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FOREWORD

We extend our deepest gratitude to the Almighty for blessing us with the resources and ability to release Volume 8, No. 4 of RESTI Journal punctually in August 2024. This milestone could not have been achieved without the unwavering commitment of our editorial team, the dedication of our reviewers, and the invaluable assistance of individuals who share our vision of academic excellence.

This issue proudly features 15 scholarly articles contributed contributed by 14 distinguished institutions in Indonesia. The authors acknowledge with immense gratitude the indispensable role played by our peer reviewers and the editorial team. Their rigorous efforts to evaluate the quality of submitted manuscripts ensure that we maintain the high academic standards that RESTI Journal has become known for.

The editors thank all the researchers who have chosen the RESTI Journal as the platform to spread the fruits of their labor. Your contributions enrich not only our publication, but also the broader scientific community, particularly in the ever-evolving field of information technology. Although we celebrate our achievements, we acknowledge that the journey to becoming a leading journal is ongoing. We invite and value your constructive criticism and suggestions, as they provide us with an opportunity to enhance the quality and reach of the RESTI Journal even further.

Thank you for your continued support and readership. May the articles in this and future volumes serve as invaluable resources that contribute to the ever-expanding corpus of scientific and technical knowledge.

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Dr. Ir. Yuhefizar, S.Kom., M.Kom., IPM

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Abstract:
Anomalies and data unavailability are significant challenges in conducting surveys, affecting the validity, reliability, and accuracy of analysis results. Various methods address these issues, including the Backpropagation Neural Network (BPNN) for data prediction. However, BPNN can get stuck in local minima, resulting in suboptimal error values. To enhance BPNN's effectiveness, this study integrates Genetic Algorithm (GA) optimization, forming the BPGA method. GA is effective in finding optimal parameter solutions and improving prediction accuracy. This research uses data from the 2022 National Socio-Economic Survey (Susenas) in Solok District to compare the prediction performance of BPNN, Multiple Imputation (MI), and BPGA methods. The comparison involves training the models with a subset of the data and testing their predictions on a separate subset. The BPGA method demonstrates superior accuracy, with the lowest mean squared error (MSE) and highest average accuracy, outperforming both BPNN and MI methods.

Abstract:
Sulawesi is a region in Indonesia known for its significant seismic activity, and its history of impactful earthquakes makes it an area of crucial importance for in-depth analysis. This study analyses earthquake occurrence data in the Sulawesi region from 2019 to 2023 using clustering methods with the DBSCAN algorithm. The utilization of the DBSCAN algorithm was chosen for its ability to cluster data based on spatial density, well-suited for analyzing the spatial patterns of earthquakes. DBSCAN is known for its effectiveness in identifying spatial clusters, especially in handling data with undefined density patterns. The primary aim of this research is to identify spatial earthquake occurrence patterns, classify regions with similar earthquake occurrence rates, describe the characteristics of the resulting spatial clusters, and identify seismic gap areas. The results of analysis and clustering using the DBSCAN algorithm have identified clusters with earthquake depth characteristics, which are expected to make a significant contribution to mapping and understanding earthquake vulnerability and distribution in this region. These findings can aid in more effective disaster mitigation planning, support sustainable development efforts, and enhance earthquake preparedness and response in Sulawesi. This study contributes to a better understanding of earthquake patterns and potential seismic gaps in Sulawesi, which is crucial for developing improved risk mitigation strategies and supporting sustainable development policies.

Abstract:
Artificial Neural Networks (ANN) are a field of computer science that mimics the way the human brain processes data. ANNs can be used to classify, estimate, predict, or simulate new data from similar sources. The commonly used algorithm for prediction in ANN is Backpropagation, which yields high accuracy but tends to be slow during the training process and is prone to local minima. To address these issues, appropriate parameters are needed in the Backpropagation training process, such as an optimal learning function. The aim of this study is to evaluate and compare various learning functions within the Backpropagation algorithm to determine the best one for prediction cases. The learning functions evaluated include Gradient Descent Backpropagation (traingd), Gradient Descent with Adaptive Learning Rate (traingda), and Gradient Descent with Momentum and Adaptive Learning Rate (traingdx). The dataset used is the average wholesale rice price in Indonesia, obtained from the Central Statistics Agency (BPS) website. The evaluation results show that the traingdx learning function with a 5-5-1 architecture model achieves the highest accuracy of 83.33%, representing an 8.3% improvement over the traingd and traingda learning functions, which both achieved a maximum accuracy of 75%. Based on this study, it can be concluded that using various learning functions in Backpropagation yields better accuracy compared to standard Backpropagation.

Abstract:
The wholesale rice trade in Indonesia encounters various challenges in forecasting prices. These challenges are influenced by factors such as weather, government policies, global market conditions, and other economic variables. Accurate price predictions are crucial for informing government policy in a timely manner. This research introduces a new approach that utilizes the Quantum Perceptron algorithm to forecast rice prices. The algorithm, an innovative method in quantum computing, is expected to enhance the efficiency and effectiveness of price predictions. Although the research is still in the analytical stage, the use of Quantum Perceptron shows promise in dynamically addressing the complexity of market data and the variability of factors affecting rice prices. The method focuses on developing models that can leverage quantum computing to process information more effectively than classical methods. By harnessing the unique properties of quantum mechanics, such as superposition and entanglement, Quantum Perceptron can identify complex patterns and optimize predictions of future rice prices. The research describes the implementation of quantum algorithms in the context of the Indonesian rice wholesale market, including the technical challenges encountered and future development prospects. The research utilizes quantum computing along with the perceptron algorithm. The researchers focused on analyzing the quantum perceptron algorithm because of the limited availability of quantum computing devices. The findings of this research are confined to analysis. In order to advance this research, the author recommends that future studies employ quantum devices to achieve more accurate predictions.

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Classification of Toraja Wood Carving Motif Images Using Convolutional Neural Network (CNN)

Nurilmiyanti Wardhani, Billy Eden William Asrul, Antonius Riman Tampang, Sitti Zuhriyah, Abdul Latief Arda
https://doi.org/10.29207/resti.v8i4.5897 486-495

Abstract:
Wood carving is a cultural heritage with deep meaning and significance for the Toraja ethnic group's culture. By understanding the meaning of each Toraja carving, both tourists and the local community can gain knowledge about Toraja culture, thereby preserving and maintaining the culture amidst modern developments. Image processing approaches, particularly the development of Convolutional Neural Networks (CNN), offer a solution for extracting information from the diverse and intricate patterns of Toraja wood carvings. This study is highly significant as it implements a deep learning model using the CNN algorithm optimized with the ResNet50 architecture. The methodology in this study involves adjusting the batch size during the model training phase and applying weak-to-strong pixel transformation during the double threshold hysteresis phase in the Canny Feature Extraction process on the edges of Toraja carving images, resulting in ResNet50 architecture accurately recognizing the patterns of Toraja wood carvings. The results demonstrate significant improvements in the performance of the ResNet50 architecture with the preprocessed dataset. average precision, recall, precision, and F1-Score improvements in each Toraja carving class. For the Pa' Lulun Pao class, it was found that the precision and recall values were 0.94, and the F1-Score was 0.94. The Pa' Somba class also showed good results, with a precision value of 0.9697, a recall of 0.96, and an F1-Score of 0.9648. The Pa' Tangke Lumu class showed even better results, with a precision value of 0.9898, a recall of 0.97, and an F1-Score of 0.9798. The Pa' Tumuru class also demonstrated good performance, with a precision value of 0.9327, a recall of 0.97, and an F1-Score of 0.9500. This study not only underscores the effectiveness of processing in enhancing CNN capabilities but also opens opportunities for further research in applying these methods to various image types and exploring different CNN architectures.

The Effect of Resampling Techniques on Model Performance Classification of Maternal Health Risks

Nia Mauliza, Aisha Shakila Iedwan, Yoga Pristyanto, Anggit Dwi Hartanto, Arif Nur Rohman
https://doi.org/10.29207/resti.v8i4.5934 496-505

Abstract:
Indonesia's maternal mortality rate was the second highest in ASEAN, reflecting the problem of class imbalance in maternal health data. This research aimed to improve prediction accuracy in the classification of pregnant women's diseases through the application of various resampling methods. The methods used in this research included Synthetic Minority Over-sampling Technique (SMOTE), SMOTE-Edited Nearest Neighbor (SMOTE-ENN), Adaptive Synthetic Sampling (ADASYN), and ADASYN-ENN, using five classification algorithms: Decision Tree, K-Nearest Neighbor (KNN), Naïve Bayes, Random Forest, and Support Vector Machine (SVM). Performance evaluation was carried out using accuracy, precision, recall, and F1-score metrics to determine the best method and algorithm. The results showed that the SMOTE-ENN and ADASYN-ENN methods significantly improved the model's performance in predicting maternal disease. Random Forest and Decision Tree algorithms showed the best results in terms of accuracy and consistency. These findings provided practical guidance for the application of resampling techniques in the classification of pregnant women's health data, which could contribute to improving the quality of maternal health services in Indonesia.

Skin Cancer Classification Using a Hybrid Pre-trained CNN with Random Forest Classifier

Okky Darmawan Kostidjan, Yudhi Purwanto, Anny Yuniarti
https://doi.org/10.29207/resti.v8i4.5857 506-515

Abstract:
Skin cancer, a leading cause of global mortality with 10 million deaths annually, is projected to increase rapidly if not diagnosed early. Traditional diagnosis relies on visual evaluation and histopathology, which are subjective and time-consuming. Recent advances in Convolutional Neural Networks (CNN) enable automated, accurate image analysis for early identification. This study explores pre-trained CNN models, including DenseNet-201, InceptionV3, MobileNet, ResNet50, and VGG16, by modifying them to better identify skin lesions as malignant or benign. The proposed models outperformed the state-of-the-art CNN models evaluated on publicity with traditional test data. The proposed models achieved 94.20% accuracy, which is higher than that of traditional CNN models.

Twitter Sentiment Analysis Towards Candidates of the 2024 Indonesian Presidential Election

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https://doi.org/10.29207/resti.v8i4.5839 516-524

Abstract:
Long before the elections were held, the topic related to elections was widely discussed on news portals and social media, including Twitter. A few studies related to the Indonesian election have tried to predict candidates who will run for the presidential election, but there has been no research that examines public sentiment on social media towards each of the potential candidates. The main objective of this study is to analyze the public sentiment in Twitter towards potential candidates for the 2024 Indonesian presidential election. This research seeks to fill the gaps in previous research and become a reference for further research regarding sentiment analysis for election prediction using Twitter. The presidential candidates used in the research are the top 3 candidates based on the Poltracking survey, namely Ganjar Pranowo, Prabowo Subianto, and Anies Baswedan. The data were taken from January until October 2022, more than a year before the general election began. To predict the sentiment, four different machine-learning methods were used and compared to each other. There are Naïve Bayes, Support Vector Machines, Random Forests, and Neural Networks. Based on the sentiment results of each candidate, the highest sentiment towards Prabowo is neutral (55.49%), the highest sentiment towards Ganjar is positive (61.34%), and the highest sentiment towards Anies is neutral (44.84%). Results from the study also show that Anies was the presidential candidate who received more negative sentiment than the other two (56.63%). Meanwhile, Ganjar Pranowo got the most positive sentiment of all (42,69%). For the neutral sentiment, Anies Baswedan also got the most results (39,87%), followed by Prabowo (38.99%) and Ganjar Pranowo (21.14%). The result of the study also discovered that random forest and neural networks have the best performance for sentiment analysis.

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Abstract:
Hate speech classification is a critical task in the domain of natural language processing, aiming to mitigate the negative impacts of harmful content on digital platforms. This study explores the application of a Multilayer Perceptron (MLP) model for hate speech classification, utilizing Bag of Words (BoW) for feature extraction. The hypothesis posits that hyperparameter tuning through sophisticated optimization techniques will significantly improve model performance. To validate this hypothesis, we employed two distinct hyperparameter tuning approaches: Random Search and Optuna. Random Search provides a straightforward yet effective means of exploring the hyperparameter space, while Optuna offers a more sophisticated, optimization-based approach to hyperparameter selection. The study involved training the MLP model on a labeled dataset is based on crawling results on the Twitter platform of hate speech and non-hate speech overall total dataset is 13.169, followed by evaluation using standard metrics. Our experimental results demonstrate the comparative effectiveness of these two hyperparameter tuning methods. Notably, the MLP model tuned with Optuna achieved a higher F1-score of 81.49%, compared to 79.70% achieved with Random Search, indicating the superior performance of Optuna in optimizing the hyperparameters. These results were obtained through extensive cross-validation to ensure robustness and generalizability. The findings underscore the importance of optimized hyperparameters in developing robust hate speech classification systems. The superior perform ance of Optuna highlights its potential for broader application in other machine learning tasks requiring hyperparameter optimization. This improvement enables more reliable and efficient automated moderation, which is crucial for the integrity and security of digital communication platforms such as Twitter.

Abstract:
Recycling of waste is a significant challenge in modern waste management. Conventional techniques that use inductive and capacitive proximity sensors exhibit limitations in accuracy and flexibility for the detection of various types of waste. Indonesia generates approximately 175,000 tons of waste per day, highlighting the urgent need for efficient waste management solutions. This study develops a waste classification system based on deep learning, leveraging the powerful EfficientNet-B0 model through transfer learning. EfficientNet-B0 is designed with a compound scaling method, which uniformly scales network depth, width, and resolution, providing an optimal balance between accuracy and computational efficiency. The model was trained on a dataset containing six classes of waste—glass, cardboard, paper, metal, plastic, and residue—totalling 7014 images. The model was trained using data augmentation and fine-tuning techniques. The training results show a test accuracy of 91.94%, a precision of 92.10%, and a recall of 91.94%, resulting in an F1-score of 91.96%. Visualization of predictions demonstrates that the model effectively classifies waste in new test data. Implementing this model in the industry can automate the waste sorting process more efficiently and accurately than methods based on inductive and capacitive proximity sensors. This study underscores the significant potential of deep learning models, particularly EfficientNet-B0, in industrial waste classification applications and opens opportunities for further integration with sensor and robotic systems for more advanced waste management solutions.

Abstract:
Predicting student dropout is essential for universities dealing with high attrition rates. This study compares two feature selection (FS) methods—correlation-based feature selection (CFS) and symmetrical uncertainty (SU)—in educational data mining for dropout prediction. We evaluate these methods using three classification algorithms: decision tree (DT), support vector machine (SVM), and naive Bayes (NB). Results show that SU outperforms CFS overall, with SVM achieving the highest accuracy (98.16%) when combined with SU Moreover, this study identifies total credits in the fourth semester, cumulative GPA, gender, and student domicile as key predictors of student dropout. This study shows how using feature selection methods can improve the accuracy of predicting student dropout, helping educational institutions retain students better.

Abstract:
Brain stroke stands out as a leading cause of death, distinguishing it from common illnesses and highlighting the critical need to utilize machine learning techniques to identify symptoms. Among these techniques, the Random Forest (RF) algorithm emerged as the main candidate because of its optimal accuracy values. RF was chosen for its ensemble learning properties that optimize accuracy while simultaneously, bagging all outputs (DT), thus increasing its efficacy. Feature Selection, an important data analysis step, which is mainly achieved through pre-processing, aims to identify influential features and ignore less impactful features. Mutual Information serves as an important feature selection method. Specifically, the highest level of accuracy was achieved by cross-validating the test data - 10, resulting in 0.7760 without feature selection and 0.7790 with mutual information. Most of the attributes in the brain stroke dataset show relevance to the stroke disease class, but the resulting decision tree shows age as a particularly important node. So, the research results show that the selection feature (Mutual Information) can increase the accuracy of brain stroke classification, although it is not significant, namely an increase of 0.0030%. With an increase, where there is no significant difference, it can be said that almost all the attributes contained in the brain stroke dataset used have an influence on their relevance to the stroke disease class.

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Abstract:
The increasing use of credit cards in global financial transactions offers significant convenience for consumers and businesses. However, credit card fraud remains a major challenge due to its potential to cause substantial financial losses. Detecting credit card fraud is a top priority, but the primary challenge lies in class imbalance, where fraudulent transactions are significantly fewer than non-fraudulent ones. This imbalance often leads to machine learning algorithms overlooking fraudulent transactions, resulting in suboptimal performance. This study aims to enhance the performance of Multilayer Perceptron (MLP) in addressing class imbalance by employing cost-sensitive learning strategies. The research utilizes a credit card transaction dataset obtained from Kaggle, with additional validation using an e-commerce transaction dataset to strengthen the robustness of the findings. The dataset undergoes preprocessing with RUS and SMOTE techniques to balance the data before comparing the performance of baseline MLP models to those optimized with cost-sensitive learning. Evaluation metrics such as accuracy, recall, F1 score, and AUC indicate that the optimized MLP model significantly outperforms the baseline, achieving an AUC of 0.99 and a recall of 0.6. The model's superior performance is further validated through statistical tests, including Friedman and T-tests. These results underscore the practical implications of implementing cost-sensitive learning in MLPs, highlighting its potential to significantly enhance fraud detection accuracy and offer substantial benefits to financial institutions.

Abstract:
Earthquake magnitude prediction is critical in seismology, with significant implications for disaster risk management and mitigation. This study presents a novel earthquake magnitude prediction model by integrating regression analysis with Convolutional Recurrent Neural Networks (CRNNs). It utilises Convolutional Neural Networks (CNNs) for spatial feature extraction from 2-dimensional seismic signal images and Long Short-Term Memory (LSTM) networks to capture temporal dependencies. The innovative model architecture incorporates residual connections and specialised regression techniques for sequential data. Validated against a comprehensive seismic dataset, the model achieves a Mean Squared Error (MSE) of 0.1909 and a Root Mean Squared Error (RMSE) of 0.4369, with a coefficient of determination of 0.79772. These metrics, alongside a correlation coefficient of 0.8980, demonstrate the model's accuracy and consistency in predicting earthquake magnitudes, establishing its potential for enhancing seismic risk assessment and informing early warning systems.

Abstract:
This study addresses the critical need for enhanced accuracy in YOLOv8 models designed for visually impaired navigation systems. Existing models often struggle with consistency in object detection and distance estimation under varying environmental conditions, leading to potential safety risks. To overcome these challenges, this research implements a rigorous approach combining data augmentation and meticulous model optimization techniques. The process begins with the meticulous collection of a diverse dataset, essential for training a robust model. Subsequent preprocessing of images in the HSV color space ensures standardized input features, crucial for consistency in model training. Augmentation techniques are then applied to enrich the dataset, enhancing model generalization and robustness. The YOLOv8 model is trained using this augmented dataset, leading to significant enhancements in key performance metrics. Specifically, mean average precision (mAP) improved by 13.3%, from 0.75 to 0.85, precision increased by 10%, from 0.80 to 0.88, and recall rose by 10.3%, from 0.78 to 0.86. Further optimization efforts, including parameter tuning and the strategic integration of a Kalman Filter, notably improved object tracking and distance estimation capabilities. Final validation in real-world scenarios confirms the efficacy of the optimized model, demonstrating its readiness for practical deployment. This comprehensive approach showcases tangible advances in navigational assistance technology, significantly improving safety and reliability for visually impaired users.
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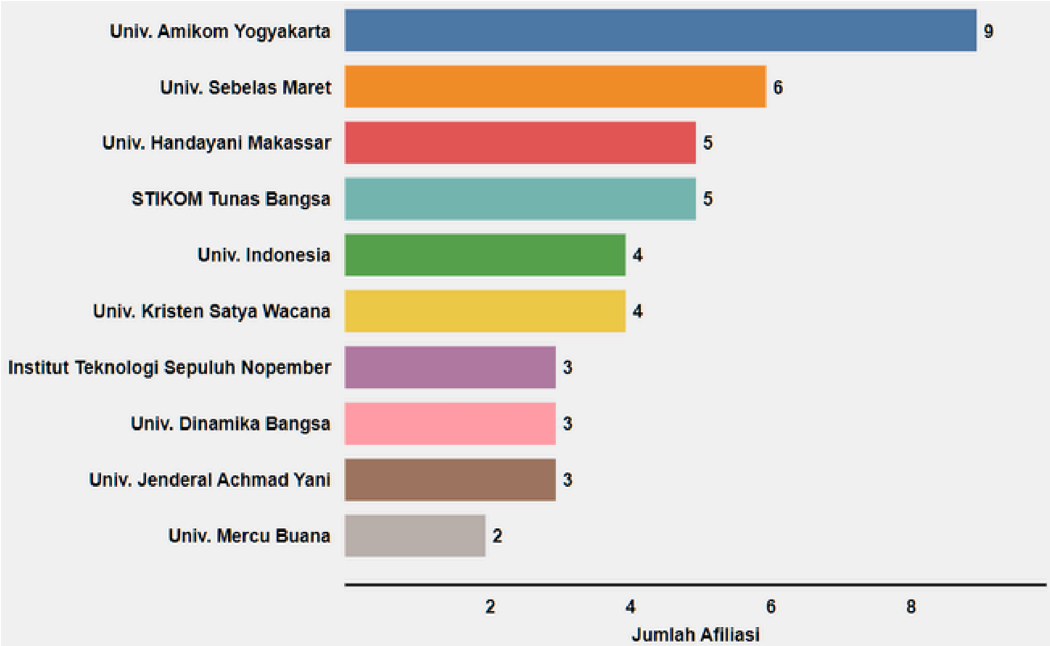

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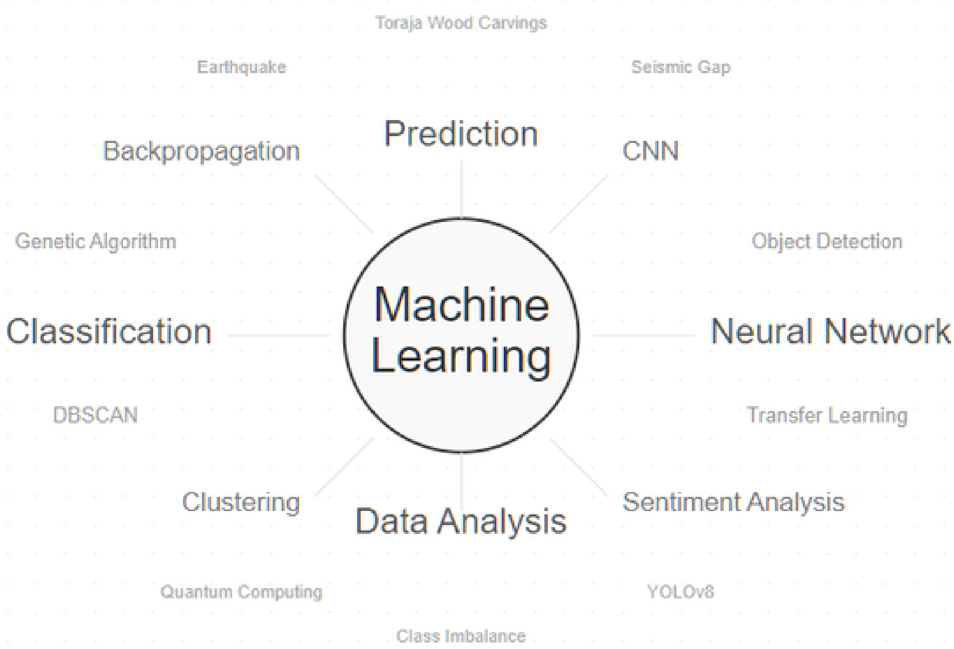

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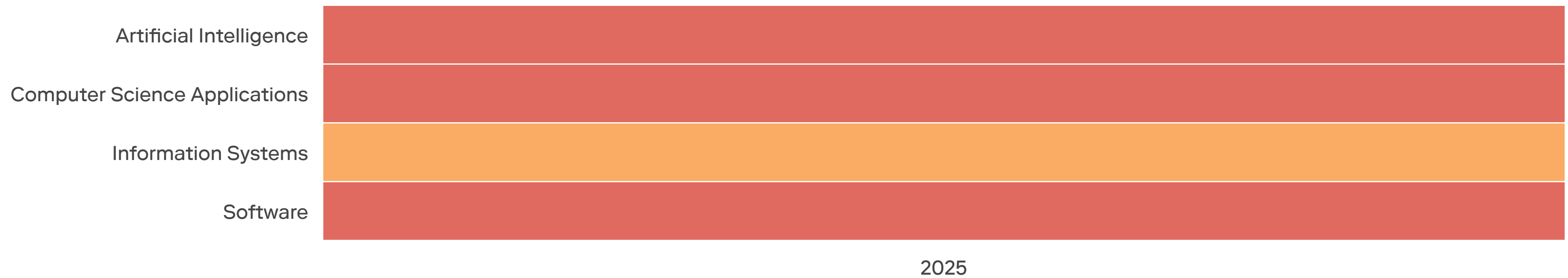

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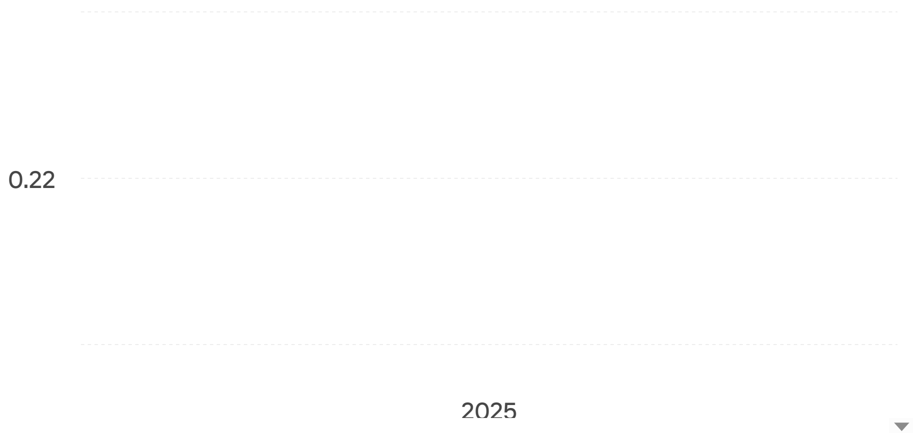

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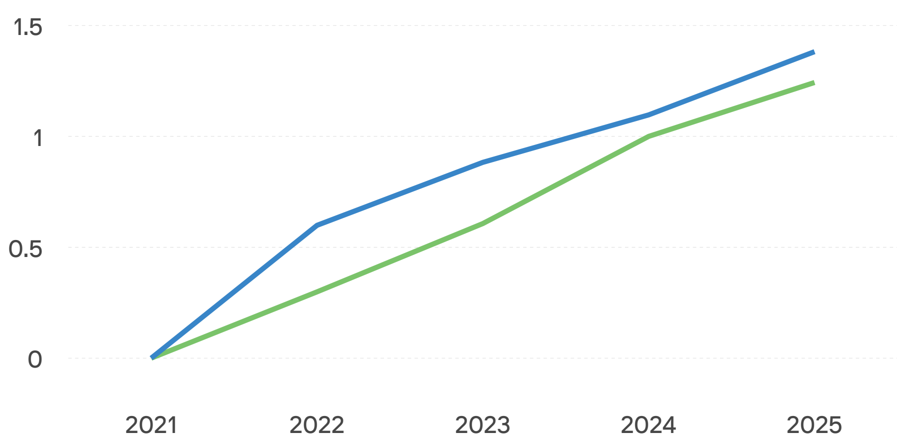

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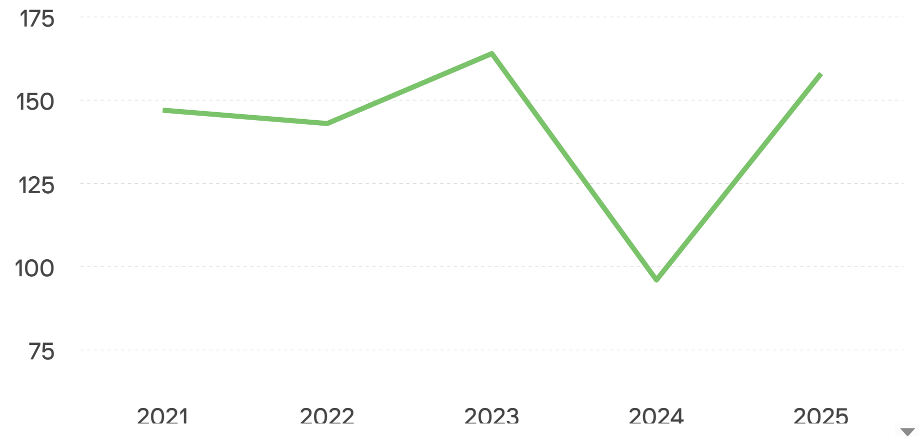

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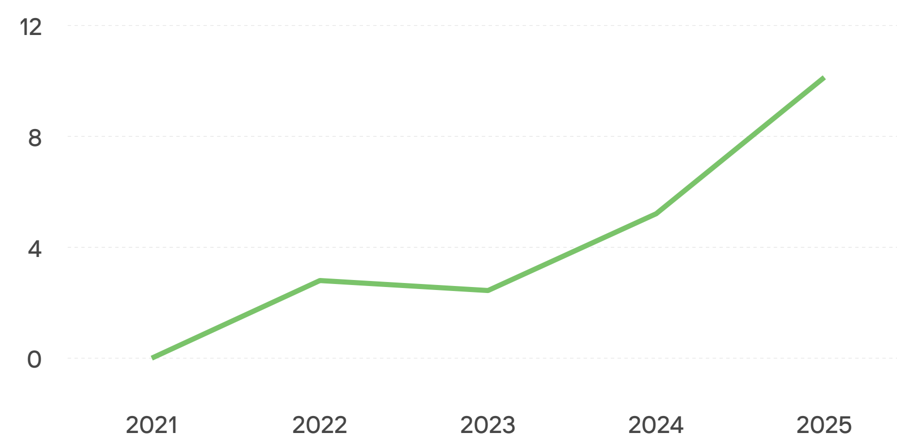

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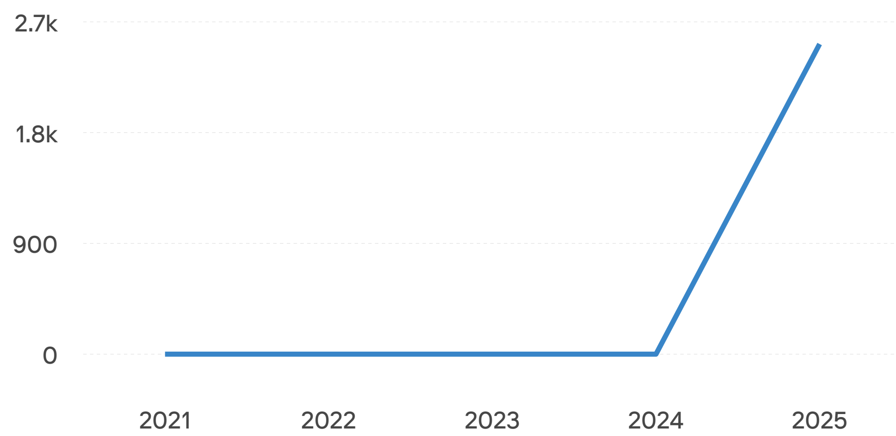

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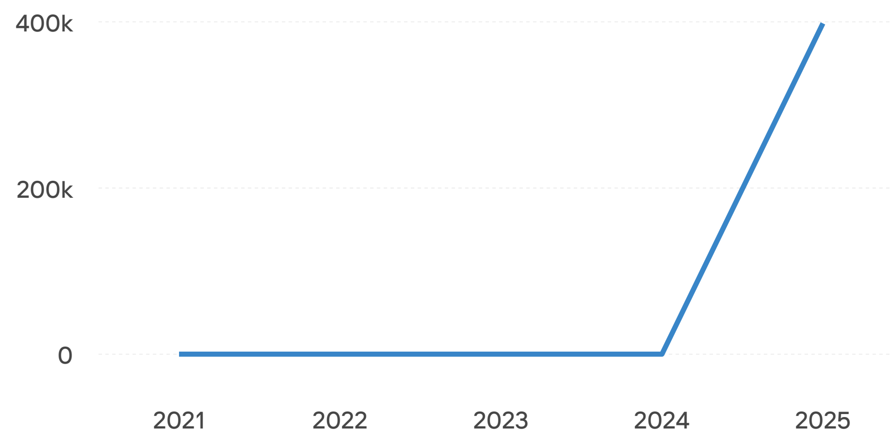

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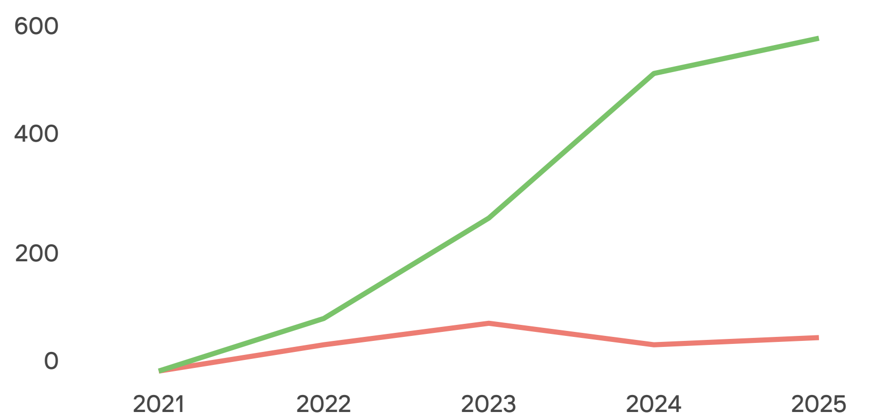

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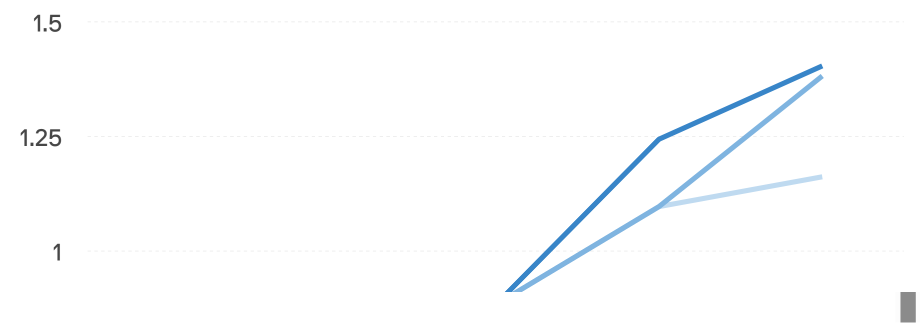

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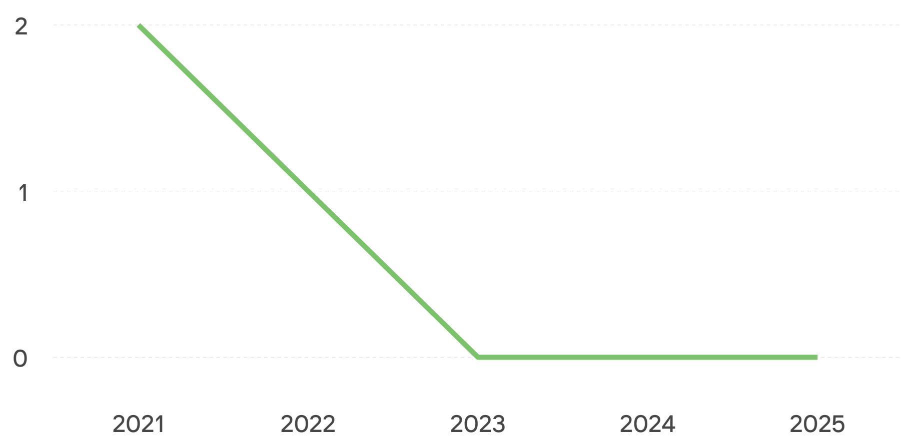

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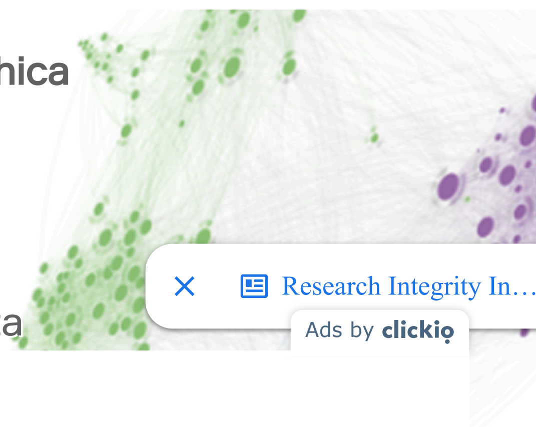

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Optimizing Multilayer Perceptron with Cost-Sensitive Learning for Addressing Class Imbalance in Credit Card Fraud Detection

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Keywords: optimizing multilayer perceptron, fraud detection, class imbalance, cost-sensitive learning, credit card

Abstract

The increasing use of credit cards in global financial transactions offers significant convenience for consumers and businesses. However, credit card fraud remains a major challenge due to its potential to cause substantial financial losses. Detecting credit card fraud is a top priority, but the primary challenge lies in class imbalance, where fraudulent transactions are significantly fewer than non-fraudulent ones. This imbalance often leads to machine learning algorithms overlooking fraudulent transactions, resulting in suboptimal performance. This study aims to enhance the performance of Multilayer Perceptron (MLP) in addressing class imbalance by employing cost-sensitive learning strategies. The research utilizes a credit card transaction dataset obtained from Kaggle, with additional validation using an e-commerce transaction dataset to strengthen the robustness of the findings. The dataset undergoes preprocessing with RUS and SMOTE techniques to balance the data before comparing the performance of baseline MLP models to those optimized with cost-sensitive learning. Evaluation metrics such as accuracy, recall, F1 score, and AUC indicate that the optimized MLP model significantly outperforms the baseline, achieving an AUC of 0.99 and a recall of 0.6. The model's superior performance is further validated through statistical tests, including Friedman and T-tests. These results underscore the practical implications of implementing cost-sensitive learning in MLPs, highlighting its potential to significantly enhance fraud detection accuracy and offer substantial benefits to financial institutions.

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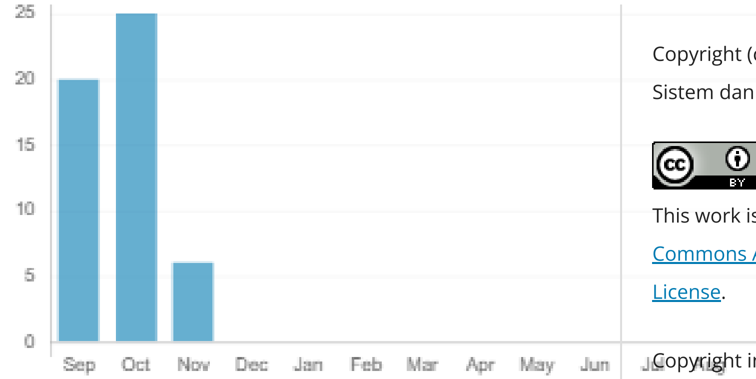

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Optimizing Multilayer Perceptron with Cost-Sensitive Learning for Addressing Class Imbalance in Credit Card Fraud Detection

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Abstract

The increasing use of credit cards in global financial transactions offers significant convenience for consumers and businesses. However, credit card fraud remains a major challenge due to its potential to cause substantial financial losses. Detecting credit card fraud is a top priority, but the primary challenge lies in class imbalance, where fraudulent transactions are significantly fewer than non-fraudulent ones. This imbalance often leads to machine learning algorithms overlooking fraudulent transactions, resulting in suboptimal performance. This study aims to enhance the performance of Multilayer Perceptron (MLP) in addressing class imbalance by employing cost-sensitive learning strategies. The research utilizes a credit card transaction dataset obtained from Kaggle, with additional validation using an e-commerce transaction dataset to strengthen the robustness of the findings. The dataset undergoes preprocessing with RUS and SMOTE techniques to balance the data before comparing the performance of baseline MLP models to those optimized with cost-sensitive learning. Evaluation metrics such as accuracy, recall, F1 score, and AUC indicate that the optimized MLP model significantly outperforms the baseline, achieving an AUC of 0.99 and a recall of 0.6. The model's superior performance is further validated through statistical tests, including Friedman and T-tests. These results underscore the practical implications of implementing cost-sensitive learning in MLPs, highlighting its potential to significantly enhance fraud detection accuracy and offer substantial benefits to financial institutions.

Keywords: optimizing multilayer perceptron; fraud detection; class imbalance; cost-sensitive learning; credit card

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1. Introduction

The increased use of credit cards in global financial transactions has provided significant convenience for consumers and businesses[1]. However, this development also presents a major challenge in the form of credit card fraud[2]. Such fraud can cause substantial financial losses for financial institutions and consumers, making credit card fraud detection (CCFD) a top priority to minimize these losses[3].

Class imbalance in classification data is a significant challenge in CCFD[4]. In the context of CCFD, fraudulent transactions are considerably fewer compared to non-fraudulent ones[5]. This imbalance often leads to machine learning models ignoring fraudulent transactions due to the dominance of non-fraudulent transactions in the training data[6]. Consequently, the resulting models perform poorly in detecting rare but critical fraud transactions[7].

Various techniques have been employed to mitigate class imbalance in credit card fraud detection (CCFD). Resampling techniques, such as SMOTE and Random Under Sampling (RUS), have been widely adopted to balance the data distribution[7]. SMOTE generates synthetic samples for the minority class to enhance its representation, though it may lead to overfitting in certain scenarios[5]. Additionally, ensemble methods like Random Forest, XGBoost, AdaBoost, and Easy Ensemble have also been proposed as effective strategies to improve classification performance. These methods work by combining multiple models to better detect minority classes, but they come with increased computational complexity and the need for extensive hyperparameter tuning, which can be challenging and

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may impact the model's overall effectiveness if not properly managed[8]. Recent studies [9] have also explored hybrid techniques, such as combining SMOTE with Generative Adversarial Networks (GANs), to further enhance the effectiveness of resampling strategies. Hybrid SMOTE-GAN techniques have shown promising results in addressing class imbalance by generating more realistic fraud samples while reducing the risks associated with overfitting. However, these techniques still face challenges such as the complexity of training GAN models and the potential for introducing noise through SMOTE, which can reduce the overall effectiveness of the approach.

One approach involves the use of cost-sensitive learning (CSL), which introduces different penalties or costs for misclassification errors depending on the importance of the class[10]. Studies have shown that CSL improves performance in handling class imbalance in various domains, including medical data[11]. Additionally, CSL can manage high-dimensional data and address class imbalance by adaptively adjusting the loss function, thus bridging the distribution between classes[10].

Multilayer Perceptron (MLP) is a type of neural network commonly used in various classification tasks, including fraud detection[12]. Although MLP can model non-linear relationships in data, it has several weaknesses in handling class imbalance issues[13]. These weaknesses include overfitting to the majority class, underfitting to the minority class, and the need for complex hyperparameter tuning to achieve optimal performance[14].To address these issues, this research aims to optimize MLP to handle class imbalance by utilizing CSL techniques and advanced weighting methods.

Compared to these approaches, the proposed method leverages the non-linear modeling capabilities of MLP and enhances it with CSL. CSL specifically adjusts the loss function by assigning higher penalties to misclassification errors in the minority class, thereby improving the model’s sensitivity to fraudulent transactions without the risk of overfitting. This integration offers a more balanced and accurate detection mechanism for credit card fraud in highly imbalanced datasets.

The novelty of this research lies in developing a more effective method for optimizing MLP to address class imbalance and offering a better solution compared to previous approaches. This study presents a novel approach that integrates CSL with MLP, providing a comprehensive analysis of its performance. The main contributions of this research include the development of a novel method for optimizing MLP to handle class imbalance and providing a comprehensive analysis of the performance of MLP optimized with CSL techniques. This study also offers practical guidelines for financial practitioners in implementing more accurate fraud detection models and significantly improving the accuracy of CCFD.

2. Research Methods

This research addresses class imbalance in credit card transaction data by optimizing MLP through weight adjustments using Cost-Sensitive Learning (CSL).

This research uses a credit card transaction dataset from Kaggle in September 2013[15]. The dataset contains 31 variables, with the target classes being fraud, comprising 492 records, and non-fraud, comprising 284,315 records. This imbalance leads to a significant challenge in training effective models for fraud detection. Figure 1 shows the distribution between the fraud and non-fraud classes.

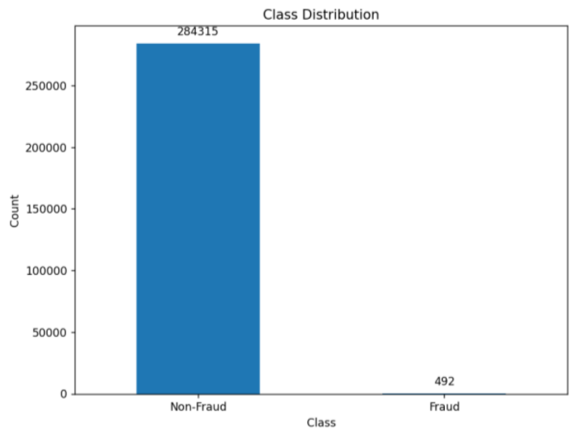

Figure 1. Visualization Data

In addition to using the credit card fraud dataset, this research employs another dataset to test the reliability of the proposed MLP model optimized with cost-sensitive learning weighting. This additional dataset includes e-commerce transactions containing fraud and credit card transaction data from January to April 2022[16]. Table 1 provides information on the credit card dataset from September 2013 and the e-commerce fraud transactions dataset.

Table 1. Dataset Information

Dataset	Sample	Fraud	Ratio
Credit Card 1	284807	492	0.0017
E-Commerce	23634	1222	0.0545
Credit Card 2	1048575	140473	0.1547

The preprocessing stage ensures that the data is clean and ready for modelling. The preprocessing steps begin with removing records with missing values. In this research, out of a total of 284,807 records, no records were found to be missing after detecting missing data. The next step is to separate the features and labels, consisting of 28 features and 1 class label. The target label 0 represents non-fraud, and the value 1 represents fraud. The final step is data normalization to ensure that the feature types support MLP modelling. Data normalization is performed using Z-score standardization, as shown in Equation 1[11].

$$X_{std} = \frac{X-\mu}{\sigma} \quad (1)$$

Random Under Sampling (RUS) is a simple technique used to address class imbalance in datasets by reducing the size of the majority class[17]. This method randomly selects a subset of data from the majority class to reduce its number, making it equivalent to the minority class. RUS helps balance class distribution and can potentially improve the performance of machine learning models by focusing more on the minority class[18].

Synthetic Minority Over-sampling Technique (SMOTE) is a sophisticated method used to handle class imbalance in machine-learning datasets[19]. Instead of simply copying existing samples, SMOTE generates new synthetic samples for the minority class by interpolating between current minority samples [20]. This approach boosts the representation of the minority class, making machine learning models better at identifying patterns specific to that class.

A Multilayer Perceptron (MLP) is a type of artificial neural network that consists of at least three layers of nodes: the input layer, one or more hidden layers, and the output layer. This layered configuration allows the MLP to perform information processing tasks with higher complexity, as each additional layer can capture more features and patterns in the processed data[21]. This process ensures that the input data is sequentially processed through each layer until it reaches the final output layer. With these characteristics, the MLP can be applied in various fields, including pattern recognition, classification, and prediction[22]. The stages of MLP are [23]: Initialization of Weights (w) and Biases (b): Randomly initialize weights and biases using Equation 1; Forward Propagation: Input data is forwarded to the hidden layer and output using Equations 2 and 3; Loss Function Calculation: Use binary cross-entropy for binary classification using Equation 4; Backpropagation: Calculate the gradient of the loss function concerning weights and biases using Equations 5 and 6; Weight and Bias Update (Gradient Descent): Update weights and biases using Equations 7 and 8; Model Evaluation: Evaluate the model using Equations 11 – 15; Fine-tuning and Hyperparameter Optimization: Improve the model by adjusting the learning rate, hidden layers, number of neurons, and activation functions.

$$w_{ij}^{(i)} dan\ b_j^{(i)} \quad (2)$$

i is the layer index, i is the neuron index for the input, and j is the neuron index in the next layer.

$$z^{(1)} = W^{(1)}.a^{(i-1)} + b^{(i)} \quad (3)$$

$$a^{(l)} = f(z^{(l)}) \quad (4)$$

$$L = -\frac{1}{m}\sum_{i=1}^{m}(yi\log(\bar{Y}i) + (1-yi)\log(1-\bar{Y}i)) \quad (5)$$

L represents the total loss value, m represents the number of data samples in the dataset, yi is the actual target value for the i and $\bar{Y}i$ is the predicted probability value for the i-th data point generated by the model.

$$\partial^{(L)} = \propto^{L} - y \quad (6)$$

$$\partial^{(l)} = (W^{l+1)})^T \delta^{(l+1)}.f'(Z^{(1)}) \quad (7)$$

$$W^{(l)} := W^{l} - \propto \frac{\partial L}{\partial W^{(l)}} \quad (8)$$

$$b^{(l)} := b^{(l)} - \propto \frac{\partial L}{\partial b^{l}} \quad (9)$$

$\partial^{(L)}$ is the gradient of the loss function, $(W^{l+1)})^T \delta^{(l+1)}$ is the weight matrix connecting layer $l+1$. $\dot{f}(z^{l})$ is the derivative of the activation function.

Cost-Sensitive Learning is an approach in machine learning that considers the costs of different misclassification errors. Cost-sensitive learning (CSL) has two approaches in binary classification to maximize weights: the Weighted Loss Function and the Weighted Cross-Entropy Loss. The Weighted Loss Function is used in this research, with the formula provided in Equation 10.

$$L(cost) = -\frac{1}{m}\sum_{i-1}^{m} C_{yi}(yi\ \log(\bar{Y}i) + (1-yi)\log(1-\bar{Y}i)) \quad (10)$$

L_{cost} is the cost-sensitive loss function, m is the number of samples, and C_{yi}a is the cost associated with y_i, where C_{yi} is more significant for the minority class.

To enhance the performance of the MLP model, the weakness of MLP in handling class imbalance is addressed during the Loss Function Calculation stage by optimizing it with cost-sensitive learning through the implementation of a weighted loss function. The weighted loss function assigns different costs for errors in the majority and minority classes based on the consequences of each error, thereby reducing errors, and improving the model's performance. The proposed method is outlined in Algorithm 1.

Algorithm 1: Optimization of MLP Using CSL

Input:
- Training dataset: D={(xi, yi)}
- Cost for misclassification errors
- K: Number of training iterations

Output:
Final Model G(X)

Cost Structure Determination
- Set the cost C_0 for errors in the majority and C1 for errors in the minority class based on the respective consequences of the error.

Initialization and Forward Propagation
- Use Equation (2) to initialize weight W and bias b in the MLP
  - For each batch of data (X,y): perform forward propagation by calculating the output $a^{(l)}$ at each layer l using the appropriate activation functions with Equations (3) and (4).

Calculate the Cost-Sensitive Loss Function: Compute the loss function using the cost-sensitive learning formula (10).

Backpropagation and Weight Update:
  - Calculate the gradients of the cost-sensitive loss function using Equations (6) and (7).
  - Update weight W and biases b using the gradient descent optimization method with Equations (8) and (9)

Evaluation and Fine-Tuning.
- Evaluate the model using Equations (11), (12), (13), (14), and (15).
- Perform fine-tuning on hyperparameters and class costs to improve model performance.

Final Model G(X)

The MLP model in this study was configured to balance complexity with performance. A learning rate of 0.001 was selected as it optimally balances convergence speed with model stability, avoiding premature convergence and excessively slow training[24]. The hidden layer was set to 32 neurons, based on cross-validation experiments that indicated this number effectively captures data complexity without leading to overfitting[25]. The Rectified Linear Unit (ReLU) activation function was employed for its effectiveness in addressing the vanishing gradient problem and its ability to accelerate convergence in complex neural network training tasks[24].

To further enhance the model's performance in detecting fraudulent transactions, particularly within the context of class imbalance, CSL was implemented. This approach involved adjusting the classification error costs by assigning higher weights to the minority class (fraud)[26]. This adjustment ensures that misclassification errors for fraud transactions are penalized more heavily during training, thereby improving the model's sensitivity to these critical cases. The specific weights were determined through an analysis of class distribution and the potential financial impact of misclassification, ensuring that the model remains focused on minimizing false negatives in the fraud class. Additionally, the loss function was modified to a weighted cross-entropy function, integrating class weights directly into the error calculation[27]. This modification was chosen because it effectively increases the model's focus on the minority class during training, thus enhancing the model's ability to correctly classify rare fraudulent transactions.

Performance Evaluation*:* The subsequent phase of this research involves assessing the effectiveness of the CCFD model. This performance testing aims to determine the model's suitability for practical use. Several evaluation parameters are used, including Accuracy (A_c), Recall (R_e), Precision (P_r), F1 Score (F1), and Area Under the Curve (AUC)[5]. These parameters provide a comprehensive assessment of the effectiveness and reliability of the classification model. The formulas for each parameter are provided in Equations 11 - 15[28].

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+PN} \tag{11}$$

$$Precision = \frac{TP}{TP+TF} \tag{12}$$

$$Recall = \frac{TP}{TP+TN} \tag{13}$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ recall}{precision+recall} \tag{14}$$

$$AUC = \int_0^1 TPR(FPR)d\ (FPR) \tag{15}$$

In this research, statistical validation is performed using the Friedman Test and the Paired T-test. The Friedman non-parametric test compares the performance of several classification models on the same dataset[29]. This test examines the null hypothesis that there are no significant differences in the performance of these models. If the Friedman Test results indicate substantial differences, further analysis is conducted using the Paired T-test to identify which pairs of models have significant performance differences. The combination of these two tests provides comprehensive validation, ensuring that the developed model is statistically superior and has practical significance in its application[30].

3. Results and Discussions

The fraud detection model for credit card transactions was designed to optimize the weights of the MLP using CSL during the loss function stage. This approach modifies the standard MLP by incorporating a cost-sensitive loss function, which ensures that the model is more cautious in its predictions to minimize the consequences of misclassification, particularly for the minority class. The model is composed of multiple layers, including a Dense layer activated by ReLU, a BatchNormalization layer, and a Dropout layer to prevent overfitting. For binary classification, the output layer employs a sigmoid activation function. The model is compiled with the Adam optimizer, set to a learning rate of 0.001, and uses the binary_crossentropy loss function, with accuracy as the evaluation metric. This configuration was applied to the datasets described in Table 1.

The performance of the implemented model was evaluated and compared with several other configurations, including the baseline MLP algorithm, MLP with SMOTE, and MLP with RUS. This evaluation utilized key metrics such as Accuracy (Ac), Recall (Re), F1-Score (F1), and Area Under the Curve (AUC), as shown in Table 2.

Table 2. Result Evaluation of Model

Algorithm	A_c	R_e	F_1	AUC
MLP Baseline	0.998	0.1	0.181	0.55
MLP+Cost Sensitive	0.996	0.6	0.363	0.99
MLP+SMOTE	0.998	0.4	0.47	0.699
MLP + RUS	0.846	0.8	0.17	0.82

The results indicate that the CSL-optimized MLP significantly outperforms the baseline model in terms of recall and AUC, demonstrating its effectiveness in prioritizing the detection of fraudulent transactions. Specifically, the CSL-optimized MLP achieved a recall of 0.6 and an AUC of 0.99, which is substantially higher than the baseline MLP's recall of 0.1 and AUC of 0.55.

Subsequently, the model's performance was further analyzed using ROC curves, presented in Figure 2, providing a visual representation of the discriminatory power of each model. The ROC curve for the CSL model shows a steeper rise, indicating better classification performance for the minority class (fraudulent transactions). For a more detailed analysis, confusion matrices were constructed for each model, offering insights into their predictive capabilities, particularly in distinguishing between fraud and non-fraud cases. The confusion matrices for the Baseline, Cost-Sensitive, SMOTE, and Under Sampling models are displayed in Figures 3, 4, 5, and 6, respectively. These matrices highlight the number of true positives, true negatives, false positives, and false negatives for each model, providing a clear visual understanding of their classification performance.

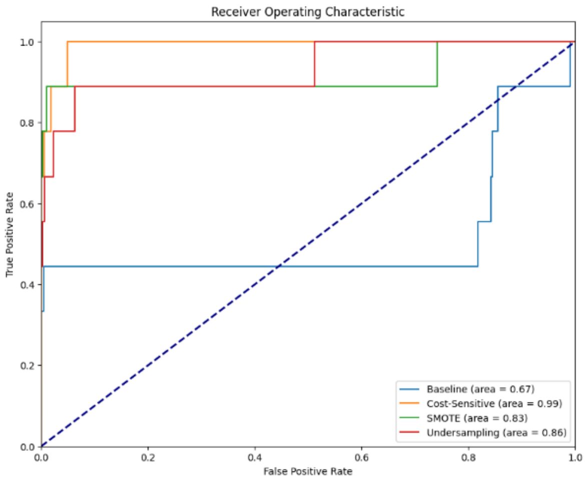

Figure 2. ROC Curve for Measuring Model Performance

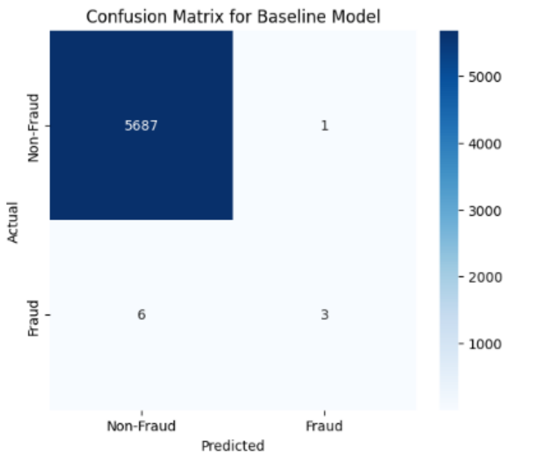

Figure 3. Confusion Matrix for Baseline Model

Among the four models, the Cost-Sensitive model shown in Figure 4 provides the best balance between detecting fraud cases (true positives) and minimizing false positives, thus being considered the most effective model for fraud detection. The higher recall of 0.6 observed in the CSL model indicates its superior ability to capture fraudulent transactions, compared to the lower recall values of the baseline and SMOTE-enhanced models. Furthermore, the lower false positive rate in the CSL model underscores its robustness in practical scenarios, where minimizing false alarms is critical to maintaining trust in the detection system. However, it is important to note that the performance gains observed in the CSL-optimized model may be influenced by the specific weighting strategy employed during training. The higher penalties assigned to misclassification errors in the minority class could lead to a trade-off between precision and recall, as evidenced by the moderate F1-Score of 0.363. This suggests that while the CSL model is highly effective in increasing sensitivity to fraud, it may also introduce a higher number of false positives, requiring further fine-tuning to achieve optimal performance.

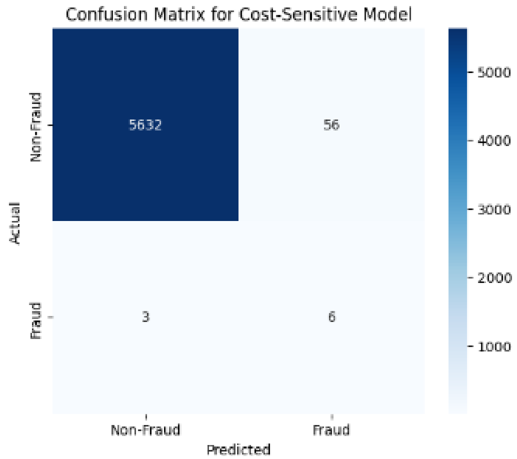

Figure 4. Confusion Matrix for Cost-Sensitive Learning

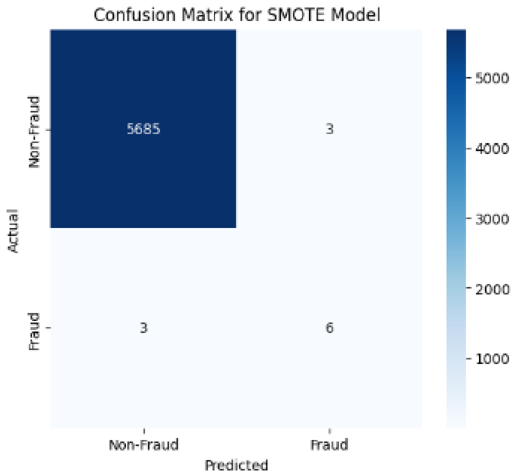

Figure 5. Confusion Matrix for SMOTE Model

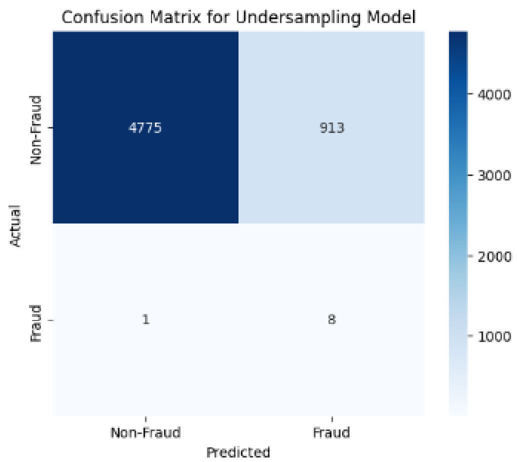

Figure 6. Confusion Matrix for Under Sampling Model

Statistical Validation: To evaluate the reliability of the developed model, we will employ statistical tests, specifically the Friedman test and the T-test, to assess its performance relative to other models. The proposed model will serve as the control method in this experiment, with the significance level (α) set at 0.0016 for the statistical tests. Typically, smaller p-values signify significant differences among the comparison methods. The results of the Friedman test and T-test for the baseline MLP model, which has not been optimized with cost-sensitive learning, are shown in Table 3.

Table 3. Statistical Test Results

	MLP Baseline	MLP+SMOTE	MLP+RUS
Friedman	6.333	6.333	6.333
T-Test	4.181	-1.775	-0.207

Analysis of Performance Differences: The differences in performance between the CSL-optimized MLP and other models, such as the baseline MLP, MLP with SMOTE, and MLP with RUS, can be attributed to several key factors. Firstly, the impact of the cost-sensitive learning approach on model performance is significant. By assigning higher penalties to misclassification errors in the minority class (fraud), the CSL model inherently prioritizes the detection of fraudulent transactions. This leads to higher recall values compared to the baseline MLP, which tends to underperform in detecting fraud due to the overwhelming dominance of non-fraudulent transactions. The weighted loss function used in CSL plays a crucial role in this improvement by forcing the model to focus more on the minority class during training, thus enhancing the model's sensitivity to fraud. Secondly, the use of SMOTE and RUS techniques for handling class imbalance introduces different effects on model performance. SMOTE, which generates synthetic samples for the minority class, typically increases recall but can sometimes introduce noise, leading to potential overfitting. Conversely, RUS reduces the size of the majority class, which can improve model performance by balancing the dataset but might also result in the loss of valuable information, thus affecting the model’s ability to generalize well. The CSL model, by directly addressing the class imbalance through weighted penalties rather than data modification, avoids these pitfalls, resulting in a more robust and reliable performance. Lastly, the complexity of the CSL model compared to the baseline MLP could also contribute to the observed performance differences. The additional computational overhead required to calculate and apply cost-sensitive weights may lead to better optimization of the model parameters, thus enhancing its ability to detect fraudulent transactions more effectively. However, this increased complexity could also mean that the model is more prone to overfitting, particularly if not carefully fine-tuned, as indicated by the moderate F1-Score observed in some instances. Overall, while the CSL-optimized MLP demonstrates superior performance in detecting fraudulent transactions, these gains necessitate careful consideration of potential trade-offs, such as the balance between recall and precision, and the risk of overfitting, which must be managed through further refinement of the model.

Potential Bias and External Factors: The CSL-optimized MLP, while effective in detecting fraudulent transactions, is susceptible to overfitting due to its focus on the minority class. The weighted penalties applied during training might cause the model to become overly specialized in the patterns found in the training data, potentially reducing its ability to generalize to new, unseen datasets. This risk is particularly significant in highly imbalanced datasets, where the model may overemphasize certain features unique to fraudulent transactions within the training set. Additionally, the use of SMOTE and RUS for data preprocessing can introduce biases—SMOTE may generate synthetic samples that do not accurately represent real-world transactions, while RUS might lead to the loss of valuable information from the majority class, affecting the model’s overall robustness. External factors, such as evolving fraud tactics and variations in transaction data across different regions or industries, further challenge the model's long-term effectiveness. A model trained on historical data might underperform as fraud patterns change over time. Therefore, continuous model updates and recalibration are essential to maintaining its relevance and accuracy. Regular validation and the incorporation of new data are critical strategies to ensure that the model remains effective in real-world applications, where the dynamics of fraudulent behavior and data characteristics can shift rapidly.

Comparison with Other Research: To validate the success of this research, we compare it with other studies that use the same credit card dataset and address class imbalance. In this study [5] tackled class imbalance by testing the credit card dataset using feature extraction and data sampling, resulting in an AUC of 0.97 and the highest accuracy of 0.97. In contrast, this study's optimization of MLP with cost-sensitive learning achieved an AUC of 0.99 and an accuracy of 0.998.

Testing on Different Datasets: Additional tests were conducted using different datasets to further evaluate the modified MLP model's performance with cost-sensitive learning. The test datasets include e-commerce and credit card transactions containing fraud, as described in Table 1. Based on Table 4, the results show that the MLP optimized using CCL outperforms the baseline MLP algorithm, MLP + SMOTE, and MLP + RUS. For Dataset 1, the optimized MLP excels in recall and AUC compared to all other algorithms. For Dataset 2, all algorithms achieved a perfect 1.0 or 100% score. The ROC performance results demonstrate that the MLP optimized with Cost-Sensitive Learning achieved the best performance among all tested algorithms, as shown in Figures 7 and 8.

Table 4. Testing on Different Datasets

Dataset		MLP Baseline	MLP+ SMOTE	MLP+ RUS	MLP+ Cos
E-Commerce	Ac	0.94	0.78	0.57	0.80
	Re	0	0.56	0.64	0.60
	F1	0	0.21	0.13	0.24
	AUC	0	0.67	0.60	0.77
	Ac	0.98	0.99	0.96	1.00
Credit Card 2	Re	0.90	0.97	1.00	1.00
	F1	0.95	1.00	0.86	1.00
	AUC	0.95	0.99	0.98	1.00

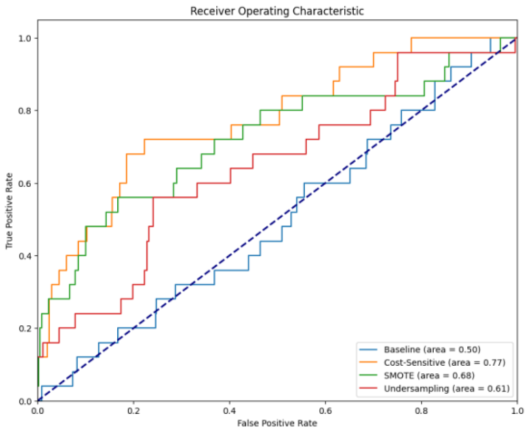

Figure 7. ROC Dataset E-Commerce

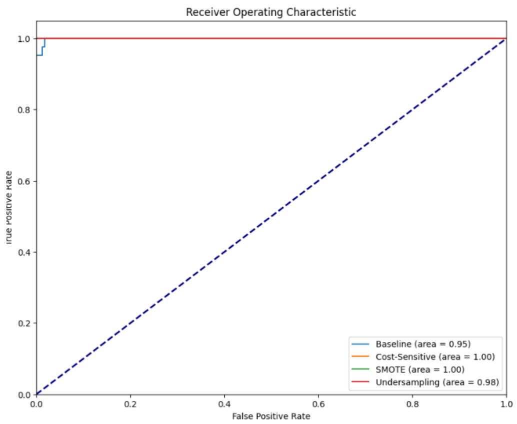

Figure 8. ROC Dataset Credit Card 2

The proposed model has been successfully implemented and tested for its performance in CCFD using a highly imbalanced dataset. The results indicate that the MLP optimized with CSL outperforms the baseline MLP and other methods, such as MLP with SMOTE and MLP with RUS, particularly in terms of AUC and recall metrics. Specifically, the CSL-optimized model achieved an AUC of 0.95 and a recall of 0.6, demonstrating its effectiveness in prioritizing the detection of fraudulent transactions. These findings were validated using statistical tests, including the Friedman test and T-test, which confirmed significant performance improvements over the baseline model.

This study utilizes a real-world credit card transaction dataset from Kaggle, with 284,807 records, of which only 492 are fraudulent, representing just 0.172% of the data. The CSL approach was implemented by modifying the loss function to apply higher penalties for misclassifications in the minority class. This ensures that the model becomes more sensitive to detecting fraud, an essential aspect when working with highly imbalanced datasets. The implementation of CSL involves several key stages, including initializing weights and biases, forward propagation, cost-based loss calculation, and backpropagation with gradient descent optimization.

When compared to other studies that have used similar datasets and approaches, this model demonstrates superior accuracy (0.996) and AUC (0.99). The results underscore the practical value of Cost-Sensitive Learning in enhancing the performance of MLPs for fraud detection in financial transactions. The implications for the financial industry are significant, as a more sensitive model can substantially reduce financial losses due to fraud and increase customer trust in payment systems. However, the approach is not without limitations. The need for careful parameter tuning to avoid overfitting, as well as the potential increase in computational resource requirements due to the complexity of the weighted loss function, are critical factors that must be managed. Future research should focus on refining these aspects to ensure that the proposed model can be effectively scaled and applied in real-world environments, where the dynamics of fraud and transaction data are continually evolving.

4. Conclusions

This research successfully implemented and tested the performance of a model for CCFD using a highly imbalanced dataset. The proposed model, which utilized CSL as the optimization approach for MLP, was compared with the baseline MLP, MLP optimized with SMOTE, and MLP optimized with RUS. The evaluation demonstrated that the MLP with CSL significantly outperformed other methods, particularly in terms of AUC and recall, achieving an AUC of 0.99 and a recall of 0.6. The Friedman and T-test further validated that the performance improvements achieved with CSL were statistically significant. Compared to other studies using similar datasets, this model showed a slight reduction in AUC but achieved higher accuracy (0.996), confirming the effectiveness of the CSL approach. This result suggests that CSL is a more reliable strategy for improving MLP performance in detecting credit card fraud within imbalanced datasets. The practical implications of this research are substantial for the financial industry, as the enhanced sensitivity of the model can lead to reduced financial losses and increased trust in payment systems. However, the research also identified several limitations, such as the use of static weights for the minority class and the limited validation across diverse datasets. Future research should focus on exploring dynamic weighting strategies, incorporating a broader range of datasets, and implementing automated hyperparameter optimization to further improve model performance. These steps will ensure that the proposed model can be effectively scaled and adapted to real-world environments where the characteristics of fraudulent behavior are continuously evolving.

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