selection: Transformer Architecture

In this study, we selected the Transformer architecture due to its ability to effectively process sequential data and capture long-range dependencies[23], which are critical for analyzing web application traffic. Traditional machine learning models, such as Random Forest and Support Vector Machines (SVM), often struggle with the dynamic and unstructured nature of web-based attacks, particularly when analyzing text-based HTTP requests that can be manipulated through attacks like SQL injection or Cross-Site Scripting (XSS)[24]. These conventional algorithms rely heavily on predefined features, making them less effective in detecting new and evolving attack patterns.

The Transformer model addresses these limitations through a self-attention mechanism that highlights key parts of an input sequence, like HTTP headers and URL parameters. This feature enables it to capture extensive dependencies and complex relationships within data, enhancing its ability to identify intricate patterns beyond the reach of traditional models[25][26].

Moreover, Transformers offer significant computational advantages over recurrent models like LSTMs and GRUs, especially in large-scale datasets[27]. Their ability to process data in parallel allows for more efficient training on large-scale datasets, such as the CSIC 2010 dataset, without sacrificing accuracy. This makes Transformers not only faster but also more scalable for real-world applications that involve large and diverse data.

In addition, the integration of NLP techniques with the Transformer model enhances its ability to extract meaningful features from web traffic data[28]. Techniques such as Word2Vec, BERT, and TF-IDF enable the model to better understand textual data and context[29], facilitating more accurate detection of web application attacks that exploit text-based inputs.

Network Intrusion Detection

Network Intrusion Detection Systems (NIDS) are crucial for identifying and mitigating security threats to web applications. Traditional NIDS relies on signature-based and anomaly-based methods. Signature-based systems are adequate for known threats but struggle to detect new attacks, while anomaly-based systems can identify unknown attacks but often have high false favorable rates[30]. Advances in machine learning (ML) and deep learning (DL) have enhanced NIDS capabilities, with convolutional neural networks (CNN) and recurrent neural networks (RNN) demonstrating improved accuracy[31]. However, these models often fail to capture network logs' temporal and contextual dependencies, which is essential for detecting sophisticated web application attacks. Transformer models and Natural Language Processing (NLP) techniques have been introduced to address this. Transformers excel in capturing long-term dependencies and contextual relationships in sequential data[18], while NLP enables effective preprocessing and representation of network logs[11]. This study develops a more robust NIDS for detecting web application attacks by combining Transformer models and NLP, aiming to reduce false positives and improve detection accuracy.

Transformer

The Transformer is an architectural model that has revolutionized the landscape of natural language processing (NLP) and various other applications. As introduced in "Attention is All You Need," the Transformer relies on the self-attention mechanism to capture relationships between elements in sequential data[17]. The self-attention mechanism allows the model to efficiently consider the entire input context without processing the data sequentially, unlike traditional approaches such as RNNs and LSTM[32]. The core formula in self-attention is shown in equation (1):

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{DK}}\right)\text{V} \qquad (1)$$

The Transformer model consists of multiple encoders and decoders, with each encoder layer comprising a self-attention mechanism and a feed-forward neural network[33]. The encoder generates contextual representations of the input, which are then used by the decoder to produce the output. This approach enables the Transformer to capture long-term dependencies and complex relationships within the data[34].

Transformers have demonstrated their superiority in various NLP tasks, including machine translation, text classification, and language modeling, outperforming previous approaches[17]. Their application in network intrusion detection leverages Transformers and NLP techniques to preprocess network logs and detect attack patterns with high efficiency and improved accuracy. This study will implement the Transformer model to enhance the detection capabilities of web application attacks, utilizing the power of self-attention to capture complex relationships in network data.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and generate human-like text. NLP encompasses sentiment analysis, machine translation, and network log analysis applications. Fundamental NLP techniques include tokenization (breaking text into smaller units), stemming, and lemmatization.

Recent advancements in NLP, such as BERT, use Transformer architecture to capture the bidirectional context in text, significantly improving the performance of NLP tasks. These models have been successfully applied in various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This research leverages NLP techniques to process network logs, converting them into vector representations, and employs Transformer models to detect web application attacks with greater accuracy. Recent advancements in NLP, such as BERT, utilize transformer architecture to capture bidirectional context in text, thereby enhancing the performance of NLP tasks. These models have been successfully applied across various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This study leverages NLP techniques to process network logs, converting them into vector representations, and employs transformer models to more accurately detect web application attacks.

integration of Transformer models with NLP

This study proposes the integration of Transformer models with NLP techniques to detect attacks on web applications through a Network NIDS. The proposed model in this research is illustrated in Figure 1.

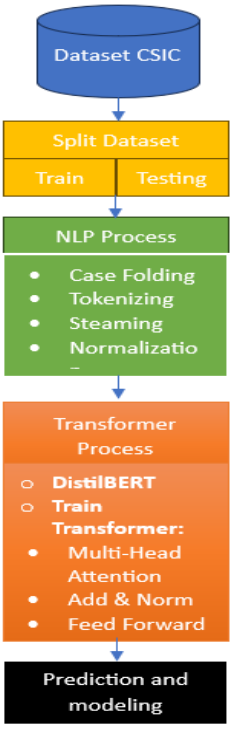

Figure 1. Intrusion Detection Architecture

Based on Figure 1, the steps for intrusion detection are further detailed in Algorithm 1. The initial stage involves initializing parameters for the Transformer and the DistilBERT tokenizer. The NLP preprocessing phase includes case folding, tokenization, stemming, and normalization to ensure that the text data is consistent and formatted adequately for analysis. The DistilBERT tokenizer then converts the preprocessed text into appropriate tokens. The following equations are used in the process: Equation (5) for converting logs, including URLs, into lowercase (case folding). Equation (6) for tokenization. Equation (7) for stemming. Equation (8) for normalization

$$lower\ (T) = map(\lambda\mathfrak{x}: \mathfrak{x} \rightarrow lowercase(\mathfrak{x}) \quad (5)$$

$$Tokend = Tokenize(T, delimiter) \quad (6)$$

$$Stem = StemmingAlgoritm(T) \quad (7)$$

$$text \longrightarrow \text{normalized text} \quad (8)$$

Next, the tokenized data is converted into tensors, enabling processing by the Transformer model. The training phase of the Transformer model involves several critical steps, including Multi-Head Attention to capture various aspects of relationships between words, Add & Norm for normalization and residual addition, and Feed Forward layers for further data transformation. After training, the model's performance is evaluated using metrics such as accuracy, recall, F1 score, and AUC to assess its effectiveness in detecting intrusions.

$$output_{residual} = input + Sublayer(input) (9)$$

$$output_{norm} = \frac{output_{residual-\mu}}{\sigma}.\gamma + \beta \quad (10)$$

$$FFN_1(\mathfrak{x}) = ReLU(W_1x + b_1 \quad (11)$$

```
Algorithm 1: Transformer NLP Integration
Input: Input: Dataset $D$={($xi$,$yi$)}
Output: Final model intrusion detection

1. Initialization:
    • Parameters for the Transformer and DistilBERT tokenizer are initialized.
2. NLP Preprocessing:
    • Case Folding
    • Tokenization
    • Steaming
    • Normalization
3. Tokenization
    • The DistilBERT Tokenizer is used to convert text into appropriate tokens:
4. Conversion to Tensors
    • The tokenized data is converted into tensors that the Transformer model can process
5. Train Transformer
    • The Transformer model is trained with the processed data
        a. Multi-Head Attention: use equation (1)
        b. Add & Norm: Normalization and residual addition. Use equations (9) and (10)
        c. Feed Forward. Use equation (11)
6. Model Evaluation
    • The model has evaluated the use of equations (12), (13, (14), (15), (16).
7. Final Model
    • The final model is returned for intrusion detection
```

Evaluation

The next step in this research is to evaluate the performance of the developed intrusion detection model. The objective of this performance testing is to determine the extent to which the model is suitable for practical use. Several evaluation parameters are utilized, including Accuracy (Ac), Recall (Re), Precision (Pr), F1 Score (F1), and Area Under the Curve (AUC)[21][35]. These parameters provide a comprehensive assessment of the model's effectiveness and reliability in classification. The formulas for each parameter are given in equations (12), (13), (14), (15), and (16)[18]. Table 1 illustrates the prediction of target labels. The next step involves reporting the model's performance using the Receiver Operating Characteristic (ROC) curve to assess the intrusion detection model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \quad (12)$$

$$Precision = \frac{TP}{TP+TF} \quad (13)$$

$$Recall = \frac{TP}{TP+TN} \quad (14)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ recall}{precision+recall} \quad (15)$$

$$AUC = \int_0^1 TPR(FPR)d\ (FPR) \quad (16)$$

Table1. Confusion Matrix

	True Normal	**True Anomalous**
Predict Normal	TP	FP
Predict Anomalous	TN	TN

Statistical Validation

In this study, statistical validation is performed using the Friedman Test and the

Paired T-test. The Friedman Test, a non-parametric test, is used to compare the performance of multiple classification models on the same dataset[36]. This test examines the null hypothesis that there is no significant difference in the performance of these models. If the Friedman Test results indicate a significant difference, further analysis is conducted using the Paired T-test to identify which pairs of models have significantly different performances[37]. The combination of these two tests provides comprehensive validation, ensuring that the developed model is not only statistically superior but also has practical significance in its application[34].

RESULT AND DISCUSSION

The proposed Transformer-NLP method demonstrates that the Transformer model excels in capturing contextual relationships in network logs, enhancing its ability to detect web application attacks. This success can be attributed to the Transformer's self-attention mechanism, which enables the model to identify intricate attack patterns by focusing on relevant sections of the input data, making it highly effective in distinguishing between normal and anomalous traffic.

Data Processing

At this stage, data cleaning was performed, where three records with missing data were removed, reducing the dataset from 61,065 to 61,062 records. The following process involved reducing the number of variables from 17 to 2, which were relevant to the context of the research. Table 1 shows the dataset after data preprocessing. Table 2 defines the target or label for classification, where 0 represents normal, and 1 represents anomalous.

Table 2. Pre-processing Result Dataset

	URL	Label
1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	0
2	http://localhost:8080/ ?OpenServer HTTP/1.1	0
61062	http://localhost:8080/tienda1/miembros.Inc HTTP/1.1	1

Text Representation Formation

In this stage, processing is conducted using NLP techniques, including tokenizing, case folding, stemming, and stop word normalization. First, tokenizing: The results of tokenization demonstrate how URLs are broken down into smaller parts that the transformer model can process. This process involves adding unique tokens, handling special characters and symbols, and sub-word tokenization to address words not present in the model's overall vocabulary. Table 3 provides a clear overview of how raw data is transformed into a format suitable for NLP modelling.

Table 3. Tokenization Results

Input Process	Output Process
http://localhost:8080/ tienda1 /publico/vaciar.jsp? B2=Vaciar+carrito HTTP/1.1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 = Vac iar + carr ito HTTP / 1 . 1 </s>

Next, all characters in the URL are converted to lowercase before tokenization using case folding. Table 4 shows the results of tokenization, demonstrating that all elements in the URL have been converted to lowercase and broken down into smaller tokens. This helps ensure consistency in text processing and makes the model more robust against variations in capitalization.

Table 4. Case Folding Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 = Vac iar + carr ito HTTP / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Table 5. Stemming Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The steaming process does not significantly alter the text in this case because most tokens are part of URLs or symbols. However, words like "vaciar" and "carr" will be processed if there are suffixes that can be removed. Table 5 presents the final results, showing that tokenization and stemming have been applied, although minimal changes occurred due to the specific characteristics of the input text (URLs and symbols).

The stop word removal stage is omitted since most tokens are part of URLs. The normalization process at this stage includes converting all text to lowercase, removing punctuation, and eliminating numbers. Lowercasing ensures consistency, allowing 'HTTP' and 'http' to be treated identically. Punctuation marks, such as periods, slashes, and question marks, are removed to streamline the text. Table 6 presents the results of applying these normalization steps to the sample input.

Table 6. Normalization Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Model Implementation

In this study, the implementation of the Transformer model with the integration of Natural Language Processing (NLP) for network intrusion detection is conducted through several key stages. The first stage is data processing, which includes normalization, batch processing, and splitting the data into training and testing sets with ratios of 70/30, 80/20, and 90/10. In the NLP processing, steps such as case folding, text normalization, tokenization, and stemming are performed to ensure the text is in a consistent format. Tokenization uses the DistilBERT Tokenizer to convert the text into tokens that the Transformer model can process.

As shown in Figure 1, the architecture for network intrusion detection with Transformer and NLP integration is implemented according to Algorithm 1. In the model training stage, DistilBERT, initialized with default parameters, is used to handle the Multi-Head Attention, Add & Norm, and Feed Forward layers. The model is trained using the Adam optimizer with a learning rate of 2e-5 and the Cross-Entropy loss function. Training is conducted over three epochs with a batch size of 8. Model evaluation is performed by measuring metrics such as accuracy, recall, F1 score, and ROC-AUC to ensure the model's performance in detecting network intrusion categories classified as "Normal" and "Anomalous." Evaluation results indicate that the integration of the Transformer model and NLP is effective in detecting web application attacks and significantly contributes to the improvement of the network intrusion detection system's accuracy. The parameters of the Transformer model integrated with NLP are shown in Table 7.

Table 7. Parameter Model

Parameter	Value
Input Shape	Input_dim
NLP Pre-preprocessing	Case Folding, Normalization, Tokenization, Stemming
Tokenization	DistilBERTTokenizer
Multi-Head Attention	Num_heads=8, dim_model=512
Add & Norm	Layer Normalization
Feed Forward	Dense (2048, Activation='ReLU'
Linear Layer	Dense (256, activation='softmax'
Softmax Layer	Dense(num_classes, activation='softmax'
Optimizer	AdamW (learning_rate=2e-5)
Loss Function	Cross-Entropy Loss
Training Parameter	Epoch=3, Batch Size=8
Evaluation Matrix	Accuracy, Recall, F1 Score, AUC

Evaluation

The implemented model is then evaluated to test its performance. Compared to traditional algorithms such as DNN, Random Forest, and SVM, the Transformer-NLP model showed marked improvements in accuracy and AUC. Previous studies using conventional methods often struggled to maintain high detection rates across varied datasets, while the Transformer model's adaptive architecture proved effective in handling diverse attack types, as evidenced by its consistently higher AUC scores across multiple data splits. The evaluation uses equations (12), (14), (15), and (16). The results are shown in Tables 8, 9, and 10. Subsequently, the model's performance is tested using the ROC curves, which are displayed in Figures 2, 3, and 4.

Table 8. Evaluation Using 80-20 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.76	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.92
DT	0.82	0.93	0.80	0.88
SVM	0.80	0.89	0.72	0.82
KNN	0.81	0.94	0.80	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.63	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 9. Evaluation Using 70-30 Training Split

Algorithm	**A_c**	**R_e**	**F_1**	**AUC**
DNN	0.79	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.88
DT	0.82	0.93	0.80	0.88
SVM	0.73	0.89	0.72	0.82
KNN	0.81	0.94	0.72	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.64	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 10. Evaluation Using 90-10 Training Split

Algorithm	**A_c**	**R_e**	**F_1**	**AUC**
DNN	0.77	0.52	0.65	0.85
RF	0.83	0.99	0.83	0.93
DT	0.83	0.94	0.82	0.90
SVM	0.72	0.86	0.72	0.84
KNN	0.80	0.87	0.78	0.89
XGBoost	0.83	0.94	0.82	0.92
NB	0.63	0.30	0.40	0.85
Trans+NLP	0.85	0.95	0.84	0.94

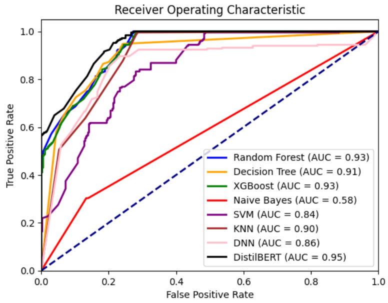

Figure 2. ROC for 90-10 Model

Statical Validation

To test the reliability of the built model, we conducted evaluations using the Friedman test and t-test to compare its performance with other models[36]. We designated the proposed model as the control method in this experiment, and the significance level α for the statistical tests was set at 0.05. Generally, a smaller p-value indicates a significant difference between comparison methods. The results of the Friedman test and t-test are shown in Table 11.

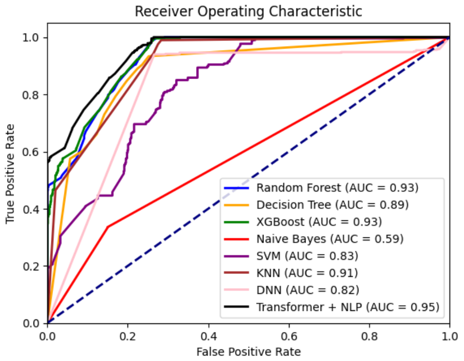

Figure 3. ROC for 80-20 Model

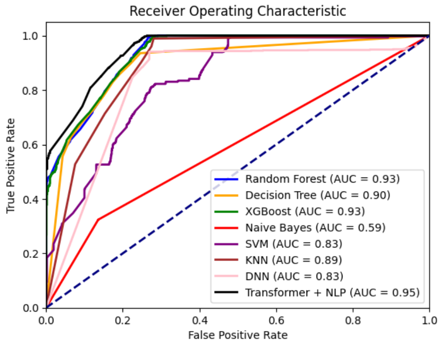

Figure 4. ROC for the 70-30 Model

Parameter Sensivitas

In this section, we examine the impact of the hyperparameter, denoted by λ, on the proposed detection model. This analysis aims to understand how variations in λ influence the model's performance and effectiveness. The study involves adjusting the λ values and observing changes in key performance metrics, such as accuracy, recall, F1 score, and ROC-AUC. The results of this hyperparameter tuning are presented in Table 12, illustrating the relationship between different λ values and the corresponding performance metrics. This detailed evaluation helps in identifying the optimal λ setting for achieving the best detection results.

Table 11. Friedman Test and T-test Results

	DNN	**DT**	**XB**	**NB**	**SVM**	**KNN**	**RF**
Friedman	0.0009	0.005	0.019	2.159	0.0001	0.006	0.04
T-Test	8.705	5.35	3.765	40.785	13.19	5.244	2.99

.Table 12. Impact of Hyperparameter λ on Model Performance

Λ	**A_c**	**R_c**	**F_1**	**Auc**
1e-05	0.856	0.944	0.843	0.948
2e-05	0.852	0.944	0.840	0.950
3e-05	0.851	0.906	0.841	0.946
5e-05	0.849	0.952	0.838	0.946

Based on Table 12, although the AUC value remains the same (0.95) for several learning rate values, other metrics such as Accuracy, Recall, and F1 Score vary. The model with a learning rate of 2e-05 shows the highest AUC of 0.9505, indicating slightly better performance compared to other learning rates. Models with learning rates of 1e-05 and 3e-05 exhibit nearly the same AUC values (around 0.9490) but with variations in Accuracy and Recall. The ROC curve, illustrating sensitivity, is shown in Figure 5.

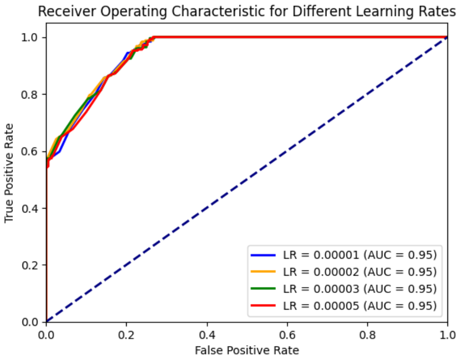

Figure 5. ROC Curve for Sensitivity Analysis of Parameters

Discussion

This study demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. The use of the Transformer model, with its self-attention mechanism, allows for capturing complex dependencies in sequential data, such as HTTP requests, which is crucial for detecting intricate attack patterns within dynamic and diverse web traffic. The CSIC 2010 dataset used in this study was processed through several pre-processing steps, including tokenization, stemming, lemmatization, and normalization, to ensure data consistency. Text representation techniques such as Word2Vec, BERT, and TF-IDF were employed to enable the Transformer model to effectively capture contextual relationships in network log data.

The model's performance evaluation demonstrated superior results compared to traditional algorithms like Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The Transformer-NLP model achieved higher accuracy (up to 85%), recall (95%), F1 score (83%), and AUC (0.95) across training/testing splits of 80/20, 70/30, and 90/10. This performance is especially significant when compared to traditional models, which showed lower AUC values, indicating that the Transformer-NLP approach provides a more robust framework for intrusion detection across various scenarios, with the best AUC value of 0.9505 at a learning rate of 2e-05, demonstrating its ability to adapt to different training scenarios. The ROC curve further illustrated the model's superior capability in distinguishing between normal and anomalous traffic, proving more reliable than the other models tested.

Statistical validation using the Friedman test and t-test confirmed the reliability and practical significance of the proposed model. Hyperparameter sensitivity analysis indicated that variations in the λ value impacted the model's performance, with a learning rate of 2e-05 providing the optimal results. These findings suggest that the proposed Transformer-NLP model is not only effective in improving detection accuracy but also offers a robust framework for reducing false positives, enhancing the overall security posture of web applications in response to increasingly sophisticated cyber threats.

Additionally, the model effectively detects complex attack patterns, especially in text-based inputs like SQL injection and XSS, enhancing web application security, and preventing unauthorized access and malicious data manipulation. The Transformer-NLP model’s unique integration of NLP for preprocessing and the self-attention mechanism significantly reduces false positive rates. This reduction enhances both efficiency and reliability in real-world scenarios, as it minimizes unnecessary alerts and focuses security resources on genuine threats. By improving precision and recall, this model presents a more reliable solution for continuous, real-time web application monitoring, minimizing unnecessary alerts and enabling security teams to focus on genuine threats. This improvement in detection accuracy directly bolsters the resilience of web applications against evolving attack methods, helping to maintain data integrity, confidentiality, and availability.

However, this study has certain limitations. First, the CSIC 2010 dataset, while useful for evaluating web application security, may not fully capture the range of modern web application attack techniques, potentially limiting the model's applicability to newer or more varied threats. Second, the computational demands of both Transformer models and NLP preprocessing may pose challenges for practical deployment, particularly in environments with constrained resources. Additionally, while this study focused on optimizing performance metrics such as accuracy and AUC, it did not extensively address potential overfitting, which can be a concern with complex models trained on relatively limited datasets. Future research should explore the use of larger, more diverse datasets and further refine the model to balance computational efficiency with detection capability.

CONCLUSION

This study demonstrates that integrating the Transformer model with NLP techniques significantly improves NIDS performance for web applications by capturing complex contextual relationships in network log data. The Transformer-NLP model outperformed traditional algorithms, including DNN, RF, DT, SVM, KNN, XGBoost, and NB, across key metrics (accuracy, recall, F1 score, and AUC), addressing a crucial gap in current NIDS methods. Statistical validation using the Friedman and t-tests further supports the model's robustness and practical effectiveness, especially in handling the dynamic nature of web traffic.

However, limitations remain. The CSIC 2010 dataset may not fully reflect modern web application threats, which could affect generalizability. Additionally, the model’s high computational demands pose challenges for real-world deployment. This study also did not deeply explore overfitting, which could impact performance given the dataset size. Future work should examine strategies such as regularization and cross-validation to enhance model robustness, along with architectural optimizations to improve computational efficiency for practical deployment in constrained environments.

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Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection

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Abstract

The increasing frequency and complexity of web application attacks necessitate more advanced detection methods. This research explores integrating Transformer models and Natural Language Processing (NLP) techniques to enhance network intrusion detection systems (NIDS). Traditional NIDS often rely on predefined signatures and rules, limiting their effectiveness against new attacks. By leveraging the Transformer's ability to capture long-term dependencies and the contextual richness of NLP, this study aims to develop a more adaptive and intelligent intrusion detection framework. Utilizing the CSIC 2010 dataset, comprehensive preprocessing steps such as tokenization, stemming, lemmatization, and normalization were applied. Techniques like Word2Vec, BERT, and TF-IDF were used for text representation, followed by the application of the Transformer architecture. Performance evaluation using accuracy, precision, recall, F1 score, and AUC demonstrated the superiority of the Transformer-NLP model over traditional machine learning methods. Statistical validation through Friedman and T-tests confirmed the model's robustness and practical significance. Despite promising results, limitations include the dataset's scope, computational complexity, and the need for further research to generalize the model to other types of network attacks. This study indicates significant improvements in detecting complex web application attacks, reducing false positives, and enhancing overall security, making it a viable solution for addressing increasingly sophisticated cybersecurity threats.

Keywords: NLP, Intrusion Detection, Transformer, Web Application Attack, Machine Learning

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INTRODUCTION

The security of web applications has become a paramount concern in the current digital era, especially with the rise of attacks targeting vulnerabilities in web applications[1]. As technology advances and the number of internet users increases, web applications are increasingly susceptible to attacks such as SQL injection, Cross-Site Scripting (XSS), and Denial of Service (DoS) attacks. Previous research indicates that attacks on web applications continue to escalate in frequency and complexity, threatening data and web services' integrity, confidentiality, and availability[2].

Research [3] provides a comprehensive overview of existing detection systems specifically designed to monitor web traffic by comparing their features with five existing detection systems: AppSensor, PHPIDS, ModSecurity, Shadow Daemon, and AQTRONIX WebKnight. Research [4] focuses on input validation against web application attacks to prevent intrusions into the web network. Meanwhile, research [5] develops an intrusion system model to avoid cyber-attacks, data breaches, and identity theft, which can aid in risk management. Traditional approaches to network intrusion detection often rely on predefined signatures and rules, making them less effective in detecting new or unknown variants of attacks[6]. One increasingly popular solution is the application of machine learning and artificial intelligence to detect intrusions more adaptively and intelligently [7]. Machine learning-based models, such as Random Forest and Support Vector Machines, have been employed to detect anomalies in network traffic [8]. Some studies utilize machine learning and deep learning for network intrusion detection, including[9]. which combines ensemble learning with NLP-based methods to enhance detection models. However, these approaches have limitations in handling highly dynamic and diverse data in web applications.

The Transformer, introduced by Vaswani in the context of natural language processing, has demonstrated exceptional performance across various NLP tasks due to its ability to capture long-range dependencies in sequential data and process them efficiently with an attention-based architecture[10]. The application of Transformer models in network intrusion detection opens new opportunities to develop more adaptive and sophisticated systems for identifying web attacks[11]. Recent studies indicate that Transformers can be used to analyze patterns and anomalies in network data with promising results, enhancing the detection of attacks that are difficult to identify using conventional methods[12].

The use of Natural Language Processing (NLP) in the context of intrusion detection also offers an innovative approach to handling complex text data in network logs[13][14]. NLP techniques enable more prosperous and contextual feature extraction from log data, enhancing the model's ability to recognize attack patterns. Research indicates that NLP techniques and text-processing algorithms can enrich intrusion detection models with more accurate and meaningful data representations[9]. enhancing the model's ability to recognize attack patterns. Research indicates that NLP techniques and text-processing algorithms can enrich intrusion detection models with more accurate and meaningful data representations[15]. This study aims to combine the Transformer model with NLP techniques for web application intrusion detection, which is expected to provide a more effective solution in addressing increasingly sophisticated cybersecurity threats. This integration represents a novel approach to building intrusion detection systems by leveraging Transformer models with NLP advancements.

METHOD

This study aims to develop and analyze a network intrusion detection model based on Transformer methods and Natural Language Processing (NLP) techniques to enhance the security of web applications. The design of this research is illustrated in Figure 1.

Dataset

The CSIC 2010 dataset, developed by the Spanish Research National Council (Consejo Superior de Investigaciones Científicas - CSIC), is designed for web application intrusion detection and network security research. On Kaggle, this dataset comprises 61,065 records and 17 variables/attributes [10].

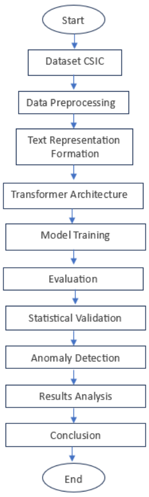

Figure 1. Research Design

Network Intrusion Detection

Network Intrusion Detection Systems (NIDS) are crucial for identifying and mitigating security threats to web applications. Traditional NIDS relies on signature-based and anomaly-based methods. Signature-based systems are adequate for known threats but struggle to detect new attacks, while anomaly-based systems can identify unknown attacks but often have high false favorable rates[16]. Advances in machine learning (ML) and deep learning (DL) have enhanced NIDS capabilities, with convolutional neural networks (CNN) and recurrent neural networks (RNN) demonstrating improved accuracy[17]. However, these models often fail to capture network logs' temporal and contextual dependencies, which is essential for detecting sophisticated web application attacks. Transformer models and Natural Language Processing (NLP) techniques have been introduced to address this. Transformers excel in capturing long-term dependencies and contextual relationships in sequential data[18], while NLP enables effective preprocessing and representation of network logs[9]. This study develops a more robust NIDS for detecting web application attacks by combining Transformer models and NLP, aiming to reduce false positives and improve detection accuracy.

Transformer

The Transformer is an architectural model that has revolutionized the landscape of natural language processing (NLP) and various other applications. As introduced in "Attention is All You Need," the Transformer relies on the self-attention mechanism to capture relationships between elements in sequential data[10]. The self-attention mechanism allows the model to efficiently consider the entire input context without processing the data sequentially, unlike traditional approaches such as RNNs and LSTM[18]. The core formula in self-attention is shown in equation (1):

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\,(\frac{QK^T}{\sqrt{DK}})\mathrm{V} \qquad (1)$$

The Transformer model consists of multiple encoders and decoders, with each encoder layer comprising a self-attention mechanism and a feed-forward neural network[19]. The encoder generates contextual representations of the input, which are then used by the decoder to produce the output. This approach enables the Transformer to capture long-term dependencies and complex relationships within the data[20].

Transformers have demonstrated their superiority in various NLP tasks, including machine translation, text classification, and language modeling, outperforming previous approaches[10]. Their application in network intrusion detection leverages Transformers and NLP techniques to preprocess network logs and detect attack patterns with high efficiency and improved accuracy. This study will implement the Transformer model to enhance the detection capabilities of web application attacks, utilizing the power of self-attention to capture complex relationships in network data.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and generate human-like text. NLP encompasses sentiment analysis, machine translation, and network log analysis applications. Fundamental NLP techniques include tokenization (breaking text into smaller units), stemming, and lemmatization.

Recent advancements in NLP, such as BERT, use Transformer architecture to capture the bidirectional context in text, significantly improving the performance of NLP tasks. These models have been successfully applied in various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This research leverages NLP techniques to process network logs, converting them into vector representations, and employs Transformer models to detect web application attacks with greater accuracy.Kemajuan terbaru dalam NLP, seperti BERT, menggunakan arsitektur transformer untuk menangkap konteks dari kedua arah dalam teks, meningkatkan kinerja tugas-tugas NLP. Model-model ini telah berhasil diterapkan dalam berbagai domain, termasuk keamanan siber, untuk memproses dan menganalisis log jaringan guna deteksi anomali. Penelitian ini memanfaatkan teknik NLP untuk memproses log jaringan, mengonversinya menjadi representasi vektor, dan menggunakan model transformer untuk mendeteksi serangan aplikasi web dengan lebih akurat.

integration of Transformer models with NLP

This study proposes the integration of Transformer models with NLP techniques to detect attacks on web applications through a Network NIDS. The proposed model in this research is illustrated in Figure 2.

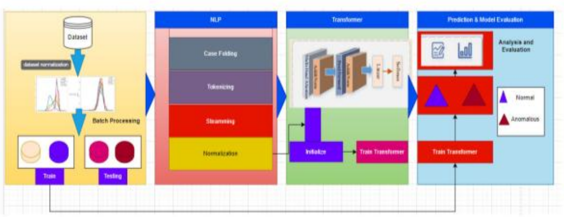

Figure 2. Arsitektur Instrusion Detection

Based on Figure 2, the steps for intrusion detection are further detailed in Algorithm 1. The initial stage involves initializing parameters for the Transformer and the DistilBERT tokenizer. The NLP preprocessing phase includes case folding, tokenization, stemming, and normalization to ensure that the text data is consistent and formatted adequately for analysis. The DistilBERT tokenizer then converts the preprocessed text into appropriate tokens. The following equations are used in the process: Equation (5) for converting logs, including URLs, into lowercase (case folding). Equation (6) for tokenization. Equation (7) for stemming. Equation (8) for normalization

$$lower\ (T) = map(\lambda\mathfrak{x}\colon \mathfrak{x} \rightarrow lowercase(\mathfrak{x})) \qquad (5)$$

$$Tokend = Tokenize(T, delimiter) \qquad (6)$$

$$Stem = StemmingAlgoritm(T) \qquad (7)$$

$$text\ \longrightarrow \text{normalized text} \qquad (8)$$

Next, the tokenized data is converted into tensors, enabling processing by the Transformer model. The training phase of the Transformer model involves several critical steps, including Multi-Head Attention to capture various aspects of relationships between words, Add & Norm for normalization and residual addition, and Feed Forward layers for further data transformation. After training, the model's performance is evaluated using metrics such as accuracy, recall, F1 score, and AUC to assess its effectiveness in detecting intrusions.

$$output_{residual} = input + Sublayer(input) \quad (9)$$

$$output_{norm} = \frac{output_{residual} - \mu}{\sigma} . \gamma + \beta \quad (10)$$

$$FFN_1(x) = ReLU(W_1 x + b_1 \quad (11)$$

Algorithm 1: Transformer NLP Integration

```
Input: Input: Dataset $D$={($xi$,$yi$)}
Output: Final model intrusion detection

1. Initialization:
     • Parameters for the Transformer and DistilBERT tokenizer are initialized.
2. NLP Preprocessing:
     • Case Folding
     • Tokenization
     • Steaming
     • Normalization
3. Tokenization
     • The DistilBERT Tokenizer is used to convert text into appropriate tokens:
4. Conversion to Tensors
     • The tokenized data is converted into tensors that the Transformer model can process
5. Train Transformer
     • The Transformer model is trained with the processed data
         a. Multi-Head Attention: use equation (1)
         b. Add & Norm: Normalization and residual addition. Use equations (9) and (10)
         c. Feed Forward. Use equation (11)
6. Model Evaluation
     • The model has evaluated the use of equations (12), (13, (14), (15), (16).
7. Final Model
     • The final model is returned for intrusion detection
```

Evaluation

The next step in this research is to evaluate the performance of the developed intrusion detection model. The objective of this performance testing is to determine the extent to which the model is suitable for practical use. Several evaluation parameters are utilized, including Accuracy (Ac), Recall (Re), Precision (Pr), F1 Score (F1), and Area Under the Curve (AUC)[21]. These parameters provide a comprehensive assessment of the model's effectiveness and reliability in classification. The formulas for each parameter are given in equations (12), (13), (14), (15), and (16)[11]. Table 1 illustrates the prediction of target labels. The next step involves reporting the model's performance using the Receiver Operating Characteristic (ROC) curve to assess the intrusion detection model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \quad (12)$$

$$Precision = \frac{TP}{TP+TF} \quad (13)$$

$$Recall = \frac{TP}{TP+TN} \quad (14)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ recall}{precision+recall} \quad (15)$$

$$AUC = \int_0^1 TPR(FPR)d\ (FPR) \quad (16)$$

Table1. Confusion Matrix

	True Normal	True Anomalous
Predict Normal	TP	FP
Predict Anomalous	TN	TN

Statistical Validation

In this study, statistical validation is performed using the Friedman Test and the Paired T-test. The Friedman Test, a non-parametric test, is used to compare the performance of multiple classification models on the same dataset[22]. This test examines the null hypothesis that there is no significant difference in the performance of these models. If the Friedman Test results indicate a significant difference, further analysis is conducted using the Paired T-test to identify which pairs of models have significantly different performances. The combination of these two tests provides comprehensive validation, ensuring that the developed model is not only statistically superior but also has practical significance in its application[20].

RESULT AND DISCUSSION

The application of the proposed Transformer-NLP method demonstrates that the Transformer model effectively captures contextual relationships in network logs to detect web application attacks through intrusion detection.

Data Processing

At this stage, data cleaning was performed, where three records with missing data were removed, reducing the dataset from 61,065 to 61,062 records. The following process involved reducing the number of variables from 17 to 2, which were relevant to the context of the research. Table 1 shows the dataset after data preprocessing. Table 3 defines the target or label for classification, where 0 represents normal, and 1 represents anomalous.

Table 3. Pre-processing Result Dataset

	URL	Label
1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	0
2	http://localhost:8080/ ?OpenServer HTTP/1.1	0
61062	http://localhost:8080/tienda1/miembros.Inc HTTP/1.1	1

Pembentukan Representasi Teks

In this stage, processing is conducted using NLP techniques, including tokenizing, case folding, stemming, and stop word normalization. First, tokenizing: The results of tokenization demonstrate how URLs are broken down into smaller parts that the transformer model can process. This process involves adding unique tokens, handling special characters and symbols, and sub-word tokenization to address words not present in the model's overall vocabulary. Table 4 provides a clear overview of how raw data is transformed into a format suitable for NLP modelling.

Table 4. Tokenization Results

Input	Proses
http://localhost:8080/tienda1/publico/vaciar.jsp?B2=Vaciar+carrito HTTP/1.1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 = Vac iar + carr ito HTTP / 1 . 1 </s>

Next, all characters in the URL are converted to lowercase before tokenization using case folding. Table 5 shows the results of tokenization, demonstrating that all elements in the URL have been converted to lowercase and broken down into smaller tokens. This helps ensure consistency in text processing and makes the model more robust against variations in capitalization.

Table 5. Case Folding Results

Input Proses	Output Proses
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 = Vac iar + carr ito HTTP / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The steaming process does not significantly alter the text in this case because most tokens are part of URLs or symbols. However, words like "vaciar" and "carr" will be processed if there are suffixes that can be removed. Table 6 presents the final results, showing that tokenization and stemming have been applied, although minimal changes occurred due to the specific characteristics of the input text (URLs and symbols).

Table 6. Stemming Results

Input Proses	Output Proses
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The Stop Word stage is not performed because most tokens are part of URLs. Normalization at this stage involves processing the text, including converting it to lowercase, removing punctuation, and removing numbers. Converting to Lowercase: All letters are converted to lowercase to ensure consistency, so "HTTP" and "http" are treated the same. Removing Punctuation: All punctuation marks, such as periods, slashes, and question marks, are removed from the text.

Table 7. Normalization Results

Input Proses	Output Proses
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Model Implementation

In this study, the implementation of the Transformer model with the integration of Natural Language Processing (NLP) for network intrusion detection is conducted through several key stages. The first stage is data processing, which includes normalization, batch processing, and splitting the data into training and testing sets with ratios of 70/30, 80/20, and 90/10. In the NLP processing, steps such as case folding, text normalization, tokenization, and stemming are performed to ensure the text is in a consistent format. Tokenization uses the DistilBERT Tokenizer to convert the text into tokens that the Transformer model can process.

As shown in Figure 2, the architecture for network intrusion detection with Transformer and NLP integration is implemented according to Algorithm 1. In the model training stage, DistilBERT, initialized with default parameters, is used to handle the Multi-Head Attention, Add & Norm, and Feed Forward layers. The model is trained using the Adam optimizer with a learning rate of 2e-5 and the Cross-Entropy loss function. Training is conducted over three epochs with a batch size of 8. Model evaluation is performed by measuring metrics such as accuracy, recall, F1 score, and ROC-AUC to ensure the model's performance in detecting network intrusion categories classified as "Normal" and "Anomalous." Evaluation results indicate that the integration of the Transformer model and NLP is effective in detecting web application attacks and significantly contributes to the improvement of the network intrusion detection system's accuracy. The parameters of the Transformer model integrated with NLP are shown in Table 8.

Table 8. Parameter Model

Parameter	**Value**
Input Shape	Input_dim
NLP Pre-preprocessing	Case Folding, Normalization, Tokenization, Stemming
Tokenization	DistilBERTTokenizer
Multi-Head Attention	Num_heads=8, dim_model=512
Add & Norm	Layer Normalization
Feed Forward	Dense (2048, Activation='ReLU'
Linear Layer	Dense (256, activation='softmax'
Softmax Layer	Dense(num_classes, activation='softmax'
Optimizer	AdamW (learning_rate=2e-5)
Loss Function	Cross-Entropy Loss
Training Parameter	Epoch=3, Batch Size=8
Evaluation Matrix	Accuracy, Recall, F1 Score, AUC

Evaluation

The implemented model is then evaluated to test its performance. This model is tested and compared with algorithms such as Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The evaluation uses equations (12), (14), (15), and (16). The results are shown in Tables 9, 10, and 11. Subsequently, the model's performance is tested using the ROC curves, which are displayed in Figures 3, 4, and 5.

Table 9. Evaluation Using 80-20 Training Split

Algorithm	**A_c**	**R_e**	**F_1**	**AUC**
DNN	0.76	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.92
DT	0.82	0.93	0.80	0.88
SVM	0.80	0.89	0.72	0.82
KNN	0.81	0.94	0.80	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.63	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 10. Evaluation Using 70-30 Training Split

Algorithm	**A_c**	**R_e**	**F_1**	**AUC**
DNN	0.79	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.88
DT	0.82	0.93	0.80	0.88
SVM	0.73	0.89	0.72	0.82
KNN	0.81	0.94	0.72	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.64	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 11. Evaluation Using 90-10 Training Split

Algorithm	**A_c**	**R_e**	**F_1**	**AUC**
DNN	0.77	0.52	0.65	0.85
RF	0.83	0.99	0.83	0.93
DT	0.83	0.94	0.82	0.90
SVM	0.72	0.86	0.72	0.84
KNN	0.80	0.87	0.78	0.89
XGBoost	0.83	0.94	0.82	0.92
NB	0.63	0.30	0.40	0.85
Trans+NLP	0.85	0.95	0.84	0.94

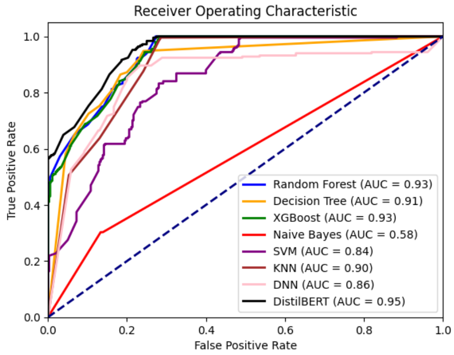

Figure 3. ROC Untuk Model 90-10

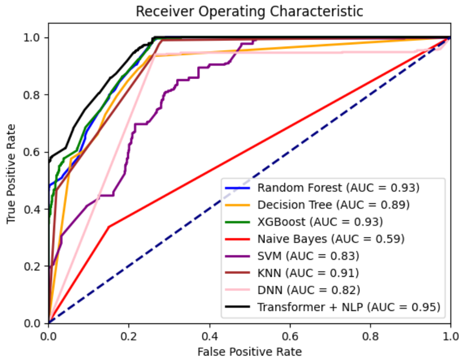

Figure 4. ROC Untuk Model 80-20

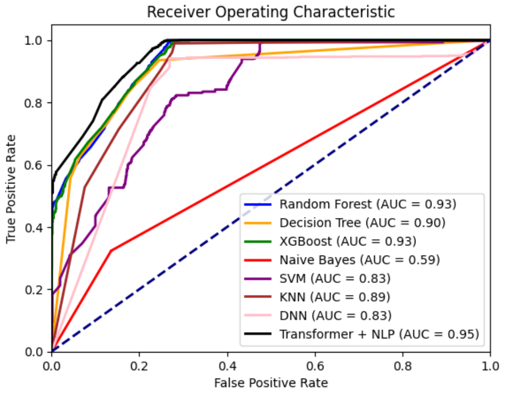

Figure 5. ROC Untuk Model 70-30

Statical Validation

To test the reliability of the built model, we conducted evaluations using the Friedman test and t-test to compare its performance with other models[22]. We designated the proposed model as the control method in this experiment, and the significance level α for the statistical tests was set at 0.05. Generally, a smaller p-value indicates a significant difference between comparison methods. The results of the Friedman test and t-test are shown in Table 12.

Table 12. Friedman Test and T-test Results

	DNN	DT	XB	NB	SVM	KNN	RF
Friedman	0.0009	0.005	0.019	2.159	0.0001	0.006	0.04
T-Test	8.705	5.35	3.765	40.785	13.19	5.244	2.99

Parameter Sensivitas

In this section, we examine the impact of the hyperparameter, denoted by λ, on the proposed detection model. This analysis aims to understand how variations in λ influence the model's performance and effectiveness. The study involves adjusting the λ values and observing changes in key performance metrics, such as accuracy, recall, F1 score, and ROC-AUC. The results of this hyperparameter tuning are presented in Table 13, illustrating the relationship between different λ values and the corresponding performance metrics. This detailed evaluation helps in identifying the optimal λ setting for achieving the best detection results.

Table 13. Impact of Hyperparameter λ on Model Performance

Λ	A_c	R_c	F_1	Auc
1e-05	0.856	0.944	0.843	0.948
2e-05	0.852	0.944	0.840	0.950
3e-05	0.851	0.906	0.841	0.946
5e-05	0.849	0.952	0.838	0.946

Based on Table 13, although the AUC value remains the same (0.95) for several learning rate values, other metrics such as Accuracy, Recall, and F1 Score vary. The model with a learning rate of 2e-05 shows the highest AUC of 0.9505, indicating slightly better performance compared to other learning rates. Models with learning rates of 1e-05 and 3e-05 exhibit nearly the same AUC values (around 0.9490) but with variations in Accuracy and Recall. The ROC curve, illustrating sensitivity, is shown in Figure 6.

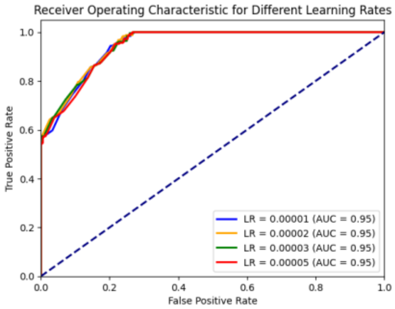

Figure 6. ROC Curve for Sensitivity Analysis of Parameters

Result dan Analysis

This study demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. Initially, the CSIC 2010 dataset used in this study was processed through various pre-processing steps such as tokenization, stemming, lemmatization, and normalization to ensure data consistency. Text representation was carried out using techniques like Word2Vec, BERT, and TF-IDF, enabling the Transformer model to capture contextual relationships in network log data.

The model's performance evaluation showed superior results compared to traditional algorithms like Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The testing was conducted with training and testing data splits of 80/20, 70/30, and 90/10 ratios. The Transformer-NLP model achieved higher accuracy, recall, F1 score, and AUC, with the best AUC value of 0.9505 at a learning rate of 2e-05. The ROC curve also demonstrated the superior performance of this model in detecting network intrusions compared to other models.

Statistical validation through the Friedman test and t-test confirmed the reliability and practical significance of the proposed model. Hyperparameter sensitivity analysis showed that variations in the λ value affected the model's performance, with a learning rate of 2e-05 providing the best results. Overall, the proposed Transformer-NLP model not only significantly reduces false positives but also enhances the overall security of web applications, making it a more adaptive and intelligent solutions in the face of increasingly sophisticated cyber threats.

CONCLUSION

This study successfully demonstrates that integrating the Transformer model with NLP techniques can significantly enhance the performance of NIDS for web applications. The proposed model effectively captures contextual relationships in network log data, enabling more accurate and adaptive detection of web application attacks. Evaluation results show that the Transformer-NLP model achieves higher accuracy, recall, F1 score, and AUC compared to traditional algorithms such as DNN, RF, DT, SVM, KNN, XGBoost, and NB. Statistical validation through the Friedman test and t-test confirms the robustness and practical significance of this model. With these promising results, the Transformer-NLP model can be considered a more adaptive and intelligent solution in facing increasingly complex and sophisticated cyber threats.

Despite the significant findings, there are several limitations to consider. First, the use of the relatively limited CSIC 2010 dataset may not reflect the broader and more recent variations in web application attacks. Second, while the Transformer-NLP model shows superior performance, its computational complexity and high resource requirements could pose challenges for practical implementation in production environments. Third, the study does not examine the potential impact of overfitting that might occur due to the use of a model with complex parameters on a limited dataset. Lastly, this research focuses on web application attacks, so generalizing to other types of network attacks requires further investigation. Therefore, while the model shows great potential, its practical application requires further consideration regarding scale, performance, and generalization.

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[JANAPATI] Editor Decision

1 pesan

Gede Saindra Santyadiputra <ejournal@undiksha.ac.id> 29 Agustus 2024 pukul 08.44
Kepada: Wowon Priatna <wowon.priatna@dsn.ubharajaya.ac.id>, Irwan Sembiring <irwan@uksw.edu>, Adi Setiawan <adi.setiawan@uksw.edu>, Iwan Iwan Setyawan <iwan@uksw.edu>

Wowon Priatna, Irwan Sembiring, Adi Setiawan, Iwan Iwan Setyawan:

We have reached a decision regarding your submission to Jurnal Nasional Pendidikan Teknik Informatika : JANAPATI, "Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection".

Our decision is to: **Resubmit for Review**, **no later than 12/09/2024**.

Reviewer A:
Recommendation: Resubmit for Review

Content consistency with the title of the article

Good

Scientific quality

Poor

Clarity of writing and grammar

Poor

Novelty and originality of ideas

Poor

The accuracy and clarity of the methodology

Poor

Clarity of results and conclusions

Poor

Notes/Review Comments

1. Specific results (include certain score) should be declared in the Abstract.
2. How the authors ensure that no similar research performing same solution as the authors had implemented.
3. "...However, these approaches have limitations in handling highly dynamic and diverse data in web applications". How can NLP solve those limitations?

4. Figure 1 should be improved to be more readable and specifically distinguish activities and objects (check standard for notation visualization).
5. The authors should narrate the suitability of used dataset. Did they fulfill the criteria following the situation in the Background? The authors should expose the sample from these datasets to prove their eligibility.
6. "Kemajuan terbaru dalam NLP, seperti BERT, menggunakan arsitektur transformer untuk menangkap konteks dari kedua arah dalam teks, meningkatkan kinerja tugas-tugas NLP. Model-model ini telah berhasil diterapkan dalam berbagai domain, termasuk keamanan siber, untuk memproses dan menganalisis log jaringan guna deteksi anomali. Penelitian ini memanfaatkan teknik NLP untuk memproses log jaringan, mengonversinya menjadi representasi vektor, dan menggunakan model transformer untuk mendeteksi serangan aplikasi web dengan lebih akurat." There are many Indonesian language showed in the manuscript. Check entire manuscript.

7. Figure 2 cannot be read well at all.
8. The results did not reveal how the experiments solve the highly dynamic and diverse data in web applications (check the Introduction). Explain it more.
9. The article had a lack of results analysis. The authors should narrate much more about causative factors on generated results and their impacts. They also should compare the generated results with the related literature to obtain final positioning and novelty.

Jurnal Nasional Pendidikan Teknik Informatika: JANAPATI

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Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection

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Abstract

The increasing frequency and complexity of web application attacks demand more advanced detection methods beyond the capabilities of traditional network intrusion detection systems (NIDS), which often rely on predefined signatures and rules, making them less effective against novel attacks. This research addresses these limitations by integrating Transformer models with Natural Language Processing (NLP) techniques to develop a more adaptive and intelligent intrusion detection framework. Leveraging the Transformer's ability to capture long-term dependencies and the contextual richness of NLP, the proposed model aims to better handle the dynamic and diverse nature of web application data. Using the CSIC 2010 dataset, comprehensive preprocessing steps such as tokenization, stemming, lemmatization, and normalization were employed, followed by text representation techniques like Word2Vec, BERT, and TF-IDF. The Transformer architecture was then applied to enhance detection capabilities. Performance evaluation revealed that the Transformer-NLP model achieved an accuracy of 85%, a precision of 95%, a recall of 83%, an F1 score of 84%, and an AUC of 0.95, demonstrating its superiority over traditional machine learning methods. Statistical validation through Friedman and T-tests confirmed the model's robustness and practical significance. Despite these promising results, limitations such as the dataset's scope, computational complexity, and the need for generalization to other types of network attacks remain. Future research should focus on expanding the dataset, optimizing model complexity, and exploring applications to a broader range of cybersecurity threats. Overall, this study highlights a significant advancement in detecting complex web application attacks, reducing false positives, and enhancing security, providing a viable solution to increasingly sophisticated cybersecurity challenges.

Keywords: NLP, Intrusion Detection, Transformer, Web Application Attack, Machine Learning

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INTRODUCTION

The security of web applications has become a paramount concern in the current digital era, especially with the rise of attacks targeting vulnerabilities in web applications[1]. As technology advances and the number of internet users increases, web applications are increasingly susceptible to various types of attacks, such as SQL injection, Cross-Site Scripting (XSS), and Denial of Service (DoS) attacks. These attacks threaten the integrity, confidentiality, and availability of data and web services, and their frequency and complexity continue to escalate[2].

Web applications are often the first point of entry for attackers, exploiting vulnerabilities like SQL injection and Cross-Site Scripting (XSS) to gain unauthorized access or inject malicious scripts. These vulnerabilities highlight the need for robust detection mechanisms specifically tailored to web applications. Therefore, this study focuses on detecting attacks targeting web applications, recognizing this as a critical aspect of maintaining overall network security[3]. Research on network intrusion detection systems (NIDS) has explored various methodologies to counteract these threats[4]. For instance, Research [5] provides a comprehensive overview of existing detection systems specifically designed to monitor web traffic, comparing the capabilities of systems like AppSensor, PHPIDS, ModSecurity, Shadow Daemon, and AQTRONIX WebKnight. Other studies have focused on input validation techniques to prevent intrusions, such as the approach detailed in Research [6], which emphasizes input validation against web application attacks. Additionally, Research [7] has developed an intrusion detection model to mitigate cyber-attacks, data breaches, and identity theft, aiding in effective risk management.

Traditional approaches to network intrusion detection rely heavily on predefined signatures and rules, which limits their effectiveness in detecting new or unknown variants of attacks[8]. This rigidity necessitates more adaptive solutions. A popular approach to overcoming these limitations involves the use of machine learning (ML) and artificial intelligence (AI) to create more intelligent and flexible intrusion detection systems [9]. Machine learning models, such as Random Forest and Support Vector Machines, have been successfully employed to detect anomalies in network traffic[10]. Some studies have advanced this further by combining ensemble learning with NLP-based methods, as indicated in Research [11], to enhance the detection models' effectiveness. However, even these sophisticated methods face challenges in handling the highly dynamic and diverse data generated by web applications. To address these challenges, this study proposes a novel approach that integrates advanced Transformer models with NLP techniques to better capture the complex patterns and contextual information inherent in web application data. This integration allows for a more nuanced detection of web attacks, particularly those that are not easily identifiable by conventional machine learning models

Recent advancements in deep learning, particularly the development of the Transformer model by Vaswani et al., offer a promising solution[12]. The Transformer's ability to capture long-range dependencies in sequential data and process this information efficiently through an attention-based architecture provides a robust framework for addressing the complexities of web application data. The application of Transformer models in network intrusion detection presents new opportunities for developing more adaptive and sophisticated systems capable of identifying a wide range of web attacks[13]. Research has shown that Transformers are particularly effective in analyzing patterns and anomalies within network data, leading to improved detection rates of complex attacks that are often missed by conventional methods[14].

Unlike previous models that focus on static or homogeneous data sets, the proposed research utilizes both Transformer models and NLP techniques to handle the diverse and ever-evolving nature of web application data. This approach differs significantly from existing studies by combining the capabilities of Transformer models to capture intricate patterns with the contextual richness provided by NLP-based techniques. While earlier studies [11][15][16] employed NLP for enhancing feature extraction in intrusion detection, this research integrates these methods more deeply within a Transformer-based architecture, representing a novel approach to the field.

The novelty of this study lies in its dual integration of NLP techniques and Transformer models for web application intrusion detection. This combination not only provides a more nuanced approach to understanding the data but also significantly enhances the model's ability to detect sophisticated web attacks. This research contributes to the field by presenting a novel framework that leverages advanced NLP and deep learning techniques to build more resilient intrusion detection systems, potentially reducing false positives and improving overall security[17]. The findings from this study are expected to offer valuable insights and practical implications for future research in cybersecurity, particularly in applying NLP and deep learning to enhance network security.

METHOD

This study aims to develop and analyze a network intrusion detection model based on Transformer methods and Natural Language Processing (NLP) techniques to enhance the security of web applications. The design of this research is illustrated in Figure 1.

Dataset

The CSIC 2010 dataset, developed by the Spanish Research National Council (Consejo Superior de Investigaciones Científicas - CSIC), is designed for web application intrusion detection and network security research. On Kaggle, this dataset comprises 61,065 records and 17 variables/attributes [12]. The study utilizes the CSIC 2010 dataset, which is specifically designed for evaluating web application security. This dataset contains a range of normal and malicious HTTP requests made to a web server, reflecting various types of web-based attacks such as SQL injection, Cross-Site Scripting (XSS), and Path Traversal. These types of attacks are particularly challenging for traditional detection systems due to their dynamic and evolving nature. As shown in the dataset sample, the features include HTTP methods (GET, POST), headers (User-Agent, Pragma, Cache-Control), and URL parameters, which are essential for detecting anomalies and potential threats in web traffic. This makes the dataset highly suitable for the development and evaluation of advanced machine learning models, such as those using Transformer architectures and NLP techniques, aimed at improving web application intrusion detection.

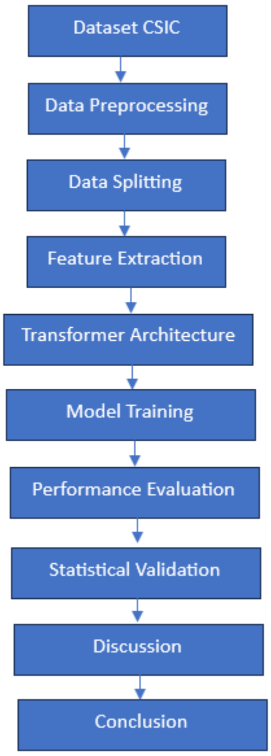

Figure 1. Research Design

Network Intrusion Detection

Network Intrusion Detection Systems (NIDS) are crucial for identifying and mitigating security threats to web applications. Traditional NIDS relies on signature-based and anomaly-based methods. Signature-based systems are adequate for known threats but struggle to detect new attacks, while anomaly-based systems can identify unknown attacks but often have high false favorable rates[18]. Advances in machine learning (ML) and deep learning (DL) have enhanced NIDS capabilities, with convolutional neural networks (CNN) and recurrent neural networks (RNN) demonstrating improved accuracy[19]. However, these models often fail to capture network logs' temporal and contextual dependencies, which is essential for detecting sophisticated web application attacks. Transformer models and Natural Language Processing (NLP) techniques have been introduced to address this. Transformers excel in capturing long-term dependencies and contextual relationships in sequential data[18], while NLP enables effective preprocessing and representation of network logs[11]. This study develops a more robust NIDS for detecting web application attacks by combining Transformer models and NLP, aiming to reduce false positives and improve detection accuracy.

Transformer

The Transformer is an architectural model that has revolutionized the landscape of natural language processing (NLP) and various other applications. As introduced in "Attention is All You Need," the Transformer relies on the self-attention mechanism to capture relationships between elements in sequential data[12]. The self-attention mechanism allows the model to efficiently consider the entire input context without processing the data sequentially, unlike traditional approaches such as RNNs and LSTM[20]. The core formula in self-attention is shown in equation (1):

$$\text{Attention}(Q, K, V) = \text{softmax}\,(\frac{QK^T}{\sqrt{DK}})\text{V} \qquad (1)$$

The Transformer model consists of multiple encoders and decoders, with each encoder layer comprising a self-attention mechanism and a feed-forward neural network[21]. The encoder generates contextual representations of the input, which are then used by the decoder to produce the output. This approach enables the Transformer to capture long-term dependencies and complex relationships within the data[22].

Transformers have demonstrated their superiority in various NLP tasks, including machine translation, text classification, and language modeling, outperforming previous approaches[12]. Their application in network intrusion detection leverages Transformers and NLP techniques to preprocess network logs and detect attack patterns with high efficiency and improved accuracy. This study will implement the Transformer model to enhance the detection capabilities of web application attacks, utilizing the power of self-attention to capture complex relationships in network data.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and generate human-like text. NLP encompasses sentiment analysis, machine translation, and network log analysis applications. Fundamental NLP techniques include tokenization (breaking text into smaller units), stemming, and lemmatization.

Recent advancements in NLP, such as BERT, use Transformer architecture to capture the bidirectional context in text, significantly improving the performance of NLP tasks. These models have been successfully applied in various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This research leverages NLP techniques to process network logs, converting them into vector representations, and employs Transformer models to detect web application attacks with greater accuracy. Recent advancements in NLP, such as BERT, utilize transformer architecture to capture bidirectional context in text, thereby enhancing the performance of NLP tasks. These models have been successfully applied across various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This study leverages NLP techniques to process network logs, converting them into vector representations, and employs transformer models to more accurately detect web application attacks.

integration of Transformer models with NLP

This study proposes the integration of Transformer models with NLP techniques to detect attacks on web applications through a Network NIDS. The proposed model in this research is illustrated in Figure 2.

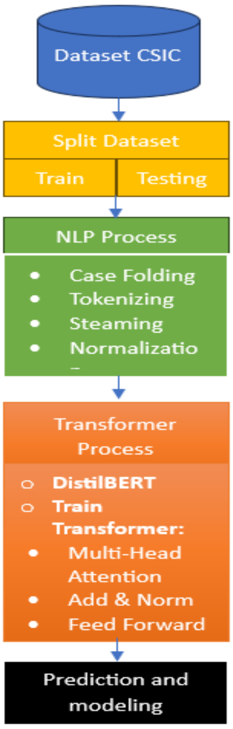

Figure 2. Arsitektur Instrusion Detection

Based on Figure 2, the steps for intrusion detection are further detailed in Algorithm 1. The initial stage involves initializing parameters for the Transformer and the DistilBERT tokenizer. The NLP preprocessing phase includes case folding, tokenization, stemming, and normalization to ensure that the text data is consistent and formatted adequately for analysis. The DistilBERT tokenizer then converts the preprocessed text into appropriate tokens. The following equations are used in the process: Equation (5) for converting logs, including URLs, into lowercase (case folding). Equation (6) for tokenization. Equation (7) for stemming. Equation (8) for normalization

$$lower\ (T) = map(\lambda \mathfrak{x}: \mathfrak{x} \rightarrow lowercase(\mathfrak{x})) \qquad (5)$$

$$Tokend = Tokenize(T, delimiter) \qquad (6)$$

$$Stem = StemmingAlgoritm(T) \qquad (7)$$

$$text\ \longrightarrow \text{normalized text} \qquad (8)$$

Next, the tokenized data is converted into tensors, enabling processing by the Transformer model. The training phase of the Transformer model involves several critical steps, including Multi-Head Attention to capture various aspects of relationships between words, Add & Norm for normalization and residual addition, and Feed Forward layers for further data transformation. After training, the model's performance is evaluated using metrics such as accuracy, recall, F1 score, and AUC to assess its effectiveness in detecting intrusions.

$$output_{residual} = input + Sublayer(input)(9)$$
$$output_{norm} = \frac{output_{residual} - \mu}{\sigma}.\gamma + \beta \qquad (10)$$
$$FFN_1(\mathfrak{x}) = ReLU(W_1 x + b_1) \qquad (11)$$

```
Algorithm 1: Transformer NLP Integration
Input: Input: Dataset $D$={($xi$,$yi$)}
Output: Final model intrusion detection

 1. Initialization:
     • Parameters for the Transformer
       and DistilBERT tokenizer are
       initialized.
 2. NLP Preprocessing:
     • Case Folding
     • Tokenization
     • Steaming
     • Normalization
 3. Tokenization
```

- The DistilBERT Tokenizer is used to convert text into appropriate tokens:

4. Conversion to Tensors
   - The tokenized data is converted into tensors that the Transformer model can process
5. Train Transformer
   - The Transformer model is trained with the processed data
     a. Multi-Head Attention: use equation (1)
     b. Add & Norm: Normalization and residual addition. Use equations (9) and (10)
     c. Feed Forward. Use equation (11)
6. Model Evaluation
   - The model has evaluated the use of equations (12), (13, (14), (15), (16).
7. Final Model
   - The final model is returned for intrusion detection

Evaluation

The next step in this research is to evaluate the performance of the developed intrusion detection model. The objective of this performance testing is to determine the extent to which the model is suitable for practical use. Several evaluation parameters are utilized, including Accuracy (Ac), Recall (Re), Precision (Pr), F1 Score (F1), and Area Under the Curve (AUC)[21]. These parameters provide a comprehensive assessment of the model's effectiveness and reliability in classification. The formulas for each parameter are given in equations (12), (13), (14), (15), and (16)[13]. Table 1 illustrates the prediction of target labels. The next step involves reporting the model's performance using the Receiver Operating Characteristic (ROC) curve to assess the intrusion detection model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \qquad (12)$$

$$Precision = \frac{TP}{TP+TF} \qquad (13)$$

$$Recall = \frac{TP}{TP+TN} \qquad (14)$$

$$F1\,Score = \frac{2\,x\,Precision\,x\,recall}{precision+recall} \qquad (15)$$

$$AUC = \int_0^1 TPR(FPR)d\,(FPR) \qquad (16)$$

Table1. Confusion Matrix

	True Normal	True Anomalous
Predict Normal	TP	FP
Predict Anomalous	TN	TN

Statistical Validation

In this study, statistical validation is performed using the Friedman Test and the Paired T-test. The Friedman Test, a non-parametric test, is used to compare the performance of multiple classification models on the same dataset[23]. This test examines the null hypothesis that there is no significant difference in the performance of these models. If the Friedman Test results indicate a significant difference, further analysis is conducted using the Paired T-test to identify which pairs of models have significantly different performances. The combination of these two tests provides comprehensive validation, ensuring that the developed model is not only statistically superior but also has practical significance in its application[22].

RESULT AND DISCUSSION

The application of the proposed Transformer-NLP method demonstrates that the Transformer model effectively captures contextual relationships in network logs to detect web application attacks through intrusion detection.

Data Processing

At this stage, data cleaning was performed, where three records with missing data were removed, reducing the dataset from 61,065 to 61,062 records. The following process involved reducing the number of variables from 17 to 2, which were relevant to the context of the research. Table 1 shows the dataset after data preprocessing. Table 3 defines the target or label for classification, where 0 represents normal, and 1 represents anomalous.

Table 3. Pre-processing Result Dataset

	URL	Label
1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	0
2	http://localhost:8080/	0

	?OpenServer HTTP/1.1	
61062	http://localhost:8080/tienda1/miembros.Inc HTTP/1.1	1

Text Representation Formation

In this stage, processing is conducted using NLP techniques, including tokenizing, case folding, stemming, and stop word normalization. First, tokenizing: The results of tokenization demonstrate how URLs are broken down into smaller parts that the transformer model can process. This process involves adding unique tokens, handling special characters and symbols, and sub-word tokenization to address words not present in the model's overall vocabulary. Table 4 provides a clear overview of how raw data is transformed into a format suitable for NLP modelling.

Table 4. Tokenization Results

Input Process	Output Process
http://localhost:8080/tienda1 /publico/vaciar.jsp?B2=Vaciar+carrito HTTP/1.1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 = Vac iar + carr ito HTTP / 1 . 1 </s>

Next, all characters in the URL are converted to lowercase before tokenization using case folding. Table 5 shows the results of tokenization, demonstrating that all elements in the URL have been converted to lowercase and broken down into smaller tokens. This helps ensure consistency in text processing and makes the model more robust against variations in capitalization.

Table 5. Case Folding Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 = Vac iar + carr ito HTTP / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The steaming process does not significantly alter the text in this case because most tokens are part of URLs or symbols. However, words like "vaciar" and "carr" will be processed if there are suffixes that can be removed. Table 6 presents the final results, showing that tokenization and stemming have been applied, although minimal changes occurred due to the specific characteristics of the input text (URLs and symbols).

Table 6. Stemming Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The Stop Word stage is not performed because most tokens are part of URLs. Normalization at this stage involves processing the text, including converting it to lowercase, removing punctuation, and removing numbers. Converting to Lowercase: All letters are converted to lowercase to ensure consistency, so "HTTP" and "http" are treated the same. Removing Punctuation: All punctuation marks, such as periods, slashes, and question marks, are removed from the text.

Table 7. Normalization Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Model Implementation

In this study, the implementation of the Transformer model with the integration of Natural Language Processing (NLP) for network intrusion detection is conducted through several key stages. The first stage is data processing, which includes normalization, batch processing, and splitting the data into training and testing sets with ratios of 70/30, 80/20, and 90/10. In the NLP processing, steps such as case folding, text normalization, tokenization, and stemming are performed to ensure the text is in a consistent format. Tokenization uses the DistilBERT Tokenizer to convert the text into tokens that the Transformer model can process.

As shown in Figure 2, the architecture for network intrusion detection with Transformer and NLP integration is implemented according to Algorithm 1. In the model training stage, DistilBERT, initialized with default parameters, is used to handle the Multi-Head Attention, Add & Norm, and Feed Forward layers. The model is trained using the Adam optimizer with a learning rate of 2e-5 and the Cross-Entropy loss function. Training is conducted over three epochs with a batch size of 8. Model evaluation is performed by measuring metrics such as accuracy, recall, F1 score, and ROC-AUC to ensure the model's performance in detecting network intrusion categories classified as "Normal" and

"Anomalous." Evaluation results indicate that the integration of the Transformer model and NLP is effective in detecting web application attacks and significantly contributes to the improvement of the network intrusion detection system's accuracy. The parameters of the Transformer model integrated with NLP are shown in Table 8.

Table 8. Parameter Model

Parameter	Value
Input Shape	Input_dim
NLP Pre-preprocessing	Case Folding, Normalization, Tokenization, Stemming
Tokenization	DistilBERTTokenizer
Multi-Head Attention	Num_heads=8, dim_model=512
Add & Norm	Layer Normalization
Feed Forward	Dense (2048, Activation='ReLU'
Linear Layer	Dense (256, activation='softmax'
Softmax Layer	Dense(num_classes, activation='softmax'
Optimizer	AdamW (learning_rate=2e-5)
Loss Function	Cross-Entropy Loss
Training Parameter	Epoch=3, Batch Size=8
Evaluation Matrix	Accuracy, Recall, F1 Score, AUC

Evaluation

The implemented model is then evaluated to test its performance. This model is tested and compared with algorithms such as Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The evaluation uses equations (12), (14), (15), and (16). The results are shown in Tables 9, 10, and 11. Subsequently, the model's performance is tested using the ROC curves, which are displayed in Figures 3, 4, and 5.

Table 9. Evaluation Using 80-20 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.76	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.92
DT	0.82	0.93	0.80	0.88
SVM	0.80	0.89	0.72	0.82
KNN	0.81	0.94	0.80	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.63	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 10. Evaluation Using 70-30 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.79	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.88
DT	0.82	0.93	0.80	0.88
SVM	0.73	0.89	0.72	0.82
KNN	0.81	0.94	0.72	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.64	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 11. Evaluation Using 90-10 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.77	0.52	0.65	0.85
RF	0.83	0.99	0.83	0.93
DT	0.83	0.94	0.82	0.90
SVM	0.72	0.86	0.72	0.84
KNN	0.80	0.87	0.78	0.89
XGBoost	0.83	0.94	0.82	0.92
NB	0.63	0.30	0.40	0.85
Trans+NLP	0.85	0.95	0.84	0.94

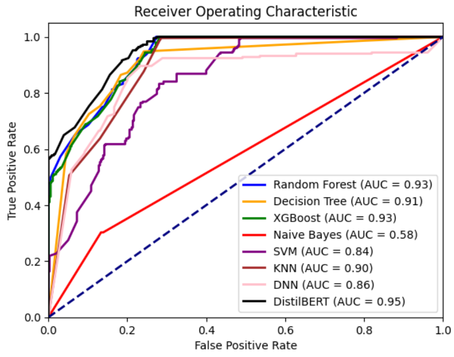

Figure 3. ROC for 90-10 Model

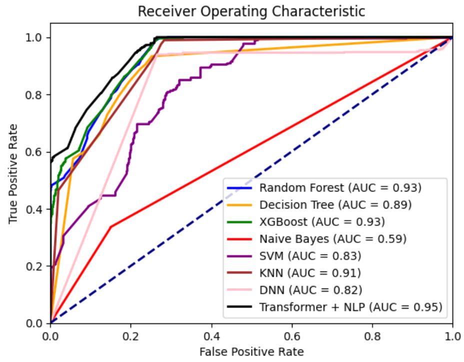

Figure 4. ROC for 80-20 Model

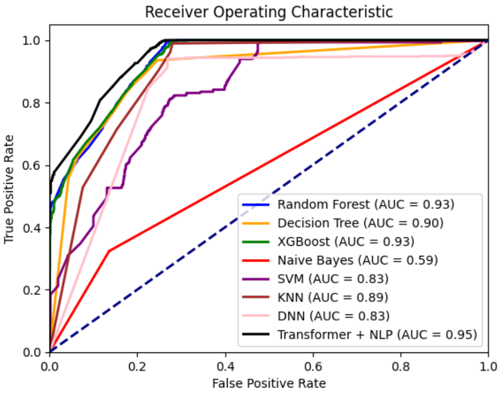

Figure 5. ROC for the 70-30 Model

Statical Validation

To test the reliability of the built model, we conducted evaluations using the Friedman test and t-test to compare its performance with other models[23]. We designated the proposed model as the control method in this experiment, and the significance level α for the statistical tests was set at 0.05. Generally, a smaller p-value indicates a significant difference between comparison methods. The results of the Friedman test and t-test are shown in Table 12.

Table 12. Friedman Test and T-test Results

	DNN	DT	XB	NB	SVM	KNN	RF
Friedman	0.0009	0.005	0.019	2.159	0.0001	0.006	0.04
T-Test	8.705	5.35	3.765	40.785	13.19	5.244	2.99

Parameter Sensivitas

In this section, we examine the impact of the hyperparameter, denoted by λ, on the proposed detection model. This analysis aims to understand how variations in λ influence the model's performance and effectiveness. The study involves adjusting the λ values and observing changes in key performance metrics, such as accuracy, recall, F1 score, and ROC-AUC. The results of this hyperparameter tuning are presented in Table 13, illustrating the relationship between different λ values and the corresponding performance metrics. This detailed evaluation helps in identifying the optimal λ setting for achieving the best detection results.

Table 13. Impact of Hyperparameter λ on Model Performance

Λ	A_c	R_c	F_1	Auc
1e-05	0.856	0.944	0.843	0.948
2e-05	0.852	0.944	0.840	0.950
3e-05	0.851	0.906	0.841	0.946
5e-05	0.849	0.952	0.838	0.946

Based on Table 13, although the AUC value remains the same (0.95) for several learning rate values, other metrics such as Accuracy, Recall, and F1 Score vary. The model with a learning rate of 2e-05 shows the highest AUC of 0.9505, indicating slightly better performance compared to other learning rates. Models with learning rates of 1e-05 and 3e-05 exhibit nearly the same AUC values (around 0.9490) but with variations in Accuracy and Recall. The ROC curve, illustrating sensitivity, is shown in Figure 6.

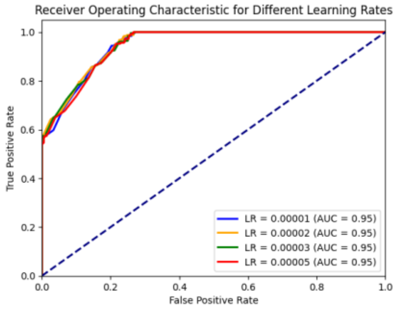

Figure 6. ROC Curve for Sensitivity Analysis of Parameters

Discussion

This study demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. The use of the Transformer model, with its self-attention mechanism, allows for the capturing of complex dependencies in sequential data, such as HTTP requests, which is crucial for detecting intricate attack patterns within dynamic and diverse web traffic. Initially, the CSIC 2010 dataset used in this study was processed through various pre-processing steps, including tokenization, stemming, lemmatization, and normalization, to ensure data consistency. Text representation was carried out using techniques like Word2Vec, BERT, and TF-IDF, enabling the Transformer model to effectively capture contextual relationships in network log data.

The model's performance evaluation showed superior results compared to traditional algorithms like Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The Transformer-NLP model demonstrated higher accuracy, recall, F1 score, and AUC across multiple training/testing data splits (80/20, 70/30, and 90/10), with the best AUC value of 0.9505 at a learning rate of 2e-05, underscoring its effectiveness in adapting to different training scenarios. The ROC curve further illustrated the model's superior capability in distinguishing between normal and anomalous traffic, proving more reliable than other models tested.

Statistical validation through the Friedman test and t-test confirmed the reliability and practical significance of the proposed model. Hyperparameter sensitivity analysis showed that variations in the λ value impacted the model's performance, with a learning rate of 2e-05 yielding the optimal results. These findings suggest that the proposed Transformer-NLP model is not only effective in improving detection accuracy but also offers a robust framework for reducing false positives, enhancing the overall security posture of web applications in response to increasingly sophisticated cyber threats.

However, it is important to note several limitations associated with this study. Firstly, the CSIC 2010 dataset, while useful for evaluating web application security, may not fully encompass the breadth of modern web application attack techniques, which could limit the model's applicability to newer or more varied types of threats. Secondly, the computational intensity required for both Transformer models and NLP preprocessing could be a barrier to practical deployment, particularly in environments with limited processing resources. Additionally, while this study focused on optimizing performance metrics like accuracy and AUC, it did not thoroughly investigate potential overfitting, which can be a risk with complex models trained on limited datasets. Future research should explore the use of larger and more diverse datasets and further refine the model to balance computational efficiency with detection capability

CONCLUSION

This study successfully demonstrates that integrating the Transformer model with NLP techniques can significantly enhance the performance of NIDS for web applications. The proposed model effectively captures contextual relationships in network log data, allowing for more accurate and adaptive detection of web application attacks. The evaluation results indicate that the Transformer-NLP model achieves superior performance in terms of accuracy, recall, F1 score, and AUC when compared to traditional algorithms such as DNN, RF, DT, SVM, KNN, XGBoost, and NB. Furthermore, the model's ability to handle the highly dynamic and diverse nature of web application traffic marks a significant improvement over conventional methods, addressing a critical gap in current network intrusion detection systems. Statistical validation through the Friedman test and t-test confirms the robustness and practical significance of this model. With these promising results, the Transformer-NLP model presents a more adaptive and intelligent solution in the face of increasingly complex and sophisticated cyber threats.

Despite the significant findings, several limitations must be considered. First, the use of the relatively limited CSIC 2010 dataset may not fully capture the broader and more recent variations in web application attacks, potentially affecting the model's generalizability to newer threats. Second, while the Transformer-NLP model shows superior performance, its computational complexity and high resource requirements could pose challenges for practical deployment in production environments. Third, the study does not delve deeply into the impact of overfitting, which could be a concern given the model's complexity and the limited dataset size. Future research should investigate overfitting mitigation strategies, such as employing regularization techniques or cross-validation methods, to ensure the model's robustness in diverse operational settings. Lastly, this research primarily focuses on web application attacks, meaning that extending its application to other types of network attacks requires further investigation. Future work should also explore optimizing the model's architecture to balance detection accuracy with computational efficiency, making it more feasible for deployment in resource-constrained environments. Therefore, while the model shows great potential, its practical application necessitates further consideration regarding scalability, performance, and generalization.

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[JANAPATI] Editor Decision

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Kepada: Wowon Priatna <wowon.priatna@dsn.ubharajaya.ac.id>, Irwan Sembiring <irwan@uksw.edu>, Adi Setiawan <adi.setiawan@uksw.edu>, Iwan Iwan Setyawan <iwan@uksw.edu>

Wowon Priatna, Irwan Sembiring, Adi Setiawan, Iwan Iwan Setyawan:

We have reached a decision regarding your submission to Jurnal Nasional Pendidikan Teknik Informatika : JANAPATI, "Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection".

Our decision is to: **RESUBMIT FOR REVIEW**

Please resubmit no later than **18/10/2024**.

Reviewer A:
Recommendation: Resubmit for Review

Content consistency with the title of the article

Very Good

Scientific quality

Poor

Clarity of writing and grammar

Poor

Novelty and originality of ideas

Poor

The accuracy and clarity of the methodology

Poor

Clarity of results and conclusions

Good

Notes/Review Comments

1. The Abstract was relatively complete following the important components as scientific writing.
2. How to proof nobody had performed similar idea to handle the same problems? More, "NLP" became trending in AI adoption so that maybe many researchers think to leverage it in detecting the intrusion.
3. "However, even these sophisticated methods face challenges in handling the highly dynamic and diverse data generated by web applications" -> How much/big this vulnerability? Was it had frequent cases?
4. The authors should detail why previous research were not solve the problems.
5. Notation as workflow in Figure 1 had many mistakes.
6. How about the dataset eligibility? Did the dataset have adequate divergence? Why should the authors perform NLP? Was it suitable? How about the size appropriateness.
7. The authors should deliver argumentation on selected algorithm much more.
8. The authors should argue whether the problems solved, especially from ability to protect the website.

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Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection

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Abstract
The increasing complexity and frequency of web application attacks demand more advanced detection methods than traditional network intrusion detection systems (NIDS), which rely heavily on predefined signatures and rules, limiting their effectiveness against novel threats. This study proposes a novel approach by integrating Transformer models with Natural Language Processing (NLP) techniques to develop an adaptive and intelligent intrusion detection framework. Leveraging the Transformer's capacity to capture long-term dependencies and NLP's ability to process contextual information, the model effectively addresses the dynamic and diverse nature of web application traffic. Using the CSIC 2010 dataset, this study applied comprehensive preprocessing, including tokenization, stemming, lemmatization, and normalization, followed by text representation techniques such as Word2Vec, BERT, and TF-IDF. The Transformer-NLP architecture significantly improved detection performance, achieving 85% accuracy, 95% precision, 83% recall, 84% F1 score, and an AUC of 0.95. Friedman and t-test validations confirmed the robustness and practical significance of the model. Despite these promising results, challenges related to computational complexity, dataset scope, and generalizability to broader network attacks remain. Future research should focus on expanding the dataset, optimizing the model, and exploring broader cybersecurity applications. This study demonstrates a significant advancement in detecting complex web application attacks, reducing false positives, and improving overall security, offering a viable solution to growing cybersecurity challenges.

Keywords: NLP, Intrusion Detection, Transformer, Web Application Attack, Machine Learning

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INTRODUCTION

The security of web applications has become a paramount concern in the current digital era, especially with the rise of attacks targeting vulnerabilities in web applications[1]. As technology advances and the number of internet users increases, web applications are increasingly susceptible to various types of attacks, such as SQL injection, Cross-Site Scripting (XSS), and Denial of Service (DoS) attacks. These attacks threaten the integrity, confidentiality, and availability of data and web services, and their frequency and complexity continue to escalate[2].

Web applications are often the first point of entry for attackers, exploiting vulnerabilities like SQL injection and Cross-Site Scripting (XSS) to gain unauthorized access or inject malicious scripts. These vulnerabilities highlight the need for robust detection mechanisms specifically tailored to web applications. Therefore, this study focuses on detecting attacks targeting web applications, recognizing this as a critical aspect of maintaining overall network security[3]. Research on network intrusion detection systems (NIDS) has explored various methodologies to counteract these threats[4]. For instance, Research [5] provides a comprehensive overview of existing detection systems specifically designed to monitor web traffic, comparing the capabilities of systems like AppSensor, PHPIDS, ModSecurity, Shadow Daemon, and AQTRONIX WebKnight. Other studies have focused on input validation techniques to prevent intrusions, such as the approach detailed in Research [6], which emphasizes input validation against web application attacks. Additionally, Research [7] has developed an intrusion detection model to mitigate cyber-attacks, data breaches, and identity theft, aiding in effective risk management.

Traditional approaches to network intrusion detection rely heavily on predefined signatures and rules, which limits their effectiveness in detecting new or unknown variants of attacks[8]. This rigidity necessitates more adaptive solutions. A popular approach to overcoming these limitations involves the use of machine learning (ML) and artificial intelligence (AI) to create more intelligent and flexible intrusion detection systems [9]. Machine learning models, such as Random Forest and Support Vector Machines, have been successfully employed to detect anomalies in network traffic[10]. Some studies have advanced this further by combining ensemble learning with NLP-based methods, as indicated in Research [11], to enhance the detection models' effectiveness. However, even these sophisticated methods face challenges in handling the highly dynamic and diverse data generated by web applications. The complexity of web application traffic stems from frequent updates, varying user inputs, and increasingly sophisticated attack vectors, making it difficult for traditional models to adapt in real time[12]. For example, studies have shown that vulnerabilities such as SQL injection and Cross-Site Scripting (XSS) are among the most common attack types, with SQL injection accounting for approximately 65% of web application attacks in 2022, according to OWASP reports[13]. The evolving nature of these vulnerabilities, along with their high frequency, underscores the critical need for more adaptive detection systems capable of handling the sheer volume and variety of data produced by modern web applications.

For instance, research [14] utilizing traditional ML models demonstrated moderate success in detecting known intrusions, but performance degraded significantly when applied to unknown or zero-day attacks. Moreover, approaches based on signature detection or anomaly detection often suffer from high false positive rates, making them impractical for real-world applications. To address these challenges, this study proposes a novel approach that integrates advanced Transformer models with NLP techniques to better capture the complex patterns and contextual information inherent in web application data[15]. While NLP techniques have been widely adopted, the deep integration of NLP with Transformer architectures for web application intrusion detection is a relatively unexplored area, offering a more nuanced detection of web attacks. This combination allows for the detection of complex[16], evolving web threats that are often missed by traditional machine-learning models.

Recent advancements in deep learning, particularly the development of the Transformer model by Vaswani et al., offer a promising solution[17]. The Transformer's ability to capture long-range dependencies in sequential data and process this information efficiently through an attention-based architecture provides a robust framework for addressing the complexities of web application data. The application of Transformer models in network intrusion detection presents new opportunities for developing more adaptive and sophisticated systems capable of identifying a wide range of web attacks[18]. Research has shown that Transformers are particularly effective in analyzing patterns and anomalies within network data, leading to improved detection rates of complex attacks that are often missed by conventional methods[19].

Unlike previous models that focus on static or homogeneous data sets, the proposed research utilizes both Transformer models and NLP techniques to handle the diverse and ever-evolving nature of web application data. This approach differs significantly from existing studies, which often rely on traditional machine learning models or shallow integration of NLP techniques. Our research leverages the Transformer's ability to handle intricate patterns within the data, providing a significant advancement over existing methods. By combining the strengths of NLP in text representation and the deep learning capabilities of Transformers, this study introduces a unique framework that significantly enhances detection performance, particularly for sophisticated web attacks. While earlier studies [11][20][21] employed NLP for enhancing feature extraction in intrusion detection, this research integrates these methods more deeply within a Transformer-based architecture, representing a novel approach to the field.

The novelty of this study lies in its dual integration of NLP techniques and Transformer models for web application intrusion detection, which has not been fully explored in prior research. This combination not only provides a more nuanced approach to understanding the data but also significantly enhances the model's ability to detect sophisticated web attacks. This research contributes to the field by presenting a novel framework that leverages advanced NLP and deep learning techniques to build more resilient intrusion detection systems, potentially reducing false positives and improving overall security[22]. The findings from this study are expected to offer valuable insights and practical implications for future research in cybersecurity, particularly in applying NLP and deep learning to enhance network security.

METHOD

This study aims to develop and analyze a network intrusion detection model based on Transformer methods and Natural Language Processing (NLP) techniques to enhance the security of web applications.

Dataset

The CSIC 2010 dataset, developed by the Spanish Research National Council, contains 61,065 records with 17 attributes, including both normal and malicious web traffic such as SQL injection, Cross-Site Scripting (XSS), and Path Traversal attacks. This dataset's diversity is crucial for training models to recognize both attack patterns and normal behaviors in web traffic, ensuring a robust evaluation of the model's ability to handle real-world scenarios[17]. The dataset's size is sufficient for training deep learning models like Transformers, which require large and diverse datasets to capture complex relationships and generalize well without overfitting. NLP techniques are essential for analyzing the textual nature of web-based attacks. Many attacks, such as SQL injection and XSS, exploit text-based inputs within HTTP requests, making them difficult to detect using traditional methods. NLP allows for deeper analysis of textual data, such as URL parameters and HTTP headers, enabling the model to identify subtle anomalies. The Transformer architecture excels at capturing long-range dependencies, making it adaptable to both known and evolving attack patterns, which is vital for detecting emerging threats in web applications.

Algorithm Selection: Transformer Architecture

In this study, we selected the Transformer architecture due to its ability to effectively process sequential data and capture long-range dependencies[23], which are critical for analyzing web application traffic. Traditional machine learning models, such as Random Forest and Support Vector Machines (SVM), often struggle with the dynamic and unstructured nature of web-based attacks, particularly when analyzing text-based HTTP requests that can be manipulated through attacks like SQL injection or Cross-Site Scripting (XSS)[24]. These conventional algorithms rely heavily on predefined features, making them less effective in detecting new and evolving attack patterns.

The Transformer model overcomes these limitations by leveraging a self-attention mechanism, allowing it to focus on the most relevant parts of an input sequence, such as HTTP headers, URL parameters, and textual fields[25]. This attention mechanism enables the model to capture long-range dependencies and intricate relationships in the data, making it particularly effective for identifying complex patterns that traditional methods might miss[26].

Moreover, Transformers offer significant computational advantages over recurrent models like LSTMs and GRUs, especially in large-scale datasets[27]. Their ability to process data in parallel allows for more efficient training on large-scale datasets, such as the CSIC 2010 dataset, without sacrificing accuracy. This makes Transformers not only faster but also more scalable for real-world applications that involve large and diverse data.

In addition, the integration of NLP techniques with the Transformer model enhances its ability to extract meaningful features from web traffic data[28]. Techniques such as Word2Vec, BERT, and TF-IDF enable the model to better understand textual data and context[29], facilitating more accurate detection of web application attacks that exploit text-based inputs.

Network Intrusion Detection

Network Intrusion Detection Systems (NIDS) are crucial for identifying and mitigating security threats to web applications. Traditional NIDS relies on signature-based and anomaly-based methods. Signature-based systems are adequate for known threats but struggle to detect new attacks, while anomaly-based systems can identify unknown attacks but often have high false favorable rates[30]. Advances in machine learning (ML) and deep learning (DL) have enhanced NIDS capabilities, with convolutional neural networks (CNN) and recurrent neural networks (RNN) demonstrating improved accuracy[31]. However, these models often fail to capture network logs' temporal and contextual dependencies, which is essential for detecting sophisticated web application attacks. Transformer models and Natural Language Processing (NLP) techniques have been introduced to address this. Transformers excel in capturing long-term dependencies and contextual relationships in sequential data[18], while NLP enables effective preprocessing and representation of network logs[11]. This study develops a more robust NIDS for detecting web application attacks by combining Transformer models and NLP, aiming to reduce false positives and improve detection accuracy.

Transformer

The Transformer is an architectural model that has revolutionized the landscape of natural language processing (NLP) and various other applications. As introduced in "Attention is All You Need," the Transformer relies on the self-attention mechanism to capture relationships between elements in sequential data[17]. The self-attention mechanism allows the model to efficiently consider the entire input context without processing the data sequentially, unlike traditional approaches such as RNNs and LSTM[32]. The core formula in self-attention is shown in equation (1):

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{DK}}\right)\text{V} \qquad (1)$$

The Transformer model consists of multiple encoders and decoders, with each encoder layer comprising a self-attention mechanism and a feed-forward neural network[33]. The encoder generates contextual representations of the input, which are then used by the decoder to produce the output. This approach enables the Transformer to capture long-term dependencies and complex relationships within the data[34].

Transformers have demonstrated their superiority in various NLP tasks, including machine translation, text classification, and language modeling, outperforming previous approaches[17]. Their application in network intrusion detection leverages Transformers and NLP techniques to preprocess network logs and detect attack patterns with high efficiency and improved accuracy. This study will implement the Transformer model to enhance the detection capabilities of web application attacks, utilizing the power of self-attention to capture complex relationships in network data.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and generate human-like text. NLP encompasses sentiment analysis, machine translation, and network log analysis applications. Fundamental NLP techniques include tokenization (breaking text into smaller units), stemming, and lemmatization.

Recent advancements in NLP, such as BERT, use Transformer architecture to capture the bidirectional context in text, significantly improving the performance of NLP tasks. These models have been successfully applied in various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This research leverages NLP techniques to process network logs, converting them into vector representations, and employs Transformer models to detect web application attacks with greater accuracy. Recent advancements in NLP, such as BERT, utilize transformer architecture to capture bidirectional context in text, thereby enhancing the performance of NLP tasks. These models have been successfully applied across various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This study leverages NLP techniques to process network logs, converting them into vector representations, and employs transformer models to more accurately detect web application attacks.

integration of Transformer models with NLP

This study proposes the integration of Transformer models with NLP techniques to detect attacks on web applications through a Network NIDS. The proposed model in this research is illustrated in Figure 1.

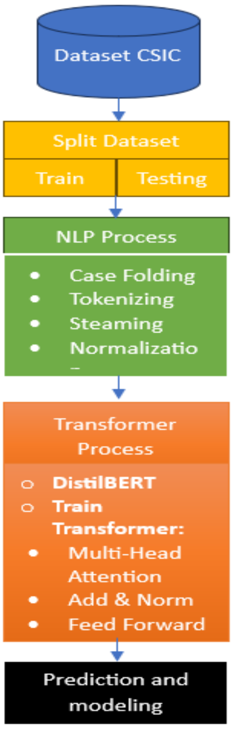

Figure 1. Arsitektur Instrusion Detection

Based on Figure 1, the steps for intrusion detection are further detailed in Algorithm 1. The initial stage involves initializing parameters for the Transformer and the DistilBERT tokenizer. The NLP preprocessing phase includes case folding, tokenization, stemming, and normalization to ensure that the text data is consistent and formatted adequately for analysis. The DistilBERT tokenizer then converts the preprocessed text into appropriate tokens. The following equations are used in the process: Equation (5) for converting logs, including URLs, into lowercase (case folding). Equation (6) for tokenization. Equation (7) for stemming. Equation (8) for normalization

$$lower\ (T) = map(\lambda \mathfrak{x}: \mathfrak{x} \rightarrow lowercase(\mathfrak{x}) \quad (5)$$

$$Tokend = Tokenize(T, delimiter) \quad (6)$$

$$Stem = StemmingAlgoritm(T) \quad (7)$$

$$text \ \longrightarrow \text{normalized text} \quad (8)$$

Next, the tokenized data is converted into tensors, enabling processing by the Transformer model. The training phase of the Transformer model involves several critical steps, including Multi-Head Attention to capture various aspects of relationships between words, Add & Norm for normalization and residual addition, and Feed Forward layers for further data transformation. After training, the model's performance is evaluated using metrics such as accuracy, recall, F1 score, and AUC to assess its effectiveness in detecting intrusions.

$$output_{residual} = input + Sublayer(input) \quad (9)$$

$$output_{norm} = \frac{output_{residual-\mu}}{\sigma} . \gamma + \beta \quad (10)$$

$$FFN_1(\mathfrak{x}) = ReLU(W_1 x + b_1 \quad (11)$$

```
Algorithm 1: Transformer NLP Integration
Input: Input: Dataset $D$={($xi$,$yi$)}
Output: Final model intrusion detection

1. Initialization:
    • Parameters for the Transformer and DistilBERT tokenizer are initialized.
2. NLP Preprocessing:
    • Case Folding
    • Tokenization
    • Steaming
    • Normalization
3. Tokenization
    • The DistilBERT Tokenizer is used to convert text into appropriate tokens:
4. Conversion to Tensors
    • The tokenized data is converted into tensors that the Transformer model can process
5. Train Transformer
    • The Transformer model is trained with the processed data
        a. Multi-Head Attention: use equation (1)
        b. Add & Norm: Normalization and residual addition. Use equations (9) and (10)
        c. Feed Forward. Use equation (11)
6. Model Evaluation
    • The model has evaluated the use of equations (12), (13, (14), (15), (16).
7. Final Model
    • The final model is returned for intrusion detection
```

Evaluation

The next step in this research is to evaluate the performance of the developed intrusion detection model. The objective of this performance testing is to determine the extent to which the model is suitable for practical use. Several evaluation parameters are utilized, including Accuracy (Ac), Recall (Re), Precision (Pr), F1 Score (F1), and Area Under the Curve (AUC)[21][35]. These parameters provide a comprehensive assessment of the model's effectiveness and reliability in classification. The formulas for each parameter are given in equations (12), (13), (14), (15), and (16)[18]. Table 1 illustrates the prediction of target labels. The next step involves reporting the model's performance using the Receiver Operating Characteristic (ROC) curve to assess the intrusion detection model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \quad (12)$$

$$Precision = \frac{TP}{TP+TF} \quad (13)$$

$$Recall = \frac{TP}{TP+TN} \quad (14)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ recall}{precision+recall} \quad (15)$$

$$AUC = \int_0^1 TPR(FPR)d\ (FPR) \quad (16)$$

Table1. Confusion Matrix

	True Normal	True Anomalous
Predict Normal	TP	FP
Predict Anomalous	TN	TN

Statistical Validation

In this study, statistical validation is performed using the Friedman Test and the

Paired T-test. The Friedman Test, a non-parametric test, is used to compare the performance of multiple classification models on the same dataset[36]. This test examines the null hypothesis that there is no significant difference in the performance of these models. If the Friedman Test results indicate a significant difference, further analysis is conducted using the Paired T-test to identify which pairs of models have significantly different performances[37]. The combination of these two tests provides comprehensive validation, ensuring that the developed model is not only statistically superior but also has practical significance in its application[34].

RESULT AND DISCUSSION

The application of the proposed Transformer-NLP method demonstrates that the Transformer model effectively captures contextual relationships in network logs to detect web application attacks through intrusion detection**.**

Data Processing

At this stage, data cleaning was performed, where three records with missing data were removed, reducing the dataset from 61,065 to 61,062 records. The following process involved reducing the number of variables from 17 to 2, which were relevant to the context of the research. Table 1 shows the dataset after data preprocessing. Table 2 defines the target or label for classification, where 0 represents normal, and 1 represents anomalous.

Table 2. Pre-processing Result Dataset

	URL	Label
1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	0
2	http://localhost:8080/ ?OpenServer HTTP/1.1	0
61062	http://localhost:8080/tienda1/miembros.Inc HTTP/1.1	1

Text Representation Formation

In this stage, processing is conducted using NLP techniques, including tokenizing, case folding, stemming, and stop word normalization. First, tokenizing: The results of tokenization demonstrate how URLs are broken down into smaller parts that the transformer model can process. This process involves adding unique tokens, handling special characters and symbols, and sub-word tokenization to address words not present in the model's overall vocabulary. Table 3 provides a clear overview of how raw data is transformed into a format suitable for NLP modelling.

Table 3. Tokenization Results

Input Process	Output Process
http://localhost:8080/tienda1 /publico/vaciar.jsp?B2=Vaciar+carrito HTTP/1.1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>

Next, all characters in the URL are converted to lowercase before tokenization using case folding. Table 4 shows the results of tokenization, demonstrating that all elements in the URL have been converted to lowercase and broken down into smaller tokens. This helps ensure consistency in text processing and makes the model more robust against variations in capitalization.

Table 4. Case Folding Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The steaming process does not significantly alter the text in this case because most tokens are part of URLs or symbols. However, words like "vaciar" and "carr" will be processed if there are suffixes that can be removed. Table 5 presents the final results, showing that tokenization and stemming have been applied, although minimal changes occurred due to the specific characteristics of the input text (URLs and symbols).

Table 5. Stemming Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The stop word removal stage is omitted since most tokens are part of URLs. The normalization process at this stage includes converting all text to lowercase, removing punctuation, and eliminating numbers. Lowercasing ensures consistency, allowing 'HTTP' and 'http' to be treated identically. Punctuation marks, such as periods, slashes, and question marks, are removed to streamline the text. Table 6 presents the results of applying these normalization steps to the sample input.

Table 6. Normalization Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Model Implementation

In this study, the implementation of the Transformer model with the integration of Natural Language Processing (NLP) for network intrusion detection is conducted through several key stages. The first stage is data processing, which includes normalization, batch processing, and splitting the data into training and testing sets with ratios of 70/30, 80/20, and 90/10. In the NLP processing, steps such as case folding, text normalization, tokenization, and stemming are performed to ensure the text is in a consistent format. Tokenization uses the DistilBERT Tokenizer to convert the text into tokens that the Transformer model can process.

As shown in Figure 1, the architecture for network intrusion detection with Transformer and NLP integration is implemented according to Algorithm 1. In the model training stage, DistilBERT, initialized with default parameters, is used to handle the Multi-Head Attention, Add & Norm, and Feed Forward layers. The model is trained using the Adam optimizer with a learning rate of 2e-5 and the Cross-Entropy loss function. Training is conducted over three epochs with a batch size of 8. Model evaluation is performed by measuring metrics such as accuracy, recall, F1 score, and ROC-AUC to ensure the model's performance in detecting network intrusion categories classified as "Normal" and "Anomalous." Evaluation results indicate that the integration of the Transformer model and NLP is effective in detecting web application attacks and significantly contributes to the improvement of the network intrusion detection system's accuracy. The parameters of the Transformer model integrated with NLP are shown in Table 7.

Table 7. Parameter Model

Parameter	Value
Input Shape	Input_dim
NLP Pre-preprocessing	Case Folding, Normalization, Tokenization, Stemming
Tokenization	DistilBERTTokenizer
Multi-Head Attention	Num_heads=8, dim_model=512
Add & Norm	Layer Normalization
Feed Forward	Dense (2048, Activation='ReLU'
Linear Layer	Dense (256, activation='softmax'
Softmax Layer	Dense(num_classes, activation='softmax'
Optimizer	AdamW (learning_rate=2e-5)
Loss Function	Cross-Entropy Loss
Training Parameter	Epoch=3, Batch Size=8
Evaluation Matrix	Accuracy, Recall, F1 Score, AUC

Evaluation

The implemented model is then evaluated to test its performance. This model is tested and compared with algorithms such as Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The evaluation uses equations (12), (14), (15), and (16). The results are shown in Tables 8, 9, and 10. Subsequently, the model's performance is tested using the ROC curves, which are displayed in Figures 2, 3, and 4.

Table 8. Evaluation Using 80-20 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.76	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.92
DT	0.82	0.93	0.80	0.88
SVM	0.80	0.89	0.72	0.82
KNN	0.81	0.94	0.80	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.63	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 9. Evaluation Using 70-30 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.79	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.88
DT	0.82	0.93	0.80	0.88
SVM	0.73	0.89	0.72	0.82
KNN	0.81	0.94	0.72	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.64	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 10. Evaluation Using 90-10 Training Split

Algorithm	**A_c**	**R_e**	**F_1**	**AUC**
DNN	0.77	0.52	0.65	0.85
RF	0.83	0.99	0.83	0.93
DT	0.83	0.94	0.82	0.90
SVM	0.72	0.86	0.72	0.84
KNN	0.80	0.87	0.78	0.89
XGBoost	0.83	0.94	0.82	0.92
NB	0.63	0.30	0.40	0.85
Trans+NLP	0.85	0.95	0.84	0.94

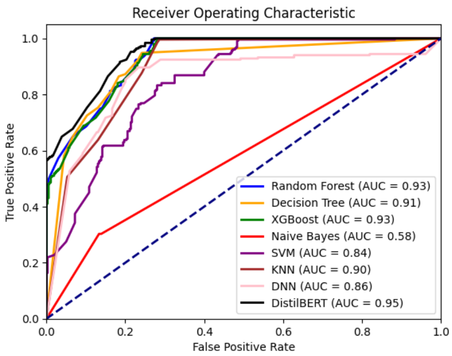

Figure 2. ROC for 90-10 Model

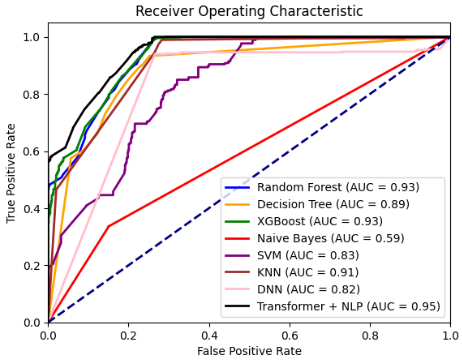

Figure 3. ROC for 80-20 Model

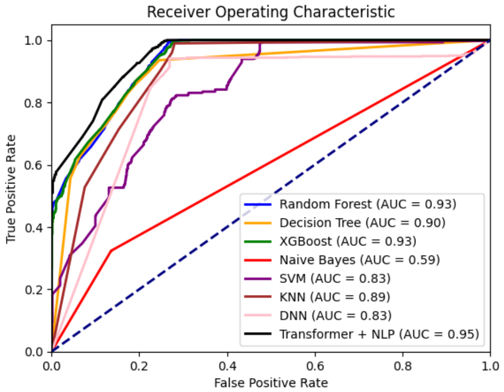

Figure 4. ROC for the 70-30 Model

Statical Validation

To test the reliability of the built model, we conducted evaluations using the Friedman test and t-test to compare its performance with other models[36]. We designated the proposed model as the control method in this experiment, and the significance level α for the statistical tests was set at 0.05. Generally, a smaller p-value indicates a significant difference between comparison methods. The results of the Friedman test and t-test are shown in Table 11.

Table 11. Friedman Test and T-test Results

	DNN	**DT**	**XB**	**NB**	**SVM**	**KNN**	**RF**
Friedman	0.0009	0.005	0.019	2.159	0.0001	0.006	0.04
T-Test	8.705	5.35	3.765	40.785	13.19	5.244	2.99

Parameter Sensivitas

In this section, we examine the impact of the hyperparameter, denoted by λ, on the proposed detection model. This analysis aims to understand how variations in λ influence the model's performance and effectiveness. The study involves adjusting the λ values and observing changes in key performance metrics, such as accuracy, recall, F1 score, and ROC-AUC. The results of this hyperparameter tuning are presented in Table 12, illustrating the relationship between different λ values and the corresponding performance metrics. This detailed evaluation helps in identifying the optimal λ setting for achieving the best detection results.

Table 12. Impact of Hyperparameter λ on Model Performance

Λ	**A_c**	**R_c**	**F_1**	**Auc**
1e-05	0.856	0.944	0.843	0.948
2e-05	0.852	0.944	0.840	0.950
3e-05	0.851	0.906	0.841	0.946
5e-05	0.849	0.952	0.838	0.946

Based on Table 12, although the AUC value remains the same (0.95) for several learning rate values, other metrics such as Accuracy, Recall, and F1 Score vary. The model with a learning rate of 2e-05 shows the highest AUC of 0.9505, indicating slightly better performance compared to other learning rates. Models with learning rates of 1e-05 and 3e-05 exhibit nearly the same AUC values (around 0.9490) but with variations in Accuracy and Recall. The ROC curve, illustrating sensitivity, is shown in Figure 5.

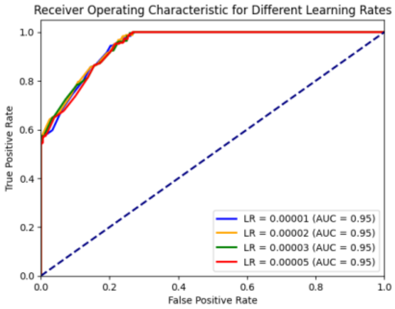

Figure 5. ROC Curve for Sensitivity Analysis of Parameters

Discussion

This study demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. The use of the Transformer model, with its self-attention mechanism, allows for capturing complex dependencies in sequential data, such as HTTP requests, which is crucial for detecting intricate attack patterns within dynamic and diverse web traffic. The CSIC 2010 dataset used in this study was processed through several pre-processing steps, including tokenization, stemming, lemmatization, and normalization, to ensure data consistency. Text representation techniques such as Word2Vec, BERT, and TF-IDF were employed to enable the Transformer model to effectively capture contextual relationships in network log data.

The model's performance evaluation demonstrated superior results compared to traditional algorithms like Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The Transformer-NLP model achieved higher accuracy, recall, F1 score, and AUC across multiple training/testing data splits (80/20, 70/30, and 90/10), with the best AUC value of 0.9505 at a learning rate of 2e-05, demonstrating its ability to adapt to different training scenarios. The ROC curve further illustrated the model's superior capability in distinguishing between normal and anomalous traffic, proving more reliable than the other models tested.

Statistical validation using the Friedman test and t-test confirmed the reliability and practical significance of the proposed model. Hyperparameter sensitivity analysis indicated that variations in the λ value impacted the model's performance, with a learning rate of 2e-05 providing the optimal results. These findings suggest that the proposed Transformer-NLP model is not only effective in improving detection accuracy but also offers a robust framework for reducing false positives, enhancing the overall security posture of web applications in response to increasingly sophisticated cyber threats.

Moreover, the model's ability to detect complex attack patterns in network traffic, particularly text-based inputs such as SQL injection and XSS attacks, significantly contributes to enhanced protection of web applications. By identifying and mitigating these sophisticated attack vectors, the model strengthens the security of web applications, preventing unauthorized access and malicious data manipulation. The reduction in false positive rates also ensures the system's efficiency and reliability in real-world scenarios, minimizing unnecessary alerts and enabling security teams to focus on genuine threats. This improvement in detection accuracy directly bolsters the resilience of web applications against evolving attack methods, helping to maintain data integrity, confidentiality, and availability.

However, this study has certain limitations. First, the CSIC 2010 dataset, while useful for evaluating web application security, may not fully capture the range of modern web application attack techniques, potentially limiting the model's applicability to newer or more varied threats. Second, the computational demands of both Transformer models and NLP preprocessing may pose challenges for practical deployment, particularly in environments with constrained resources. Additionally, while this study focused on optimizing performance metrics such as accuracy and AUC, it did not extensively address potential overfitting, which can be a concern with complex models trained on relatively limited datasets. Future research should explore the use of larger, more diverse datasets and further refine the model to balance computational efficiency with detection capability.

CONCLUSION

This study successfully demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. The proposed model effectively captures contextual relationships in network log data, allowing for more accurate and adaptive detection of web-based attacks. The evaluation results show that the Transformer-NLP model outperforms traditional algorithms such as DNN, RF, DT, SVM, KNN, XGBoost, and NB in terms of accuracy, recall, F1 score, and AUC. Additionally, the model's ability to handle the highly dynamic and diverse nature of web traffic represents a substantial improvement over conventional methods, addressing a critical gap in current Network Intrusion Detection Systems. Statistical validation through the Friedman test and t-test confirms the robustness and practical significance of the model. With these promising results, the Transformer-NLP model offers a more adaptive and intelligent solution to increasingly complex and sophisticated cyber threats.

Despite these significant findings, there are several limitations to consider. First, the CSIC 2010 dataset may not fully capture the breadth of modern web application attacks, potentially limiting the model's generalizability to newer and more diverse threats. Second, the Transformer-NLP model has high computational complexity and resource requirements, which could challenge practical deployment in production environments. Third, the study does not thoroughly explore the impact of overfitting, which may be a concern given the model's complexity and the relatively limited dataset. Future research should investigate overfitting mitigation strategies, such as employing regularization techniques or cross-validation methods, to ensure the model's robustness in more diverse operational settings. Lastly, this research focuses primarily on web application attacks, and extending the model's application to other types of network attacks requires further investigation. Future work should also explore optimizing the model's architecture to balance detection accuracy with computational efficiency, making it more feasible for deployment in resource-constrained environments

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[JANAPATI] Editor Decision

1 pesan

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Dear Wowon Priatna, Irwan Sembiring, Adi Setiawan, Iwan Iwan Setyawan,

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Notes/Review Comments

1. Issues no.1, 3, 4, 5, 6, 7, 8, and 9 are solved.
2. The authors should check much more about Indonesian language, such as "arsitektur".
3. Issues no.2 was not specified the location for revision. However, the reviewer believes that it has been followed up in last two paragraph in the Introduction.

4. In Discussion, the authors can put their interpretation about generated results. More, they also can compare the results with related literature to clarify whether any alignment or may be contrast among them.

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Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection

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Abstract

The increasing complexity and frequency of web application attacks demand more advanced detection methods than traditional network intrusion detection systems (NIDS), which rely heavily on predefined signatures and rules, limiting their effectiveness against novel threats. This study proposes a novel approach by integrating Transformer models with Natural Language Processing (NLP) techniques to develop an adaptive and intelligent intrusion detection framework. Leveraging the Transformer's capacity to capture long-term dependencies and NLP's ability to process contextual information, the model effectively addresses the dynamic and diverse nature of web application traffic. Using the CSIC 2010 dataset, this study applied comprehensive preprocessing, including tokenization, stemming, lemmatization, and normalization, followed by text representation techniques such as Word2Vec, BERT, and TF-IDF. The Transformer-NLP architecture significantly improved detection performance, achieving 85% accuracy, 95% precision, 83% recall, 84% F1 score, and an AUC of 0.95. Friedman and t-test validations confirmed the robustness and practical significance of the model. Despite these promising results, challenges related to computational complexity, dataset scope, and generalizability to broader network attacks remain. Future research should focus on expanding the dataset, optimizing the model, and exploring broader cybersecurity applications. This study demonstrates a significant advancement in detecting complex web application attacks, reducing false positives, and improving overall security, offering a viable solution to growing cybersecurity challenges.

Keywords: NLP, Intrusion Detection, Transformer, Web Application Attack, Machine Learning

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INTRODUCTION

The security of web applications has become a paramount concern in the current digital era, especially with the rise of attacks targeting vulnerabilities in web applications[1].As technology evolves and internet usage grows, web applications become more vulnerable to attacks like SQL injection, Cross-Site Scripting (XSS), and Denial of Service (DoS). These attacks compromise data integrity, confidentiality, and service availability, with rising frequency and complexity over time [2].

Web applications are often the first point of entry for attackers, exploiting vulnerabilities like SQL injection and Cross-Site Scripting (XSS) to gain unauthorized access or inject malicious scripts. These vulnerabilities highlight the need for robust detection mechanisms specifically tailored to web applications. Therefore, this study focuses on detecting attacks targeting web applications, recognizing this as a critical aspect of maintaining overall network security[3]. Research on network intrusion detection systems (NIDS) has explored various methodologies to counteract these threats[4]. For instance, Research [5] provides a comprehensive overview of existing detection systems specifically designed to monitor web traffic, comparing the capabilities of systems like AppSensor, PHPIDS, ModSecurity, Shadow Daemon, and AQTRONIX WebKnight. Other studies have focused on input validation techniques to prevent intrusions, such as the approach detailed in Research [6], which emphasizes input validation against web application attacks. Additionally, Research [7] has developed an intrusion detection model to mitigate cyber-attacks, data breaches, and identity theft, aiding in effective risk management.

Traditional approaches to network intrusion detection rely heavily on predefined signatures and rules, which limits their effectiveness in detecting new or unknown variants of attacks[8]. This rigidity necessitates more adaptive solutions. A popular approach to overcoming these limitations involves the use of machine learning (ML) and artificial intelligence (AI) to create more intelligent and flexible intrusion detection systems [9]. Machine learning models, such as Random Forest and Support Vector Machines, have been successfully employed to detect anomalies in network traffic[10]. Some studies have advanced this further by combining ensemble learning with NLP-based methods, as indicated in Research [11], to enhance the detection models' effectiveness. However, even these sophisticated methods face challenges in handling the highly dynamic and diverse data generated by web applications. The complexity of web application traffic stems from frequent updates, varying user inputs, and increasingly sophisticated attack vectors, making it difficult for traditional models to adapt in real time[12]. For example, studies have shown that vulnerabilities such as SQL injection and Cross-Site Scripting (XSS) are among the most common attack types, with SQL injection accounting for approximately 65% of web application attacks in 2022, according to OWASP reports[13]. The evolving nature of these vulnerabilities, along with their high frequency, underscores the critical need for more adaptive detection systems capable of handling the sheer volume and variety of data produced by modern web applications.

For instance, research [14] utilizing traditional ML models demonstrated moderate success in detecting known intrusions, but performance degraded significantly when applied to unknown or zero-day attacks. Moreover, approaches based on signature detection or anomaly detection often suffer from high false positive rates, making them impractical for real-world applications. To address these challenges, this study proposes a novel approach that integrates advanced Transformer models with NLP techniques to better capture the complex patterns and contextual information inherent in web application data[15]. While NLP techniques have been widely adopted, the deep integration of NLP with Transformer architectures for web application intrusion detection is a relatively unexplored area, offering a more nuanced detection of web attacks. This combination allows for the detection of complex[16], evolving web threats that are often missed by traditional machine-learning models.

Recent advancements in deep learning, particularly the development of the Transformer model by Vaswani et al., offer a promising solution[17]. The Transformer's ability to capture long-range dependencies in sequential data and process this information efficiently through an attention-based architecture provides a robust framework for addressing the complexities of web application data. The application of Transformer models in network intrusion detection presents new opportunities for developing more adaptive and sophisticated systems capable of identifying a wide range of web attacks[18]. Research has shown that Transformers are particularly effective in analyzing patterns and anomalies within network data, leading to improved detection rates of complex attacks that are often missed by conventional methods[19].

Unlike previous models that focus on static or homogeneous data sets, the proposed research utilizes both Transformer models and NLP techniques to handle the diverse and ever-evolving nature of web application data. This approach differs significantly from existing studies, which often rely on traditional machine learning models or shallow integration of NLP techniques. Our research leverages the Transformer's ability to handle intricate patterns within the data, providing a significant advancement over existing methods. By combining the strengths of NLP in text representation and the deep learning capabilities of Transformers, this study introduces a unique framework that significantly enhances detection performance, particularly for sophisticated web attacks. While earlier studies [11][20][21] employed NLP for enhancing feature extraction in intrusion detection, this research integrates these methods more deeply within a Transformer-based architecture, representing a novel approach to the field.

The novelty of this study lies in its dual integration of NLP techniques and Transformer models for web application intrusion detection, which has not been fully explored in prior research. This combination not only provides a more nuanced approach to understanding the data but also significantly enhances the model's ability to detect sophisticated web attacks. This research contributes to the field by presenting a novel framework that leverages advanced NLP and deep learning techniques to build more resilient intrusion detection systems, potentially reducing false positives and improving overall security[22]. The findings from this study are expected to offer valuable insights and practical implications for future research in cybersecurity, particularly in applying NLP and deep learning to enhance network security.

METHOD

This study aims to develop and analyze a network intrusion detection model based on Transformer methods and Natural Language Processing (NLP) techniques to enhance the security of web applications.

Dataset

The CSIC 2010 dataset, developed by the Spanish Research National Council, contains 61,065 records with 17 attributes, including both normal and malicious web traffic such as SQL injection, Cross-Site Scripting (XSS), and Path Traversal attacks. This dataset’s diversity is crucial for training models to recognize both attack patterns and normal behaviors in web traffic, ensuring a robust evaluation of the model’s ability to handle real-world scenarios[17]. The dataset's size is sufficient for training deep learning models like Transformers, which require large and diverse datasets to capture complex relationships and generalize well without overfitting. NLP techniques are essential for analyzing the textual nature of web-based attacks. Many attacks, such as SQL injection and XSS, exploit text-based inputs within HTTP requests, making them difficult to detect using traditional methods. NLP allows for deeper analysis of textual data, such as URL parameters and HTTP headers, enabling the model to identify subtle anomalies. The Transformer architecture excels at capturing long-range dependencies, making it adaptable to both known and evolving attack patterns, which is vital for detecting emerging threats in web applications.

Algorithm Selection: Transformer Architecture

In this study, we selected the Transformer architecture due to its ability to effectively process sequential data and capture long-range dependencies[23], which are critical for analyzing web application traffic. Traditional machine learning models, such as Random Forest and Support Vector Machines (SVM), often struggle with the dynamic and unstructured nature of web-based attacks, particularly when analyzing text-based HTTP requests that can be manipulated through attacks like SQL injection or Cross-Site Scripting (XSS)[24]. These conventional algorithms rely heavily on predefined features, making them less effective in detecting new and evolving attack patterns.

The Transformer model addresses these limitations through a self-attention mechanism that highlights key parts of an input sequence, like HTTP headers and URL parameters. This feature enables it to capture extensive dependencies and complex relationships within data, enhancing its ability to identify intricate patterns beyond the reach of traditional models[25][26].

Moreover, Transformers offer significant computational advantages over recurrent models like LSTMs and GRUs, especially in large-scale datasets[27]. Their ability to process data in parallel allows for more efficient training on large-scale datasets, such as the CSIC 2010 dataset, without sacrificing accuracy. This makes Transformers not only faster but also more scalable for real-world applications that involve large and diverse data.

In addition, the integration of NLP techniques with the Transformer model enhances its ability to extract meaningful features from web traffic data[28]. Techniques such as Word2Vec, BERT, and TF-IDF enable the model to better understand textual data and context[29], facilitating more accurate detection of web application attacks that exploit text-based inputs.

Network Intrusion Detection

Network Intrusion Detection Systems (NIDS) are crucial for identifying and mitigating security threats to web applications. Traditional NIDS relies on signature-based and anomaly-based methods. Signature-based systems are adequate for known threats but struggle to detect new attacks, while anomaly-based systems can identify unknown attacks but often have high false favorable rates[30]. Advances in machine learning (ML) and deep learning (DL) have enhanced NIDS capabilities, with convolutional neural networks (CNN) and recurrent neural networks (RNN) demonstrating improved accuracy[31]. However, these models often fail to capture network logs' temporal and contextual dependencies, which is essential for detecting sophisticated web application attacks. Transformer models and Natural Language Processing (NLP) techniques have been introduced to address this. Transformers excel in capturing long-term dependencies and contextual relationships in sequential data[18], while NLP enables effective preprocessing and representation of network logs[11]. This study develops a more robust NIDS for detecting web application attacks by combining Transformer models and NLP, aiming to reduce false positives and improve detection accuracy.

Transformer

The Transformer is an architectural model that has revolutionized the landscape of natural language processing (NLP) and various other applications. As introduced in "Attention is All You Need," the Transformer relies on the self-attention mechanism to capture relationships between elements in sequential data[17]. The self-attention mechanism allows the model to efficiently consider the entire input context without processing the data sequentially, unlike traditional approaches such as RNNs and LSTM[32]. The core formula in self-attention is shown in equation (1):

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}\,(\frac{QK^T}{\sqrt{DK}})\mathrm{V} \qquad (1)$$

The Transformer model consists of multiple encoders and decoders, with each encoder layer comprising a self-attention mechanism and a feed-forward neural network[33]. The encoder generates contextual representations of the input, which are then used by the decoder to produce the output. This approach enables the Transformer to capture long-term dependencies and complex relationships within the data[34].

Transformers have demonstrated their superiority in various NLP tasks, including machine translation, text classification, and language modeling, outperforming previous approaches[17]. Their application in network intrusion detection leverages Transformers and NLP techniques to preprocess network logs and detect attack patterns with high efficiency and improved accuracy. This study will implement the Transformer model to enhance the detection capabilities of web application attacks, utilizing the power of self-attention to capture complex relationships in network data.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and generate human-like text. NLP encompasses sentiment analysis, machine translation, and network log analysis applications. Fundamental NLP techniques include tokenization (breaking text into smaller units), stemming, and lemmatization.

Recent advancements in NLP, such as BERT, use Transformer architecture to capture the bidirectional context in text, significantly improving the performance of NLP tasks. These models have been successfully applied in various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This research leverages NLP techniques to process network logs, converting them into vector representations, and employs Transformer models to detect web application attacks with greater accuracy. Recent advancements in NLP, such as BERT, utilize transformer architecture to capture bidirectional context in text, thereby enhancing the performance of NLP tasks. These models have been successfully applied across various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This study leverages NLP techniques to process network logs, converting them into vector representations, and employs transformer models to more accurately detect web application attacks.

integration of Transformer models with NLP

This study proposes the integration of Transformer models with NLP techniques to detect attacks on web applications through a Network NIDS. The proposed model in this research is illustrated in Figure 1.

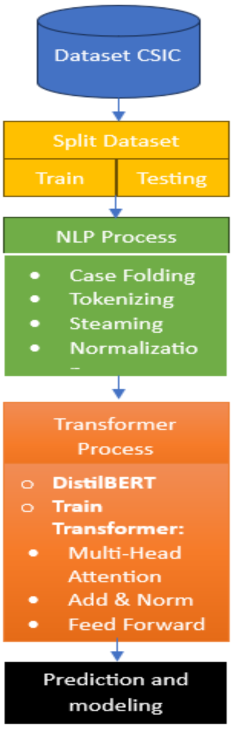

Figure 1. Intrusion Detection Architecture

Based on Figure 1, the steps for intrusion detection are further detailed in Algorithm 1. The initial stage involves initializing parameters for the Transformer and the DistilBERT tokenizer. The NLP preprocessing phase includes case folding, tokenization, stemming, and normalization to ensure that the text data is consistent and formatted adequately for analysis. The DistilBERT tokenizer then converts the preprocessed text into appropriate tokens. The following equations are used in the process: Equation (5) for converting logs, including URLs, into lowercase (case folding). Equation (6) for tokenization. Equation (7) for stemming. Equation (8) for normalization

$$lower\ (T) = map(\lambda\mathfrak{x}: \mathfrak{x} \rightarrow lowercase(\mathfrak{x}) \quad (5)$$

$$Tokend = Tokenize(T, delimiter) \quad (6)$$

$$Stem = StemmingAlgoritm(T) \quad (7)$$

$$text\ \longrightarrow \text{normalized text} \quad (8)$$

Next, the tokenized data is converted into tensors, enabling processing by the Transformer model. The training phase of the Transformer model involves several critical steps, including Multi-Head Attention to capture various aspects of relationships between words, Add & Norm for normalization and residual addition, and Feed Forward layers for further data transformation. After training, the model's performance is evaluated using metrics such as accuracy, recall, F1 score, and AUC to assess its effectiveness in detecting intrusions.

$$output_{residual} = input + Sublayer(input) (9)$$

$$output_{norm} = \frac{output_{residual - \mu}}{\sigma} . \gamma + \beta \quad (10)$$

$$FFN_1(\mathfrak{x}) = ReLU(W_1 x + b_1 \quad (11)$$

Algorithm 1: Transformer NLP Integration

```
Input: Input: Dataset $D$={($xi$,$yi$)}
Output: Final model intrusion detection

1. Initialization:
     • Parameters for the Transformer and DistilBERT tokenizer are initialized.
2. NLP Preprocessing:
     • Case Folding
     • Tokenization
     • Steaming
     • Normalization
3. Tokenization
     • The DistilBERT Tokenizer is used to convert text into appropriate tokens:
4. Conversion to Tensors
     • The tokenized data is converted into tensors that the Transformer model can process
5. Train Transformer
     • The Transformer model is trained with the processed data
         a. Multi-Head Attention: use equation (1)
         b. Add & Norm: Normalization and residual addition. Use equations (9) and (10)
         c. Feed Forward. Use equation (11)
6. Model Evaluation
     • The model has evaluated the use of equations (12), (13, (14), (15), (16).
7. Final Model
     • The final model is returned for intrusion detection
```

Evaluation

The next step in this research is to evaluate the performance of the developed intrusion detection model. The objective of this performance testing is to determine the extent to which the model is suitable for practical use. Several evaluation parameters are utilized, including Accuracy (Ac), Recall (Re), Precision (Pr), F1 Score (F1), and Area Under the Curve (AUC)[21][35]. These parameters provide a comprehensive assessment of the model's effectiveness and reliability in classification. The formulas for each parameter are given in equations (12), (13), (14), (15), and (16)[18]. Table 1 illustrates the prediction of target labels. The next step involves reporting the model's performance using the Receiver Operating Characteristic (ROC) curve to assess the intrusion detection model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \quad (12)$$

$$Precision = \frac{TP}{TP+TF} \quad (13)$$

$$Recall = \frac{TP}{TP+TN} \quad (14)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ recall}{precision+recall} \quad (15)$$

$$AUC = \int_0^1 TPR(FPR)d\ (FPR) \quad (16)$$

Table1. Confusion Matrix

	True Normal	True Anomalous
Predict Normal	TP	FP
Predict Anomalous	TN	TN

Statistical Validation

In this study, statistical validation is performed using the Friedman Test and the Paired T-test. The Friedman Test, a non-parametric test, is used to compare the performance of multiple classification models on the same dataset[36]. This test examines the null hypothesis that there is no significant difference in the performance of these models. If the Friedman Test results indicate a significant difference, further analysis is conducted using the Paired T-test to identify which pairs of models have significantly different performances[37]. The combination of these two tests provides comprehensive validation, ensuring that the developed model is not only statistically superior but also has practical significance in its application[34].

RESULT AND DISCUSSION

The proposed Transformer-NLP method demonstrates that the Transformer model excels in capturing contextual relationships in network logs, enhancing its ability to detect web application attacks. This success can be attributed to the Transformer's self-attention mechanism, which enables the model to identify intricate attack patterns by focusing on relevant sections of the input data, making it highly effective in distinguishing between normal and anomalous traffic.

Data Processing

At this stage, data cleaning was performed, where three records with missing data were removed, reducing the dataset from 61,065 to 61,062 records. The following process involved reducing the number of variables from 17 to 2, which were relevant to the context of the research. Table 1 shows the dataset after data preprocessing. Table 2 defines the target or label for classification, where 0 represents normal, and 1 represents anomalous.

Table 2. Pre-processing Result Dataset

	URL	Label
1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	0
2	http://localhost:8080/ ?OpenServer HTTP/1.1	0
61062	http://localhost:8080/tienda1/miembros.Inc HTTP/1.1	1

Text Representation Formation

In this stage, processing is conducted using NLP techniques, including tokenizing, case folding, stemming, and stop word normalization. First, tokenizing: The results of tokenization demonstrate how URLs are broken down into smaller parts that the transformer model can process. This process involves adding unique tokens, handling special characters and symbols, and sub-word tokenization to address words not present in the model's overall vocabulary. Table 3 provides a clear overview of how raw data is transformed into a format suitable for NLP modelling.

Table 3. Tokenization Results

Input Process	Output Process
http://localhost:8080/tienda1 /publico/vaciar.jsp? B2=Vaciar+carrito HTTP/1.1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>

Next, all characters in the URL are converted to lowercase before tokenization using case folding. Table 4 shows the results of tokenization, demonstrating that all elements in the URL have been converted to lowercase and broken down into smaller tokens. This helps ensure consistency in text processing and makes the model more robust against variations in capitalization.

Table 4. Case Folding Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The steaming process does not significantly alter the text in this case because most tokens are part of URLs or symbols. However, words like "vaciar" and "carr" will be processed if there are suffixes that can be removed. Table 5 presents the final results, showing that tokenization and stemming have been applied, although minimal changes occurred due to the specific characteristics of the input text (URLs and symbols).

Table 5. Stemming Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The stop word removal stage is omitted since most tokens are part of URLs. The normalization process at this stage includes converting all text to lowercase, removing punctuation, and eliminating numbers. Lowercasing ensures consistency, allowing 'HTTP' and 'http' to be treated identically. Punctuation marks, such as periods, slashes, and question marks, are removed to streamline the text. Table 6 presents the results of applying these normalization steps to the sample input.

Table 6. Normalization Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Model Implementation

In this study, the implementation of the Transformer model with the integration of Natural Language Processing (NLP) for network intrusion detection is conducted through several key stages. The first stage is data processing, which includes normalization, batch processing, and splitting the data into training and testing sets with ratios of 70/30, 80/20, and 90/10. In the NLP processing, steps such as case folding, text normalization, tokenization, and stemming are performed to ensure the text is in a consistent format. Tokenization uses the DistilBERT Tokenizer to convert the text into tokens that the Transformer model can process.

As shown in Figure 1, the architecture for network intrusion detection with Transformer and NLP integration is implemented according to Algorithm 1. In the model training stage, DistilBERT, initialized with default parameters, is used to handle the Multi-Head Attention, Add & Norm, and Feed Forward layers. The model is trained using the Adam optimizer with a learning rate of 2e-5 and the Cross-Entropy loss function. Training is conducted over three epochs with a batch size of 8. Model evaluation is performed by measuring metrics such as accuracy, recall, F1 score, and ROC-AUC to ensure the model's performance in detecting network intrusion categories classified as "Normal" and "Anomalous." Evaluation results indicate that the integration of the Transformer model and NLP is effective in detecting web application attacks and significantly contributes to the improvement of the network intrusion detection system's accuracy. The parameters of the Transformer model integrated with NLP are shown in Table 7.

Table 7. Parameter Model

Parameter	Value
Input Shape	Input_dim
NLP Pre-preprocessing	Case Folding, Normalization, Tokenization, Stemming
Tokenization	DistilBERTTokenizer
Multi-Head Attention	Num_heads=8, dim_model=512
Add & Norm	Layer Normalization
Feed Forward	Dense (2048, Activation='ReLU'
Linear Layer	Dense (256, activation='softmax'
Softmax Layer	Dense(num_classes, activation='softmax'
Optimizer	AdamW (learning_rate=2e-5)
Loss Function	Cross-Entropy Loss
Training Parameter	Epoch=3, Batch Size=8
Evaluation Matrix	Accuracy, Recall, F1 Score, AUC

Evaluation

The implemented model is then evaluated to test its performance. Compared to traditional algorithms such as DNN, Random Forest, and SVM, the Transformer-NLP model showed marked improvements in accuracy and AUC. Previous studies using conventional methods often struggled to maintain high detection rates across varied datasets, while the Transformer model's adaptive architecture proved effective in handling diverse attack types, as evidenced by its consistently higher AUC scores across multiple data splits. The evaluation uses equations (12), (14), (15), and (16). The results are shown in Tables 8, 9, and 10. Subsequently, the model's performance is tested using the ROC curves, which are displayed in Figures 2, 3, and 4.

Table 8. Evaluation Using 80-20 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.76	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.92
DT	0.82	0.93	0.80	0.88
SVM	0.80	0.89	0.72	0.82
KNN	0.81	0.94	0.80	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.63	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 9. Evaluation Using 70-30 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.79	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.88
DT	0.82	0.93	0.80	0.88
SVM	0.73	0.89	0.72	0.82
KNN	0.81	0.94	0.72	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.64	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 10. Evaluation Using 90-10 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.77	0.52	0.65	0.85
RF	0.83	0.99	0.83	0.93
DT	0.83	0.94	0.82	0.90
SVM	0.72	0.86	0.72	0.84
KNN	0.80	0.87	0.78	0.89
XGBoost	0.83	0.94	0.82	0.92
NB	0.63	0.30	0.40	0.85
Trans+NLP	0.85	0.95	0.84	0.94

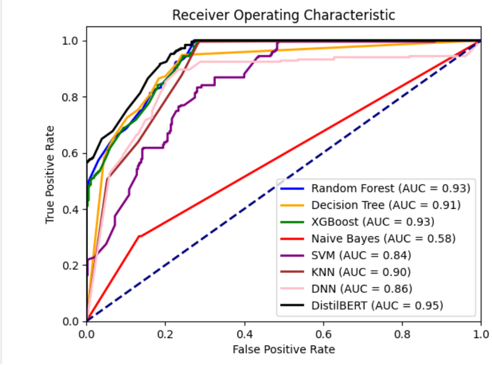

Figure 2. ROC for 90-10 Model

Statical Validation

To test the reliability of the built model, we conducted evaluations using the Friedman test and t-test to compare its performance with other models[36]. We designated the proposed model as the control method in this experiment, and the significance level α for the statistical tests was set at 0.05. Generally, a smaller p-value indicates a significant difference between comparison methods. The results of the Friedman test and t-test are shown in Table 11.

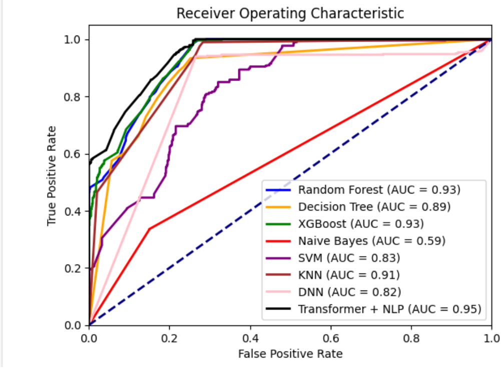

Figure 3. ROC for 80-20 Model

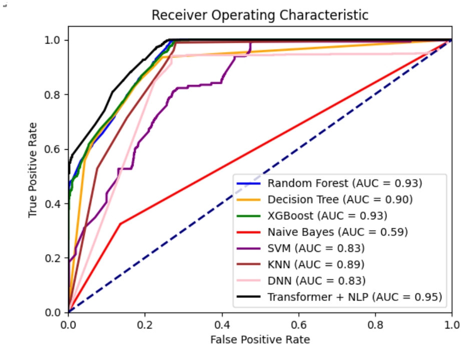

Figure 4. ROC for the 70-30 Model

Parameter Sensitivitas

In this section, we examine the impact of the hyperparameter, denoted by λ, on the proposed detection model. This analysis aims to understand how variations in λ influence the model's performance and effectiveness. The study involves adjusting the λ values and observing changes in key performance metrics, such as accuracy, recall, F1 score, and ROC-AUC. The results of this hyperparameter tuning are presented in Table 12, illustrating the relationship between different λ values and the corresponding performance metrics. This detailed evaluation helps in identifying the optimal λ setting for achieving the best detection results.

Table 11. Friedman Test and T-test Results

	DNN	DT	XB	NB	SVM	KNN	RF
Friedman	0.0009	0.005	0.019	2.159	0.0001	0.006	0.04
T-Test	8.705	5.35	3.765	40.785	13.19	5.244	2.99

.Table 12. Impact of Hyperparameter λ on Model Performance

Λ	A_c	R_c	F_1	Auc
1e-05	0.856	0.944	0.843	0.948
2e-05	0.852	0.944	0.840	0.950
3e-05	0.851	0.906	0.841	0.946
5e-05	0.849	0.952	0.838	0.946

Based on Table 12, although the AUC value remains the same (0.95) for several learning rate values, other metrics such as Accuracy, Recall, and F1 Score vary. The model with a learning rate of 2e-05 shows the highest AUC of 0.9505, indicating slightly better performance compared to other learning rates. Models with learning rates of 1e-05 and 3e-05 exhibit nearly the same AUC values (around 0.9490) but with variations in Accuracy and Recall. The ROC curve, illustrating sensitivity, is shown in Figure 5.

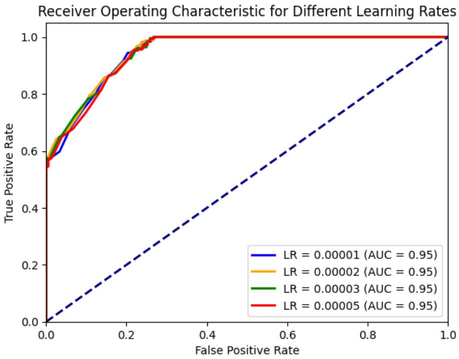

Figure 5. ROC Curve for Sensitivity Analysis of Parameters

Discussion

This study demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. The use of the Transformer model, with its self-attention mechanism, allows for capturing complex dependencies in sequential data, such as HTTP requests, which is crucial for detecting intricate attack patterns within dynamic and diverse web traffic. The CSIC 2010 dataset used in this study was processed through several pre-processing steps, including tokenization, stemming, lemmatization, and normalization, to ensure data consistency. Text representation techniques such as Word2Vec, BERT, and TF-IDF were employed to enable the Transformer model to effectively capture contextual relationships in network log data.

The model's performance evaluation demonstrated superior results compared to traditional algorithms like Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The Transformer-NLP model achieved higher accuracy (up to 85%), recall (95%), F1 score (83%), and AUC (0.95) across training/testing splits of 80/20, 70/30, and 90/10. This performance is especially significant when compared to traditional models, which showed lower AUC values, indicating that the Transformer-NLP approach provides a more robust framework for intrusion detection across various scenarios, with the best AUC value of 0.9505 at a learning rate of 2e-05, demonstrating its ability to adapt to different training scenarios. The ROC curve further illustrated the model's superior capability in distinguishing between normal and anomalous traffic, proving more reliable than the other models tested.

Statistical validation using the Friedman test and t-test confirmed the reliability and practical significance of the proposed model. Hyperparameter sensitivity analysis indicated that variations in the λ value impacted the model's performance, with a learning rate of 2e-05 providing the optimal results. These findings suggest that the proposed Transformer-NLP model is not only effective in improving detection accuracy but also offers a robust framework for reducing false positives, enhancing the overall security posture of web applications in response to increasingly sophisticated cyber threats.

Additionally, the model effectively detects complex attack patterns, especially in text-based inputs like SQL injection and XSS, enhancing web application security, and preventing unauthorized access and malicious data manipulation. The Transformer-NLP model’s unique integration of NLP for preprocessing and the self-attention mechanism significantly reduces false positive rates. This reduction enhances both efficiency and reliability in real-world scenarios, as it minimizes unnecessary alerts and focuses security resources on genuine threats. By improving precision and recall, this model presents a more reliable solution for continuous, real-time web application monitoring, minimizing unnecessary alerts and enabling security teams to focus on genuine threats. This improvement in detection accuracy directly bolsters the resilience of web applications against evolving attack methods, helping to maintain data integrity, confidentiality, and availability.

However, this study has certain limitations. First, the CSIC 2010 dataset, while useful for evaluating web application security, may not fully capture the range of modern web application attack techniques, potentially limiting the model's applicability to newer or more varied threats. Second, the computational demands of both Transformer models and NLP preprocessing may pose challenges for practical deployment, particularly in environments with constrained resources. Additionally, while this study focused on optimizing performance metrics such as accuracy and AUC, it did not extensively address potential overfitting, which can be a concern with complex models trained on relatively limited datasets. Future research should explore the use of larger, more diverse datasets and further refine the model to balance computational efficiency with detection capability.

CONCLUSION

This study demonstrates that integrating the Transformer model with NLP techniques significantly improves NIDS performance for web applications by capturing complex contextual relationships in network log data. The Transformer-NLP model outperformed traditional algorithms, including DNN, RF, DT, SVM, KNN, XGBoost, and NB, across key metrics (accuracy, recall, F1 score, and AUC), addressing a crucial gap in current NIDS methods. Statistical validation using the Friedman and t-tests further supports the model's robustness and practical effectiveness, especially in handling the dynamic nature of web traffic.

However, limitations remain. The CSIC 2010 dataset may not fully reflect modern web application threats, which could affect generalizability. Additionally, the model’s high computational demands pose challenges for real-world deployment. This study also did not deeply explore overfitting, which could impact performance given the dataset size. Future work should examine strategies such as regularization and cross-validation to enhance model robustness, along with architectural optimizations to improve computational efficiency for practical deployment in constrained environments.

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Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection

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Abstract

The increasing frequency and complexity of web application attacks necessitate more advanced detection methods. This research explores integrating Transformer models and Natural Language Processing (NLP) techniques to enhance network intrusion detection systems (NIDS). Traditional NIDS often rely on predefined signatures and rules, limiting their effectiveness against new attacks. By leveraging the Transformer's ability to capture long-term dependencies and the contextual richness of NLP, this study aims to develop a more adaptive and intelligent intrusion detection framework. Utilizing the CSIC 2010 dataset, comprehensive preprocessing steps such as tokenization, stemming, lemmatization, and normalization were applied. Techniques like Word2Vec, BERT, and TF-IDF were used for text representation, followed by the application of the Transformer architecture. Performance evaluation using accuracy, precision, recall, F1 score, and AUC demonstrated the superiority of the Transformer-NLP model over traditional machine learning methods. Statistical validation through Friedman and T-tests confirmed the model's robustness and practical significance. Despite promising results, limitations include the dataset's scope, computational complexity, and the need for further research to generalize the model to other types of network attacks. This study indicates significant improvements in detecting complex web application attacks, reducing false positives, and enhancing overall security, making it a viable solution for addressing increasingly sophisticated cybersecurity threats.

Keywords: NLP, Intrusion Detection, Transformer, Web Application Attack, Machine Learning

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INTRODUCTION

The security of web applications has become a paramount concern in the current digital era, especially with the rise of attacks targeting vulnerabilities in web applications[1]. As technology advances and the number of internet users increases, web applications are increasingly susceptible to attacks such as SQL injection, Cross-Site Scripting (XSS), and Denial of Service (DoS) attacks. Previous research indicates that attacks on web applications continue to escalate in frequency and complexity, threatening data and web services' integrity, confidentiality, and availability[2].

Research [3] provides a comprehensive overview of existing detection systems specifically designed to monitor web traffic by comparing their features with five existing detection systems: AppSensor, PHPIDS, ModSecurity, Shadow Daemon, and AQTRONIX WebKnight. Research [4] focuses on input validation against web application attacks to prevent intrusions into the web network. Meanwhile, research [5] develops an intrusion system model to avoid cyber-attacks, data breaches, and identity theft, which can aid in risk management. Traditional approaches to network intrusion detection often rely on predefined signatures and rules, making them less effective in detecting new or unknown variants of attacks[6]. One increasingly popular solution is the application of machine learning and artificial intelligence to detect intrusions more adaptively and intelligently [7]. Machine learning-based models, such as Random Forest and Support Vector Machines, have been employed to detect anomalies in network traffic [8]. Some studies utilize machine learning and deep learning for network intrusion detection, including[9]. which combines ensemble learning with NLP-based methods to enhance detection models. However, these approaches have limitations in handling highly dynamic and diverse data in web applications.

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The Transformer, introduced by Vaswani in the context of natural language processing, has demonstrated exceptional performance across various NLP tasks due to its ability to capture long-range dependencies in sequential data and process them efficiently with an attention-based architecture[10]. The application of Transformer models in network intrusion detection opens new opportunities to develop more adaptive and sophisticated systems for identifying web attacks[11]. Recent studies indicate that Transformers can be used to analyze patterns and anomalies in network data with promising results, enhancing the detection of attacks that are difficult to identify using conventional methods[12].

The use of Natural Language Processing (NLP) in the context of intrusion detection also offers an innovative approach to handling complex text data in network logs[13][14]. NLP techniques enable more prosperous and contextual feature extraction from log data, enhancing the model's ability to recognize attack patterns. Research indicates that NLP techniques and text-processing algorithms can enrich intrusion detection models with more accurate and meaningful data representations[9]. enhancing the model's ability to recognize attack patterns. Research indicates that NLP techniques and text-processing algorithms can enrich intrusion detection models with more accurate and meaningful data representations[15]. This study aims to combine the Transformer model with NLP techniques for web application intrusion detection, which is expected to provide a more effective solution in addressing increasingly sophisticated cybersecurity threats. This integration represents a novel approach to building intrusion detection systems by leveraging Transformer models with NLP advancements.

METHOD

This study aims to develop and analyze a network intrusion detection model based on Transformer methods and Natural Language Processing (NLP) techniques to enhance the security of web applications. The design of this research is illustrated in Figure 1.

Dataset

The CSIC 2010 dataset, developed by the Spanish Research National Council (Consejo Superior de Investigaciones Científicas - CSIC), is designed for web application intrusion detection and network security research. On Kaggle, this dataset comprises 61,065 records and 17 variables/attributes [10].

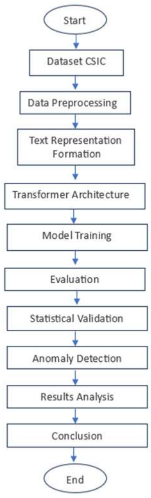

Figure 1. Research Design

Network Intrusion Detection

Network Intrusion Detection Systems (NIDS) are crucial for identifying and mitigating security threats to web applications. Traditional NIDS relies on signature-based and anomaly-based methods. Signature-based systems are adequate for known threats but struggle to detect new attacks, while anomaly-based systems can identify unknown attacks but often have high false favorable rates[16]. Advances in machine learning (ML) and deep learning (DL) have enhanced NIDS capabilities, with convolutional neural networks (CNN) and recurrent neural networks (RNN) demonstrating improved accuracy[17]. However, these models often fail to capture network logs' temporal and contextual dependencies, which is essential for detecting sophisticated web application attacks. Transformer models and Natural Language Processing (NLP) techniques have been introduced to address this. Transformers excel in capturing long-term dependencies and contextual relationships in sequential data[18], while NLP enables effective preprocessing and representation of network logs[9]. This study develops a more robust NIDS for detecting web application attacks by combining Transformer models and NLP, aiming to reduce false positives and improve detection accuracy.

Transformer

The Transformer is an architectural model that has revolutionized the landscape of natural language processing (NLP) and various other applications. As introduced in "Attention is All You Need," the Transformer relies on the self-attention mechanism to capture relationships between elements in sequential

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data[10]. The self-attention mechanism allows the model to efficiently consider the entire input context without processing the data sequentially, unlike traditional approaches such as RNNs and LSTM[18]. The core formula in self-attention is shown in equation (1):

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{DK}}\right)\text{V} \qquad (1)$$

The Transformer model consists of multiple encoders and decoders, with each encoder layer comprising a self-attention mechanism and a feed-forward neural network[19]. The encoder generates contextual representations of the input, which are then used by the decoder to produce the output. This approach enables the Transformer to capture long-term dependencies and complex relationships within the data[20].

Transformers have demonstrated their superiority in various NLP tasks, including machine translation, text classification, and language modeling, outperforming previous approaches[10]. Their application in network intrusion detection leverages Transformers and NLP techniques to preprocess network logs and detect attack patterns with high efficiency and improved accuracy. This study will implement the Transformer model to enhance the detection capabilities of web application attacks, utilizing the power of self-attention to capture complex relationships in network data.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and generate human-like text. NLP encompasses sentiment analysis, machine translation, and network log analysis applications. Fundamental NLP techniques include tokenization (breaking text into smaller units), stemming, and lemmatization.

Recent advancements in NLP, such as BERT, use Transformer architecture to capture the bidirectional context in text, significantly improving the performance of NLP tasks. These models have been successfully applied in various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This research leverages NLP techniques to process network logs, converting them into vector representations, and employs Transformer models to detect web application attacks with greater accuracy.Kemajuan terbaru dalam NLP, seperti BERT, menggunakan arsitektur transformer untuk menangkap konteks dari kedua arah dalam teks, meningkatkan kinerja tugas-tugas NLP. Model-model ini telah berhasil diterapkan dalam berbagai domain, termasuk keamanan siber, untuk memproses dan menganalisis log jaringan guna deteksi anomali. Penelitian ini memanfaatkan teknik NLP untuk memproses log jaringan, mengonversinya menjadi representasi vektor, dan menggunakan model transformer untuk mendeteksi serangan aplikasi web dengan lebih akurat.

integration of Transformer models with NLP

This study proposes the integration of Transformer models with NLP techniques to detect attacks on web applications through a Network NIDS. The proposed model in this research is illustrated in Figure 2.

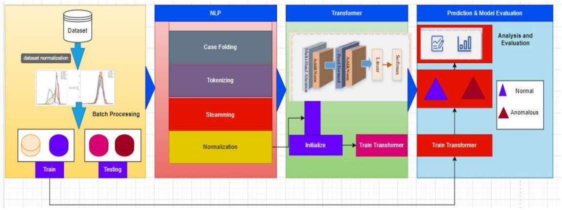

Figure 2. Arsitektur Instrusion Detection

Based on Figure 2, the steps for intrusion detection are further detailed in Algorithm 1. The initial stage involves initializing parameters for the Transformer and the DistilBERT tokenizer. The NLP preprocessing phase includes case folding, tokenization, stemming, and normalization to ensure that the text data is consistent and formatted adequately for analysis. The DistilBERT tokenizer then converts the preprocessed text into appropriate tokens. The following equations are used in the process: Equation (5) for converting logs, including URLs, into lowercase (case folding). Equation (6) for tokenization. Equation (7) for stemming. Equation (8) for normalization

$$lower\ (T) = map(\lambda \mathfrak{x}: \mathfrak{x} \rightarrow lowercase(\mathfrak{x}) \qquad (5)$$

$$Tokend = Tokenize(T, delimiter) \qquad (6)$$

$$Stem = StemmingAlgoritm(T) \qquad (7)$$

$$text\ \longrightarrow \text{normalized text} \qquad (8)$$

Next, the tokenized data is converted into tensors, enabling processing by the Transformer model. The training phase of the Transformer model involves several critical steps, including Multi-Head Attention to capture various aspects of relationships between words, Add & Norm for normalization and residual addition, and Feed Forward layers for

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further data transformation. After training, the model's performance is evaluated using metrics such as accuracy, recall, F1 score, and AUC to assess its effectiveness in detecting intrusions.

$$output_{residual} = input + Sublayer(input)(9)$$

$$output_{norm} = \frac{output_{residual-\mu}}{\sigma}.\gamma + \beta \qquad (10)$$

$$FFN_1(x) = ReLU(W_1x + b_1 \qquad (11)$$

```
Algorithm 1: Transformer NLP Integration
Input: Input: Dataset $D$={($xi$,$yi$)}
Output: Final model intrusion detection

1. Initialization:
    • Parameters for the Transformer and DistilBERT tokenizer are initialized.
2. NLP Preprocessing:
    • Case Folding
    • Tokenization
    • Steaming
    • Normalization
3. Tokenization
    • The DistilBERT Tokenizer is used to convert text into appropriate tokens:
4. Conversion to Tensors
    • The tokenized data is converted into tensors that the Transformer model can process
5. Train Transformer
    • The Transformer model is trained with the processed data
        a. Multi-Head Attention: use equation (1)
        b. Add & Norm: Normalization and residual addition. Use equations (9) and (10)
        c. Feed Forward. Use equation (11)
6. Model Evaluation
    • The model has evaluated the use of equations (12), (13, (14), (15), (16).
7. Final Model
    • The final model is returned for intrusion detection
```

Evaluation

The next step in this research is to evaluate the performance of the developed intrusion detection model. The objective of this performance testing is to determine the extent to which the model is suitable for practical use. Several evaluation parameters are utilized, including Accuracy (Ac), Recall (Re), Precision (Pr), F1 Score (F1), and Area Under the Curve (AUC)[21]. These parameters provide a comprehensive assessment of the model's effectiveness and reliability in classification. The formulas for each parameter are given in equations (12), (13), (14), (15), and (16)[11]. Table 1 illustrates the prediction of target labels. The next step involves reporting the model's performance using the Receiver Operating Characteristic (ROC) curve to assess the intrusion detection model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \qquad (12)$$

$$Precision = \frac{TP}{TP+TF} \qquad (13)$$

$$Recall = \frac{TP}{TP+TN} \qquad (14)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ recall}{precision+recall} \qquad (15)$$

$$AUC = \int_0^1 TPR(FPR)d\ (FPR) \qquad (16)$$

Table1. Confusion Matrix

	True Normal	True Anomalous
Predict Normal	TP	FP
Predict Anomalous	TN	TN

Statistical Validation

In this study, statistical validation is performed using the Friedman Test and the Paired T-test. The Friedman Test, a non-parametric test, is used to compare the performance of multiple classification models on the same dataset[22]. This test examines the null hypothesis that there is no significant difference in the performance of these models. If the Friedman Test results indicate a significant difference, further analysis is conducted using the Paired T-test to identify which pairs of models have significantly different performances. The combination of these two tests provides comprehensive validation, ensuring that the developed model is not only statistically superior but also has practical significance in its application[20].

RESULT AND DISCUSSION

The application of the proposed Transformer-NLP method demonstrates that the Transformer model effectively captures contextual relationships in network logs to detect web application attacks through intrusion detection.

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Data Processing

At this stage, data cleaning was performed, where three records with missing data were removed, reducing the dataset from 61,065 to 61,062 records. The following process involved reducing the number of variables from 17 to 2, which were relevant to the context of the research. Table 1 shows the dataset after data preprocessing. Table 3 defines the target or label for classification, where 0 represents normal, and 1 represents anomalous.

Table 3. Pre-processing Result Dataset

	URL	Label
1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	0
2	http://localhost:8080/ ?OpenServer HTTP/1.1	0
61062	http://localhost:8080/tienda1/miembros.Inc HTTP/1.1	1

Pembentukan Representasi Teks

In this stage, processing is conducted using NLP techniques, including tokenizing, case folding, stemming, and stop word normalization. First, tokenizing: The results of tokenization demonstrate how URLs are broken down into smaller parts that the transformer model can process. This process involves adding unique tokens, handling special characters and symbols, and sub-word tokenization to address words not present in the model's overall vocabulary. Table 4 provides a clear overview of how raw data is transformed into a format suitable for NLP modelling.

Table 4. Tokenization Results

Input	Proses
http://localhost:8080/tienda1 /publico/vaciar.jsp? B2=Vaciar+carrito HTTP/1.1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>

Next, all characters in the URL are converted to lowercase before tokenization using case folding. Table 5 shows the results of tokenization, demonstrating that all elements in the URL have been converted to lowercase and broken down into smaller tokens. This helps ensure consistency in text processing and makes the model more robust against variations in capitalization.

Table 5. Case Folding Results

Input Proses	Output Proses
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The steaming process does not significantly alter the text in this case because most tokens are part of URLs or symbols. However, words like "vaciar" and "carr" will be processed if there are suffixes that can be removed. Table 6 presents the final results, showing that tokenization and stemming have been applied, although minimal changes occurred due to the specific characteristics of the input text (URLs and symbols).

Table 6. Stemming Results

Input Proses	Output Proses
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The Stop Word stage is not performed because most tokens are part of URLs. Normalization at this stage involves processing the text, including converting it to lowercase, removing punctuation, and removing numbers. Converting to Lowercase: All letters are converted to lowercase to ensure consistency, so "HTTP" and "http" are treated the same. Removing Punctuation: All punctuation marks, such as periods, slashes, and question marks, are removed from the text.

Table 7. Normalization Results

Input Proses	Output Proses
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Model Implementation

In this study, the implementation of the Transformer model with the integration of Natural Language Processing (NLP) for network intrusion detection is conducted through several

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key stages. The first stage is data processing, which includes normalization, batch processing, and splitting the data into training and testing sets with ratios of 70/30, 80/20, and 90/10. In the NLP processing, steps such as case folding, text normalization, tokenization, and stemming are performed to ensure the text is in a consistent format. Tokenization uses the DistilBERT Tokenizer to convert the text into tokens that the Transformer model can process.

As shown in Figure 2, the architecture for network intrusion detection with Transformer and NLP integration is implemented according to Algorithm 1. In the model training stage, DistilBERT, initialized with default parameters, is used to handle the Multi-Head Attention, Add & Norm, and Feed Forward layers. The model is trained using the Adam optimizer with a learning rate of 2e-5 and the Cross-Entropy loss function. Training is conducted over three epochs with a batch size of 8. Model evaluation is performed by measuring metrics such as accuracy, recall, F1 score, and ROC-AUC to ensure the model's performance in detecting network intrusion categories classified as "Normal" and "Anomalous." Evaluation results indicate that the integration of the Transformer model and NLP is effective in detecting web application attacks and significantly contributes to the improvement of the network intrusion detection system's accuracy. The parameters of the Transformer model integrated with NLP are shown in Table 8.

Table 8. Parameter Model

Parameter	**Value**
Input Shape	Input_dim
NLP Pre-preprocessing	Case Folding, Normalization, Tokenization, Stemming
Tokenization	DistilBERTTokenizer
Multi-Head Attention	Num_heads=8, dim_model=512
Add & Norm	Layer Normalization
Feed Forward	Dense (2048, Activation='ReLU'
Linear Layer	Dense (256, activation='softmax'
Softmax Layer	Dense(num_classes, activation='softmax'
Optimizer	AdamW (learning_rate=2e-5)
Loss Function	Cross-Entropy Loss
Training Parameter	Epoch=3, Batch Size=8
Evaluation Matrix	Accuracy, Recall, F1 Score, AUC

Evaluation

The implemented model is then evaluated to test its performance. This model is tested and compared with algorithms such as Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The evaluation uses equations (12), (14), (15), and (16). The results are shown in Tables 9, 10, and 11. Subsequently, the model's performance is tested using the ROC curves, which are displayed in Figures 3, 4, and 5.

Table 9. Evaluation Using 80-20 Training Split

Algorithm	A_c	R_e	F_1	**AUC**
DNN	0.76	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.92
DT	0.82	0.93	0.80	0.88
SVM	0.80	0.89	0.72	0.82
KNN	0.81	0.94	0.80	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.63	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 10. Evaluation Using 70-30 Training Split

Algorithm	A_c	R_e	F_1	**AUC**
DNN	0.79	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.88
DT	0.82	0.93	0.80	0.88
SVM	0.73	0.89	0.72	0.82
KNN	0.81	0.94	0.72	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.64	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 11. Evaluation Using 90-10 Training Split

Algorithm	A_c	R_e	F_1	**AUC**
DNN	0.77	0.52	0.65	0.85
RF	0.83	0.99	0.83	0.93
DT	0.83	0.94	0.82	0.90
SVM	0.72	0.86	0.72	0.84
KNN	0.80	0.87	0.78	0.89
XGBoost	0.83	0.94	0.82	0.92
NB	0.63	0.30	0.40	0.85
Trans+NLP	0.85	0.95	0.84	0.94

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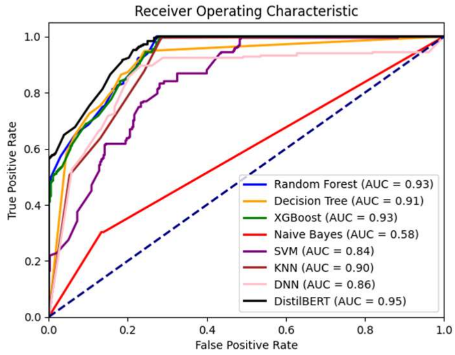

Figure 3. ROC Untuk Model 90-10

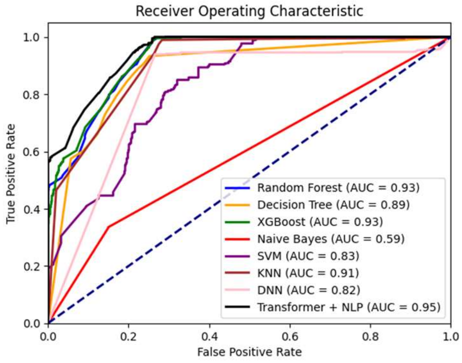

Figure 4. ROC Untuk Model 80-20

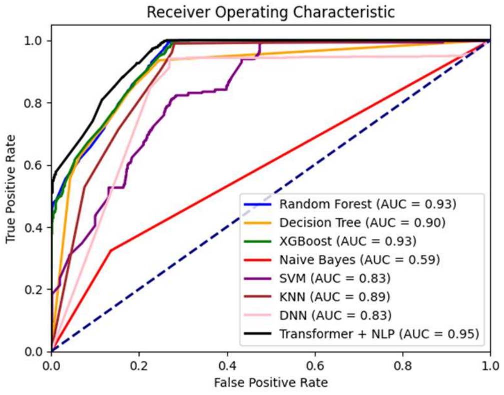

Figure 5. ROC Untuk Model 70-30

Statical Validation

To test the reliability of the built model, we conducted evaluations using the Friedman test and t-test to compare its performance with other models[22]. We designated the proposed model as the control method in this experiment, and the significance level α for the statistical tests was set at 0.05. Generally, a smaller p-value indicates a significant difference between comparison methods. The results of the Friedman test and t-test are shown in Table 12.

Table 12. Friedman Test and T-test Results

	DNN	DT	XB	NB	SVM	KNN	RF
Friedman	0.0009	0.005	0.019	2.159	0.0001	0.006	0.004
T-Test	8.705	5.35	3.765	40.785	13.19	5.244	2.999

Parameter Sensitivitas

In this section, we examine the impact of the hyperparameter, denoted by λ, on the proposed detection model. This analysis aims to understand how variations in λ influence the model's performance and effectiveness. The study involves adjusting the λ values and observing changes in key performance metrics, such as accuracy, recall, F1 score, and ROC-AUC. The results of this hyperparameter tuning are presented in Table 13, illustrating the relationship between different λ values and the corresponding performance metrics. This detailed evaluation helps in identifying the optimal λ setting for achieving the best detection results.

Table 13. Impact of Hyperparameter λ on Model Performance

Λ	A_c	R_c	F_1	Auc
1e-05	0.856	0.944	0.843	0.948
2e-05	0.852	0.944	0.840	0.950
3e-05	0.851	0.906	0.841	0.946
5e-05	0.849	0.952	0.838	0.946

Based on Table 13, although the AUC value remains the same (0.95) for several learning rate values, other metrics such as Accuracy, Recall, and F1 Score vary. The model with a learning rate of 2e-05 shows the highest AUC of 0.9505, indicating slightly better performance compared to other learning rates. Models with learning rates of 1e-05 and 3e-05 exhibit nearly the same AUC values (around 0.9490) but with variations in Accuracy and Recall. The ROC curve, illustrating sensitivity, is shown in Figure 6.

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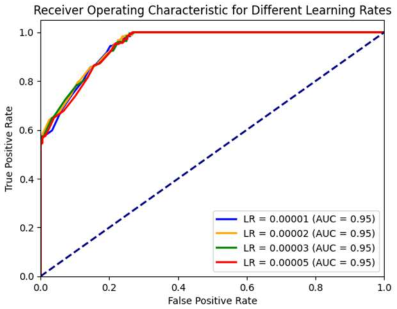

Figure 6. ROC Curve for Sensitivity Analysis of Parameters

Result dan Analysis

This study demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. Initially, the CSIC 2010 dataset used in this study was processed through various pre-processing steps such as tokenization, stemming, lemmatization, and normalization to ensure data consistency. Text representation was carried out using techniques like Word2Vec, BERT, and TF-IDF, enabling the Transformer model to capture contextual relationships in network log data.

The model's performance evaluation showed superior results compared to traditional algorithms like Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The testing was conducted with training and testing data splits of 80/20, 70/30, and 90/10 ratios. The Transformer-NLP model achieved higher accuracy, recall, F1 score, and AUC, with the best AUC value of 0.9505 at a learning rate of 2e-05. The ROC curve also demonstrated the superior performance of this model in detecting network intrusions compared to other models.

Statistical validation through the Friedman test and t-test confirmed the reliability and practical significance of the proposed model. Hyperparameter sensitivity analysis showed that variations in the λ value affected the model's performance, with a learning rate of 2e-05 providing the best results. Overall, the proposed Transformer-NLP model not only significantly reduces false positives but also enhances the overall security of web applications, making it a more adaptive and intelligent solutions in the face of increasingly sophisticated cyber threats.

CONCLUSION

This study successfully demonstrates that integrating the Transformer model with NLP techniques can significantly enhance the performance of NIDS for web applications. The proposed model effectively captures contextual relationships in network log data, enabling more accurate and adaptive detection of web application attacks. Evaluation results show that the Transformer-NLP model achieves higher accuracy, recall, F1 score, and AUC compared to traditional algorithms such as DNN, RF, DT, SVM, KNN, XGBoost, and NB. Statistical validation through the Friedman test and t-test confirms the robustness and practical significance of this model. With these promising results, the Transformer-NLP model can be considered a more adaptive and intelligent solution in facing increasingly complex and sophisticated cyber threats.

Despite the significant findings, there are several limitations to consider. First, the use of the relatively limited CSIC 2010 dataset may not reflect the broader and more recent variations in web application attacks. Second, while the Transformer-NLP model shows superior performance, its computational complexity and high resource requirements could pose challenges for practical implementation in production environments. Third, the study does not examine the potential impact of overfitting that might occur due to the use of a model with complex parameters on a limited dataset. Lastly, this research focuses on web application attacks, so generalizing to other types of network attacks requires further investigation. Therefore, while the model shows great potential, its practical application requires further consideration regarding scale, performance, and generalization.

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Network Intrusion Detection Using Transformer Models and Natural Language Processing for Enhanced Web Application Attack Detection

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Abstract

The increasing complexity and frequency of web application attacks demand more advanced detection methods than traditional network intrusion detection systems (NIDS), which rely heavily on predefined signatures and rules, limiting their effectiveness against novel threats. This study proposes a novel approach by integrating Transformer models with Natural Language Processing (NLP) techniques to develop an adaptive and intelligent intrusion detection framework. Leveraging the Transformer's capacity to capture long-term dependencies and NLP's ability to process contextual information, the model effectively addresses the dynamic and diverse nature of web application traffic. Using the CSIC 2010 dataset, this study applied comprehensive preprocessing, including tokenization, stemming, lemmatization, and normalization, followed by text representation techniques such as Word2Vec, BERT, and TF-IDF. The Transformer-NLP architecture significantly improved detection performance, achieving 85% accuracy, 95% precision, 83% recall, 84% F1 score, and an AUC of 0.95. Friedman and t-test validations confirmed the robustness and practical significance of the model. Despite these promising results, challenges related to computational complexity, dataset scope, and generalizability to broader network attacks remain. Future research should focus on expanding the dataset, optimizing the model, and exploring broader cybersecurity applications. This study demonstrates a significant advancement in detecting complex web application attacks, reducing false positives, and improving overall security, offering a viable solution to growing cybersecurity challenges.

Keywords: NLP, Intrusion Detection, Transformer, Web Application Attack, Machine Learning

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INTRODUCTION

The security of web applications has become a paramount concern in the current digital era, especially with the rise of attacks targeting vulnerabilities in web applications[1]. As technology advances and the number of internet users increases, web applications are increasingly susceptible to various types of attacks, such as SQL injection, Cross-Site Scripting (XSS), and Denial of Service (DoS) attacks. These attacks threaten the integrity, confidentiality, and availability of data and web services, and their frequency and complexity continue to escalate[2].

Web applications are often the first point of entry for attackers, exploiting vulnerabilities like SQL injection and Cross-Site Scripting (XSS) to gain unauthorized access or inject malicious scripts. These vulnerabilities highlight the need for robust detection mechanisms specifically tailored to web applications. Therefore, this study focuses on detecting attacks targeting web applications, recognizing this as a critical aspect of maintaining overall network security[3]. Research on network intrusion detection systems (NIDS) has explored various methodologies to counteract these threats[4]. For instance, Research [5] provides a comprehensive overview of existing detection systems specifically designed to monitor web traffic, comparing the capabilities of systems like AppSensor, PHPIDS, ModSecurity, Shadow Daemon, and AQTRONIX WebKnight. Other studies have focused on input validation techniques to prevent intrusions, such as the approach detailed in Research [6], which emphasizes input validation against web application attacks. Additionally, Research [7] has developed an intrusion detection model to mitigate cyber-attacks, data breaches, and

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identity theft, aiding in effective risk management.

Traditional approaches to network intrusion detection rely heavily on predefined signatures and rules, which limits their effectiveness in detecting new or unknown variants of attacks[8]. This rigidity necessitates more adaptive solutions. A popular approach to overcoming these limitations involves the use of machine learning (ML) and artificial intelligence (AI) to create more intelligent and flexible intrusion detection systems [9]. Machine learning models, such as Random Forest and Support Vector Machines, have been successfully employed to detect anomalies in network traffic[10]. Some studies have advanced this further by combining ensemble learning with NLP-based methods, as indicated in Research [11], to enhance the detection models' effectiveness. However, even these sophisticated methods face challenges in handling the highly dynamic and diverse data generated by web applications. The complexity of web application traffic stems from frequent updates, varying user inputs, and increasingly sophisticated attack vectors, making it difficult for traditional models to adapt in real time[12]. For example, studies have shown that vulnerabilities such as SQL injection and Cross-Site Scripting (XSS) are among the most common attack types, with SQL injection accounting for approximately 65% of web application attacks in 2022, according to OWASP reports[13]. The evolving nature of these vulnerabilities, along with their high frequency, underscores the critical need for more adaptive detection systems capable of handling the sheer volume and variety of data produced by modern web applications.

For instance, research [14] utilizing traditional ML models demonstrated moderate success in detecting known intrusions, but performance degraded significantly when applied to unknown or zero-day attacks. Moreover, approaches based on signature detection or anomaly detection often suffer from high false positive rates, making them impractical for real-world applications. To address these challenges, this study proposes a novel approach that integrates advanced Transformer models with NLP techniques to better capture the complex patterns and contextual information inherent in web application data[15]. While NLP techniques have been widely adopted, the deep integration of NLP with Transformer architectures for web application intrusion detection is a relatively unexplored area, offering a more nuanced detection of web attacks. This combination allows for the detection of complex[16], evolving web threats that are often missed by traditional machine-learning models.

Recent advancements in deep learning, particularly the development of the Transformer model by Vaswani et al., offer a promising solution[17]. The Transformer's ability to capture long-range dependencies in sequential data and process this information efficiently through an attention-based architecture provides a robust framework for addressing the complexities of web application data. The application of Transformer models in network intrusion detection presents new opportunities for developing more adaptive and sophisticated systems capable of identifying a wide range of web attacks[18]. Research has shown that Transformers are particularly effective in analyzing patterns and anomalies within network data, leading to improved detection rates of complex attacks that are often missed by conventional methods[19].

Unlike previous models that focus on static or homogeneous data sets, the proposed research utilizes both Transformer models and NLP techniques to handle the diverse and ever-evolving nature of web application data. This approach differs significantly from existing studies, which often rely on traditional machine learning models or shallow integration of NLP techniques. Our research leverages the Transformer's ability to handle intricate patterns within the data, providing a significant advancement over existing methods. By combining the strengths of NLP in text representation and the deep learning capabilities of Transformers, this study introduces a unique framework that significantly enhances detection performance, particularly for sophisticated web attacks. While earlier studies [11][20][21] employed NLP for enhancing feature extraction in intrusion detection, this research integrates these methods more deeply within a Transformer-based architecture, representing a novel approach to the field.

The novelty of this study lies in its dual integration of NLP techniques and Transformer models for web application intrusion detection, which has not been fully explored in prior research. This combination not only provides a more nuanced approach to understanding the data but also significantly enhances the model's ability to detect sophisticated web attacks. This research contributes to the field by presenting a novel framework that leverages advanced NLP and deep learning techniques to build more resilient intrusion detection systems, potentially reducing false positives and improving overall security[22]. The findings from this study are

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expected to offer valuable insights and practical implications for future research in cybersecurity, particularly in applying NLP and deep learning to enhance network security.

METHOD

This study aims to develop and analyze a network intrusion detection model based on Transformer methods and Natural Language Processing (NLP) techniques to enhance the security of web applications.

Dataset

The CSIC 2010 dataset, developed by the Spanish Research National Council, contains 61,065 records with 17 attributes, including both normal and malicious web traffic such as SQL injection, Cross-Site Scripting (XSS), and Path Traversal attacks. This dataset's diversity is crucial for training models to recognize both attack patterns and normal behaviors in web traffic, ensuring a robust evaluation of the model's ability to handle real-world scenarios[17]. The dataset's size is sufficient for training deep learning models like Transformers, which require large and diverse datasets to capture complex relationships and generalize well without overfitting. NLP techniques are essential for analyzing the textual nature of web-based attacks. Many attacks, such as SQL injection and XSS, exploit text-based inputs within HTTP requests, making them difficult to detect using traditional methods. NLP allows for deeper analysis of textual data, such as URL parameters and HTTP headers, enabling the model to identify subtle anomalies. The Transformer architecture excels at capturing long-range dependencies, making it adaptable to both known and evolving attack patterns, which is vital for detecting emerging threats in web applications.

Algorithm Selection: Transformer Architecture

In this study, we selected the Transformer architecture due to its ability to effectively process sequential data and capture long-range dependencies[23], which are critical for analyzing web application traffic. Traditional machine learning models, such as Random Forest and Support Vector Machines (SVM), often struggle with the dynamic and unstructured nature of web-based attacks, particularly when analyzing text-based HTTP requests that can be manipulated through attacks like SQL injection or Cross-Site Scripting (XSS)[24]. These conventional algorithms rely heavily on predefined features, making them less effective in detecting new and evolving attack patterns.

The Transformer model overcomes these limitations by leveraging a self-attention mechanism, allowing it to focus on the most relevant parts of an input sequence, such as HTTP headers, URL parameters, and textual fields[25]. This attention mechanism enables the model to capture long-range dependencies and intricate relationships in the data, making it particularly effective for identifying complex patterns that traditional methods might miss[26].

Moreover, Transformers offer significant computational advantages over recurrent models like LSTMs and GRUs, especially in large-scale datasets[27]. Their ability to process data in parallel allows for more efficient training on large-scale datasets, such as the CSIC 2010 dataset, without sacrificing accuracy. This makes Transformers not only faster but also more scalable for real-world applications that involve large and diverse data.

In addition, the integration of NLP techniques with the Transformer model enhances its ability to extract meaningful features from web traffic data[28]. Techniques such as Word2Vec, BERT, and TF-IDF enable the model to better understand textual data and context[29], facilitating more accurate detection of web application attacks that exploit text-based inputs.

Network Intrusion Detection

Network Intrusion Detection Systems (NIDS) are crucial for identifying and mitigating security threats to web applications. Traditional NIDS relies on signature-based and anomaly-based methods. Signature-based systems are adequate for known threats but struggle to detect new attacks, while anomaly-based systems can identify unknown attacks but often have high false favorable rates[30]. Advances in machine learning (ML) and deep learning (DL) have enhanced NIDS capabilities, with convolutional neural networks (CNN) and recurrent neural networks (RNN) demonstrating improved accuracy[31]. However, these models often fail to capture network logs' temporal and contextual dependencies, which is essential for detecting sophisticated web application attacks. Transformer models and Natural Language Processing (NLP) techniques have been introduced to address this. Transformers excel in capturing long-term dependencies and contextual relationships in sequential data[18], while NLP enables effective preprocessing and representation of network logs[11]. This study develops a more robust NIDS for detecting web application attacks by combining Transformer models and NLP, aiming to reduce false positives and improve detection accuracy.

Transformer

The Transformer is an architectural model that has revolutionized the landscape of natural language processing (NLP) and various other applications. As introduced in "Attention is All You Need," the Transformer relies on the self-attention mechanism to capture relationships between elements in sequential data[17]. The self-attention mechanism allows the model to efficiently consider the entire input context without processing the data sequentially, unlike traditional approaches such as RNNs and LSTM[32]. The core formula in self-attention is shown in equation (1):

$$\text{Attention}(Q,K,V) = \text{softmax}\left(\frac{QK^T}{\sqrt{DK}}\right)\text{V} \qquad (1)$$

The Transformer model consists of multiple encoders and decoders, with each encoder layer comprising a self-attention mechanism and a feed-forward neural network[33]. The encoder generates contextual representations of the input, which are then used by the decoder to produce the output. This approach enables the Transformer to capture long-term dependencies and complex relationships within the data[34].

Transformers have demonstrated their superiority in various NLP tasks, including machine translation, text classification, and language modeling, outperforming previous approaches[17]. Their application in network intrusion detection leverages Transformers and NLP techniques to preprocess network logs and detect attack patterns with high efficiency and improved accuracy. This study will implement the Transformer model to enhance the detection capabilities of web application attacks, utilizing the power of self-attention to capture complex relationships in network data.

Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that enables computers to understand and generate human-like text. NLP encompasses sentiment analysis, machine translation, and network log analysis applications. Fundamental NLP techniques include tokenization (breaking text into smaller units), stemming, and lemmatization.

Recent advancements in NLP, such as BERT, use Transformer architecture to capture the bidirectional context in text, significantly improving the performance of NLP tasks. These models have been successfully applied in various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This research leverages NLP techniques to process network logs, converting them into vector representations, and employs Transformer models to detect web application attacks with greater accuracy. Recent advancements in NLP, such as BERT, utilize transformer architecture to capture bidirectional context in text, thereby enhancing the performance of NLP tasks. These models have been successfully applied across various domains, including cybersecurity, to process and analyze network logs for anomaly detection. This study leverages NLP techniques to process network logs, converting them into vector representations, and employs transformer models to more accurately detect web application attacks.

integration of Transformer models with NLP

This study proposes the integration of Transformer models with NLP techniques to detect attacks on web applications through a Network NIDS. The proposed model in this research is illustrated in Figure 1.

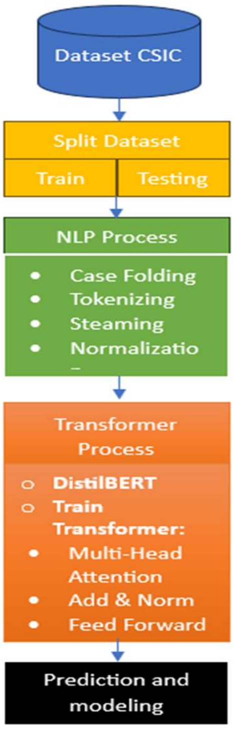

Figure 1. Arsitektur Instrusion Detection

Based on Figure 1, the steps for intrusion detection are further detailed in Algorithm 1. The initial stage involves initializing parameters for the Transformer and the DistilBERT tokenizer. The NLP preprocessing phase includes case folding, tokenization, stemming, and normalization to ensure that the text data is consistent and formatted adequately for analysis. The DistilBERT

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tokenizer then converts the preprocessed text into appropriate tokens. The following equations are used in the process: Equation (5) for converting logs, including URLs, into lowercase (case folding). Equation (6) for tokenization. Equation (7) for stemming. Equation (8) for normalization

$$lower\ (T) = map(\lambda x: x \rightarrow lowercase(x)) \quad (5)$$

$$Tokend = Tokenize(T, delimiter) \quad (6)$$

$$Stem = StemmingAlgoritm(T) \quad (7)$$

$$text \longrightarrow \text{normalized text} \quad (8)$$

Next, the tokenized data is converted into tensors, enabling processing by the Transformer model. The training phase of the Transformer model involves several critical steps, including Multi-Head Attention to capture various aspects of relationships between words, Add & Norm for normalization and residual addition, and Feed Forward layers for further data transformation. After training, the model's performance is evaluated using metrics such as accuracy, recall, F1 score, and AUC to assess its effectiveness in detecting intrusions.

$$output_{residual} = input + Sublayer(input)(9)$$

$$output_{norm} = \frac{output_{residual} - \mu}{\sigma}.\gamma + \beta \quad (10)$$

$$FFN_1(x) = ReLU(W_1 x + b_1 \quad (11)$$

```
Algorithm 1: Transformer NLP Integration
Input: Input: Dataset $D$={($xi$,$yi$)}
Output: Final model intrusion detection

1. Initialization:
    • Parameters for the Transformer and DistilBERT tokenizer are initialized.
2. NLP Preprocessing:
    • Case Folding
    • Tokenization
    • Steaming
    • Normalization
3. Tokenization
    • The DistilBERT Tokenizer is used to convert text into appropriate tokens:
4. Conversion to Tensors
    • The tokenized data is converted into tensors that the Transformer model can process
5. Train Transformer
    • The Transformer model is trained with the processed data
        a. Multi-Head Attention: use equation (1)
        b. Add & Norm: Normalization and residual addition. Use equations (9) and (10)
        c. Feed Forward. Use equation (11)
6. Model Evaluation
    • The model has evaluated the use of equations (12), (13, (14), (15), (16).
7. Final Model
    • The final model is returned for intrusion detection
```

Evaluation

The next step in this research is to evaluate the performance of the developed intrusion detection model. The objective of this performance testing is to determine the extent to which the model is suitable for practical use. Several evaluation parameters are utilized, including Accuracy (Ac), Recall (Re), Precision (Pr), F1 Score (F1), and Area Under the Curve (AUC)[21][35]. These parameters provide a comprehensive assessment of the model's effectiveness and reliability in classification. The formulas for each parameter are given in equations (12), (13), (14), (15), and (16)[18]. Table 1 illustrates the prediction of target labels. The next step involves reporting the model's performance using the Receiver Operating Characteristic (ROC) curve to assess the intrusion detection model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \quad (12)$$

$$Precision = \frac{TP}{TP+TF} \quad (13)$$

$$Recall = \frac{TP}{TP+TN} \quad (14)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ recall}{precision+rec} \quad (15)$$

$$AUC = \int_0^1 TPR(FPR)d\ (FPR) \quad (16)$$

Table1. Confusion Matrix

	True Normal	True Anomalous
Predict Normal	TP	FP
Predict Anomalous	TN	TN

Statistical Validation

In this study, statistical validation is performed using the Friedman Test and the

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Paired T-test. The Friedman Test, a non-parametric test, is used to compare the performance of multiple classification models on the same dataset[36]. This test examines the null hypothesis that there is no significant difference in the performance of these models. If the Friedman Test results indicate a significant difference, further analysis is conducted using the Paired T-test to identify which pairs of models have significantly different performances[37]. The combination of these two tests provides comprehensive validation, ensuring that the developed model is not only statistically superior but also has practical significance in its application[34].

RESULT AND DISCUSSION

The application of the proposed Transformer-NLP method demonstrates that the Transformer model effectively captures contextual relationships in network logs to detect web application attacks through intrusion detection**.**

Data Processing

At this stage, data cleaning was performed, where three records with missing data were removed, reducing the dataset from 61,065 to 61,062 records. The following process involved reducing the number of variables from 17 to 2, which were relevant to the context of the research. Table 1 shows the dataset after data preprocessing. Table 2 defines the target or label for classification, where 0 represents normal, and 1 represents anomalous.

Table 2. Pre-processing Result Dataset

	URL	**Label**
1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	0
2	http://localhost:8080/ ?OpenServer HTTP/1.1	0
61062	http://localhost:8080/tienda1/miembros.Inc HTTP/1.1	1

Text Representation Formation

In this stage, processing is conducted using NLP techniques, including tokenizing, case folding, stemming, and stop word normalization. First, tokenizing: The results of tokenization demonstrate how URLs are broken down into smaller parts that the transformer model can process. This process involves adding unique tokens, handling special characters and symbols, and sub-word tokenization to address words not present in the model's overall vocabulary. Table 3 provides a clear overview of how raw data is transformed into a format suitable for NLP modelling.

Table 3. Tokenization Results

Input Process	**Output Process**
http://localhost:8080/tienda1 /publico/vaciar.jsp?B2=Vaciar+carrito HTTP/1.1	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>

Next, all characters in the URL are converted to lowercase before tokenization using case folding. Table 4 shows the results of tokenization, demonstrating that all elements in the URL have been converted to lowercase and broken down into smaller tokens. This helps ensure consistency in text processing and makes the model more robust against variations in capitalization.

Table 4. Case Folding Results

Input Process	**Output Process**
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? B 2 **=** Vac iar + carr ito HTTP / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The steaming process does not significantly alter the text in this case because most tokens are part of URLs or symbols. However, words like "vaciar" and "carr" will be processed if there are suffixes that can be removed. Table 5 presents the final results, showing that tokenization and stemming have been applied, although minimal changes occurred due to the specific characteristics of the input text (URLs and symbols).

Table 5. Stemming Results

Input Process	**Output Process**
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

The stop word removal stage is omitted since most tokens are part of URLs. The normalization process at this stage includes

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converting all text to lowercase, removing punctuation, and eliminating numbers. Lowercasing ensures consistency, allowing 'HTTP' and 'http' to be treated identically. Punctuation marks, such as periods, slashes, and question marks, are removed to streamline the text. Table 6 presents the results of applying these normalization steps to the sample input.

Table 6. Normalization Results

Input Process	Output Process
<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>	<s> http :// localhost : 8080 / tienda 1 / publico / vaciar . jsp ? b 2 = vac iar + carr ito http / 1 . 1 </s>

Model Implementation

In this study, the implementation of the Transformer model with the integration of Natural Language Processing (NLP) for network intrusion detection is conducted through several key stages. The first stage is data processing, which includes normalization, batch processing, and splitting the data into training and testing sets with ratios of 70/30, 80/20, and 90/10. In the NLP processing, steps such as case folding, text normalization, tokenization, and stemming are performed to ensure the text is in a consistent format. Tokenization uses the DistilBERT Tokenizer to convert the text into tokens that the Transformer model can process.

As shown in Figure 1, the architecture for network intrusion detection with Transformer and NLP integration is implemented according to Algorithm 1. In the model training stage, DistilBERT, initialized with default parameters, is used to handle the Multi-Head Attention, Add & Norm, and Feed Forward layers. The model is trained using the Adam optimizer with a learning rate of 2e-5 and the Cross-Entropy loss function. Training is conducted over three epochs with a batch size of 8. Model evaluation is performed by measuring metrics such as accuracy, recall, F1 score, and ROC-AUC to ensure the model's performance in detecting network intrusion categories classified as "Normal" and "Anomalous." Evaluation results indicate that the integration of the Transformer model and NLP is effective in detecting web application attacks and significantly contributes to the improvement of the network intrusion detection system's accuracy. The parameters of the Transformer model integrated with NLP are shown in Table 7.

Table 7. Parameter Model

Parameter	Value
Input Shape	Input_dim
NLP Pre-preprocessing	Case Folding, Normalization, Tokenization, Stemming
Tokenization	DistilBERTTokenizer
Multi-Head Attention	Num_heads=8, dim_model=512
Add & Norm	Layer Normalization
Feed Forward	Dense (2048, Activation='ReLU'
Linear Layer	Dense (256, activation='softmax'
Softmax Layer	Dense(num_classes, activation='softmax'
Optimizer	AdamW (learning_rate=2e-5)
Loss Function	Cross-Entropy Loss
Training Parameter	Epoch=3, Batch Size=8
Evaluation Matrix	Accuracy, Recall, F1 Score, AUC

Evaluation

The implemented model is then evaluated to test its performance. This model is tested and compared with algorithms such as Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The evaluation uses equations (12), (14), (15), and (16). The results are shown in Tables 8, 9, and 10. Subsequently, the model's performance is tested using the ROC curves, which are displayed in Figures 2, 3, and 4.

Table 8. Evaluation Using 80-20 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.76	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.92
DT	0.82	0.93	0.80	0.88
SVM	0.80	0.89	0.72	0.82
KNN	0.81	0.94	0.80	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.63	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

Table 9. Evaluation Using 70-30 Training Split

Algorithm	A_c	R_e	F_1	AUC
DNN	0.79	0.78	0.74	0.83
RF	0.83	0.98	0.82	0.88
DT	0.82	0.93	0.80	0.88
SVM	0.73	0.89	0.72	0.82
KNN	0.81	0.94	0.72	0.90
XGBoost	0.83	0.96	0.82	0.93
NB	0.64	0.33	0.42	0.59
Trans+NLP	0.85	0.95	0.83	0.94

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Table 10. Evaluation Using 90-10 Training Split

Algorithm	**A_c**	**R_e**	**F_1**	**AUC**
DNN	0.77	0.52	0.65	0.85
RF	0.83	0.99	0.83	0.93
DT	0.83	0.94	0.82	0.90
SVM	0.72	0.86	0.72	0.84
KNN	0.80	0.87	0.78	0.89
XGBoost	0.83	0.94	0.82	0.92
NB	0.63	0.30	0.40	0.85
Trans+NLP	0.85	0.95	0.84	0.94

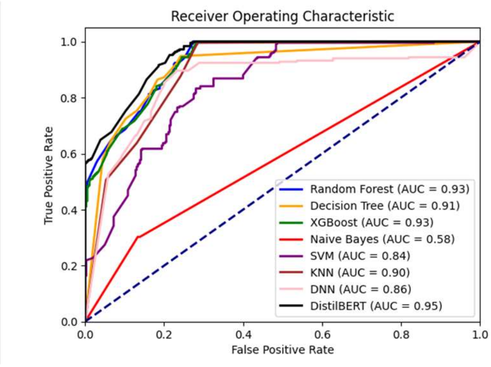

Figure 2. ROC for 90-10 Model

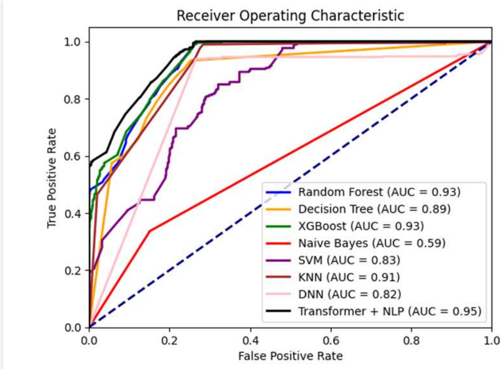

Figure 3. ROC for 80-20 Model

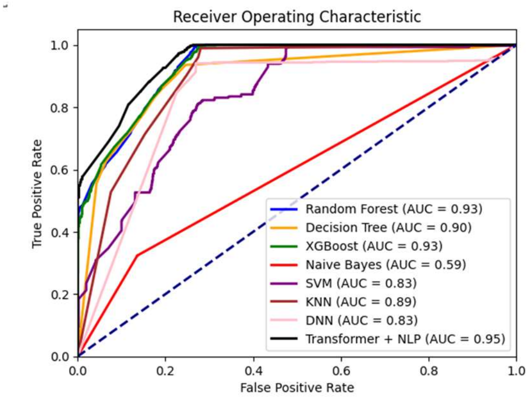

Figure 4. ROC for the 70-30 Model

Statical Validation

To test the reliability of the built model, we conducted evaluations using the Friedman test and t-test to compare its performance with other models[36]. We designated the proposed model as the control method in this experiment, and the significance level α for the statistical tests was set at 0.05. Generally, a smaller p-value indicates a significant difference between comparison methods. The results of the Friedman test and t-test are shown in Table 11.

Table 11. Friedman Test and T-test Results

	DNN	**DT**	**XB**	**NB**	**SVM**	**KNN**	**RF**
Friedman	0.0009	0.005	0.019	2.159	0.0001	0.006	0.004
T-Test	8.705	5.35	3.765	40.785	13.19	5.244	2.99

Parameter Sensivitas

In this section, we examine the impact of the hyperparameter, denoted by λ, on the proposed detection model. This analysis aims to understand how variations in λ influence the model's performance and effectiveness. The study involves adjusting the λ values and observing changes in key performance metrics, such as accuracy, recall, F1 score, and ROC-AUC. The results of this hyperparameter tuning are presented in Table 12, illustrating the relationship between different λ values and the corresponding performance metrics. This detailed evaluation helps in identifying the optimal λ setting for achieving the best detection results.

Table 12. Impact of Hyperparameter λ on Model Performance

Λ	**A_c**	**R_c**	**F_1**	**Auc**
1e-05	0.856	0.944	0.843	0.948
2e-05	0.852	0.944	0.840	0.950
3e-05	0.851	0.906	0.841	0.946
5e-05	0.849	0.952	0.838	0.946

Based on Table 12, although the AUC value remains the same (0.95) for several learning rate values, other metrics such as Accuracy, Recall, and F1 Score vary. The model with a learning rate of 2e-05 shows the highest AUC of 0.9505, indicating slightly better performance compared to other learning rates. Models with learning rates of 1e-05 and 3e-05 exhibit nearly the same AUC values (around 0.9490) but with variations in Accuracy and Recall. The ROC curve, illustrating sensitivity, is shown in Figure 5.

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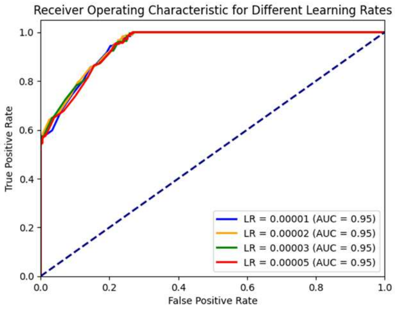

Figure 5. ROC Curve for Sensitivity Analysis of Parameters

Discussion

This study demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. The use of the Transformer model, with its self-attention mechanism, allows for capturing complex dependencies in sequential data, such as HTTP requests, which is crucial for detecting intricate attack patterns within dynamic and diverse web traffic. The CSIC 2010 dataset used in this study was processed through several pre-processing steps, including tokenization, stemming, lemmatization, and normalization, to ensure data consistency. Text representation techniques such as Word2Vec, BERT, and TF-IDF were employed to enable the Transformer model to effectively capture contextual relationships in network log data.

The model's performance evaluation demonstrated superior results compared to traditional algorithms like Deep Neural Network (DNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), k-nearest Neighbor (KNN), XGBoost, and Naive Bayes (NB). The Transformer-NLP model achieved higher accuracy, recall, F1 score, and AUC across multiple training/testing data splits (80/20, 70/30, and 90/10), with the best AUC value of 0.9505 at a learning rate of 2e-05, demonstrating its ability to adapt to different training scenarios. The ROC curve further illustrated the model's superior capability in distinguishing between normal and anomalous traffic, proving more reliable than the other models tested.

Statistical validation using the Friedman test and t-test confirmed the reliability and practical significance of the proposed model. Hyperparameter sensitivity analysis indicated that variations in the λ value impacted the model's performance, with a learning rate of 2e-05 providing the optimal results. These findings suggest that the proposed Transformer-NLP model is not only effective in improving detection accuracy but also offers a robust framework for reducing false positives, enhancing the overall security posture of web applications in response to increasingly sophisticated cyber threats.

Moreover, the model's ability to detect complex attack patterns in network traffic, particularly text-based inputs such as SQL injection and XSS attacks, significantly contributes to enhanced protection of web applications. By identifying and mitigating these sophisticated attack vectors, the model strengthens the security of web applications, preventing unauthorized access and malicious data manipulation. The reduction in false positive rates also ensures the system's efficiency and reliability in real-world scenarios, minimizing unnecessary alerts and enabling security teams to focus on genuine threats. This improvement in detection accuracy directly bolsters the resilience of web applications against evolving attack methods, helping to maintain data integrity, confidentiality, and availability.

However, this study has certain limitations. First, the CSIC 2010 dataset, while useful for evaluating web application security, may not fully capture the range of modern web application attack techniques, potentially limiting the model's applicability to newer or more varied threats. Second, the computational demands of both Transformer models and NLP preprocessing may pose challenges for practical deployment, particularly in environments with constrained resources. Additionally, while this study focused on optimizing performance metrics such as accuracy and AUC, it did not extensively address potential overfitting, which can be a concern with complex models trained on relatively limited datasets. Future research should explore the use of larger, more diverse datasets and further refine the model to balance computational efficiency with detection capability.

CONCLUSION

This study successfully demonstrates that integrating the Transformer model with NLP techniques significantly enhances the performance of NIDS for web applications. The proposed model effectively captures contextual relationships in network log data, allowing for more accurate and adaptive detection of web-based attacks. The evaluation results show that the Transformer-NLP model outperforms traditional algorithms such as DNN, RF, DT, SVM, KNN, XGBoost, and NB in terms of accuracy, recall, F1 score, and AUC. Additionally, the model's ability to handle the highly dynamic and diverse nature of web traffic represents a substantial improvement over conventional methods, addressing a critical gap in current Network Intrusion Detection Systems. Statistical validation through the Friedman test and t-test confirms the robustness and practical significance of the model. With these promising results, the Transformer-NLP model offers a more adaptive and intelligent solution to increasingly complex and sophisticated cyber threats.

Despite these significant findings, there are several limitations to consider. First, the CSIC 2010 dataset may not fully capture the breadth of modern web application attacks, potentially limiting the model's generalizability to newer and more diverse threats. Second, the Transformer-NLP model has high computational complexity and resource requirements, which could challenge practical deployment in production environments. Third, the study does not thoroughly explore the impact of overfitting, which may be a concern given the model's complexity and the relatively limited dataset. Future research should investigate overfitting mitigation strategies, such as employing regularization techniques or cross-validation methods, to ensure the model's robustness in more diverse operational settings. Lastly, this research focuses primarily on web application attacks, and extending the model's application to other types of network attacks requires further investigation. Future work should also explore optimizing the model's architecture to balance detection accuracy with computational efficiency, making it more feasible for deployment in resource-constrained environments

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