**UNIVERSITAS BHAYANGKARA JAKARTA RAYA**
**FAKULTAS ILMU KOMPUTER**
Kampus I: Jl. Harsono RM No. 67, Ragunan, Pasar Minggu, Jakarta Selatan, 12550
Telepon: (021) 27808121 – 27808882
Kampus II: Jl. Raya Perjuangan, Marga Mulya, Bekasi Utara, Jawa Barat, 17142
Telepon: (021) 88955882, Fax.: (021) 88955871
Web: fasilkom.ubharajaya.ac.id, E-mail: fasilkom@ubharajaya.ac.id

# SURAT TUGAS

Nomor: ST/347/V/2023/FASILKOM-UBJ

1. Dasar: Kalender Akademik Universitas Bhayangkara Jakarta Raya Tahun Akademik 2022/2023.

2. Dalam rangka mewujudkan Tri Dharma Perguruan Tinggi untuk Dosen di Universitas Bhayangkara Jakarta Raya maka dihimbau untuk melakukan penelitian.

3. Sehubungan dengan hal tersebut di atas, maka Dekan Fakultas Ilmu Komputer Universitas Bhayangkara Jakarta Raya menugaskan:

| NO. | NAMA | NIDN | JABATAN | KETERANGAN |
|---|---|---|---|---|
| 1. | Dr. Tb. Ai Munandar, S.Kom., M.T. | 0413098403 | Dosen Tetap Prodi Informatika | Sebagai Penulis Pertama |

Membuat Artikel Ilmiah dengan judul **"*Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data*"** dengan menerima LoA pada tanggal 19 Mei 2023 untuk dipublikasikan di media JOIN (Jurnal *Online* Informatika), Vol. 8, No. 1, Juni 2023, Hal. 91-98, P-ISSN: 2528-1682, E-ISSN: 2527-9165.

4. Demikian penugasan ini agar dapat dilaksanakan dengan penuh rasa tanggung jawab.

Jakarta, 22 Mei 2023
**DEKAN FAKULTAS ILMU KOMPUTER**

**Dr. Dra. Tyastuti Sri Lestari, M.M.**
**NIP. 1408206**

**JOIN (Jurnal Online Informatika)**
p-ISSN: 2528-1682, e-ISSN: 2527-9165
Volume 8 Number 1 | June 2023: 91-98
DOI: 10.15575/join.v8i1.1027

# Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data

**Tb Ai Munandar**
Department of Informatics, Universitas Bhayangkara Jakarta Raya, Indonesia

**Article Info**

***Article history:***

Received Feb 12, 2023
Revised April 05, 2023
Accepted May 19, 2023

***Keywords:***

Data mining
Echocardiogram
Electrocardiogram
Heart disease
Multi-layer perceptron

**ABSTRACT**

Traditional methods of detecting cardiac illness are often problematic in the medical field. The doctor must next study and interpret the findings of the patient's medical record received from the electrocardiogram and echocardiogram. These tasks often take a long time and require patience. The use of computational technology in medicine, especially the study of cardiac disease, is not new. Scientists are continuously striving for the most reliable method of diagnosing a patient's cardiac illness, particularly when an integrated system is constructed. The study attempted to propose an alternative for identifying cardiac illness using a supervised learning technique, namely the multi-layer perceptron (MLP). The study started with the collection of patient medical record data, which yielded up to 534 data points, followed by pre-processing and transformation to provide up to 324 data points suitable to be employed by learning algorithms. The last step is to create a heart disease classification model with distinct activation functions using MLP. The degree of classification accuracy, k-fold cross-validation, and bootstrap are all used to test the model. According to the findings of the study, MLP with the Tanh activation function is a more accurate prediction model than logistics and Relu. The classification accuracy level (CA) for MLP with Tanh and k-fold cross-validation is 0.788 in a data-sharing situation, while it is 0.672 with Bootstrap. MLP using the Tanh activation function is the best model based on the CA level and the AUC value, with values of 0.832 (k-fold cross-validation) and 0.857 (bootstrap).

***Corresponding Author:***

Tb Ai Munandar,
Informatics Department, Faculty of Computer Science, Universitas Bhayangkara Jakarta Raya,
Jl. Raya Perjuangan Bekasi Utara, Kota Bekasi, Jawa Barat 17121, Indonesia
Email: tbaimunandar@gmail.com

## 1. INTRODUCTION

Heart disease is one of the main causes of death in many parts of the world [1], [2], [3], and it may affect anybody, regardless of age, gender, or socioeconomic status [4]. If this sickness infects humans, it is extremely deadly [5] since it is difficult to anticipate adequately and efficiently [6]. Traditional analytical approaches are used by clinicians, particularly in hospitals, to diagnose heart illness. The study was based on the patient's observation findings, which were then combined with the results of the ECG and echocardiography data examinations. However, normal medical analysis is frequently ineffectual and has little consequence on diagnosis [7]. Even doctors make mistakes while diagnosing heart issues [8]. Traditional medical analysis frequently struggles to match diagnostic findings with other diagnostic data due to the enormous amount of medical record data.

The health business now generates a large amount of medical record data [9], but they lack a very powerful analysis tool that can be used to diagnosis disease kinds based on hidden relationship information in the data [10]. An artificial intelligence approach may be used in computer science to

extract hidden information from data for decision-making purposes. Artificial intelligence is not a new concept, particularly in the detection of cardiovascular disease. A decade ago, several research on the application of artificial intelligence to the difficulty of diagnosing heart illness were conducted [11], [12], [13], [14], and [15]. Data mining is a branch of artificial intelligence that is frequently used to detect heart illness.

Data mining is the process of detecting patterns and correlations in data for data analytic purposes such as trend forecasting, classification, and grouping [9]. Furthermore, it has the potential to predict heart disease and identify unique illnesses such as cardiac amyloidosis (CA) [16]. Several other studies have used data mining to diagnose cardiac illness, including [17], [18], [19], and [20]. The bulk of researchers execute data mining tasks using machine learning [21], [22], and [23].

Several studies have been conducted to diagnose cardiac disease using simply echocardiography or electrocardiogram (ECG) data. Echocardiogram parameters have been used in studies [24], [25], and [26] to identify heart disease and other conditions. Meanwhile, [27], [28], [29], and [30] employ ECG characteristics to detect cardiac disease and other conditions. The present study employs a data mining method to integrate these two factors in order to generate more accurate identification results.

Despite significant research into using data mining and machine learning techniques to predict heart disease, it remains difficult for health practitioners and academics to use data mining to aid in research and diagnose illnesses based on patient medical record data. This work contributes to a comprehensive understanding of the stages of data mining in the health industry, particularly in the prediction of heart disease. The discussion chapter uses ECG data to show how a multilayer perceptron technique with three activation functions may be utilized to forecast heart disease. This work employs training and testing data sharing approaches such as k-fold cross-validation and bootstrapping to assess the accuracy of the three MLP activation functions utilized to test the MLP model. The metrics area under the curve (AUC), classification accuracy (CA), F1, precision, and recall are used to determine the optimum activation function of MLP.

## 2. METHOD

This study starts with identifying the issue and ends with the collection of patient medical data from one of Banten Province's government general hospitals. The information was gathered manually by collecting patient medical records, which were then combined into a single file to aid in the analytic process. There were 354 data occurrences in the initial data collection results. Following data cleaning and preprocessing, 324 valid datasets were retrieved. There are fifteen predictor variables and one response variable in the dataset. The fifteen prediction criteria were established based on echocardiography and ECG data gathered from the medical records of heart disease patients. The data is ready for use after the preparation step. The *.csv file extension is associated with data analysis. The data is then separated into training data and testing data. For training data, there are two distribution possibilities. The first example uses k-fold cross-validation, whereas the second uses bootstrapping. After that, the training data is sent into the MLP algorithm, which generates a model. Three activation functions are used for training the algorithm using training data. The three roles of activation are logistics, Tanh, and Relu. Validation of the model is performed using scenario-specific test data. The last step is model selection. The chosen model is then used to predict new data, which is then examined. This study also used Orange Data Mining (ODM), a visual programming tool. Several widgets are used to facilitate analysis. The *.xls extension is changed to *.csv for simpler display on ODM work screens.

## 3. RESULT AND DISCUSSION

### *3.1. Result*

#### *3.1.1. Business and data understanding and preparation*

Data mining begins with business knowledge and progresses to data comprehension. In the first phase, we define research objectives, which are subsequently translated into issue descriptions and handled by data mining. We also created a research goal at this time, which was to create an MLP-based model for predicting cardiac illness.

Following the identification of objectives and impediments, the next stage of data understanding is data gathering. The data was gathered from the medical records of heart disease patients at one of Banten Province's regional public facilities. There are fifteen predictor factors and one response variable. The fifteen characteristics were generated from the medical records of individuals who had undergone echocardiogram (ECHO) and electrocardiogram (ECG). Echocardiography data comprises cardiac functions, EDD (end-diastolic diameter), ESD (end-systolic diameter), IVS Diastole, IVSSystole, PW (posterior wall) Diastole, and PW (posterior wall) Systole. HR (heart rate in pulses per minute), PR (PQ), QRS, QT, QTC, and P waves are ECG variables.

Each characteristic has its own heart disease distribution. In the LEFT-ATRIUM variable, for example, the greatest distribution of disease types occurs between 40 and 42:48, with hypertensive heart disease (41.67%), coronary artery disease (39.58%), left ventricular HSHHD (12.50%), rheumatic heart disease (4.17%), and normal resting echocardiography (2.07%) dominating the distribution. Numerous kinds of cardiovascular illness have varying distributions as well. Figures 1 and 2 show the distribution and relative percentages of the LEFT-ATRIUM and end-diastolic diameter (EDD) variables for all forms of heart disease.

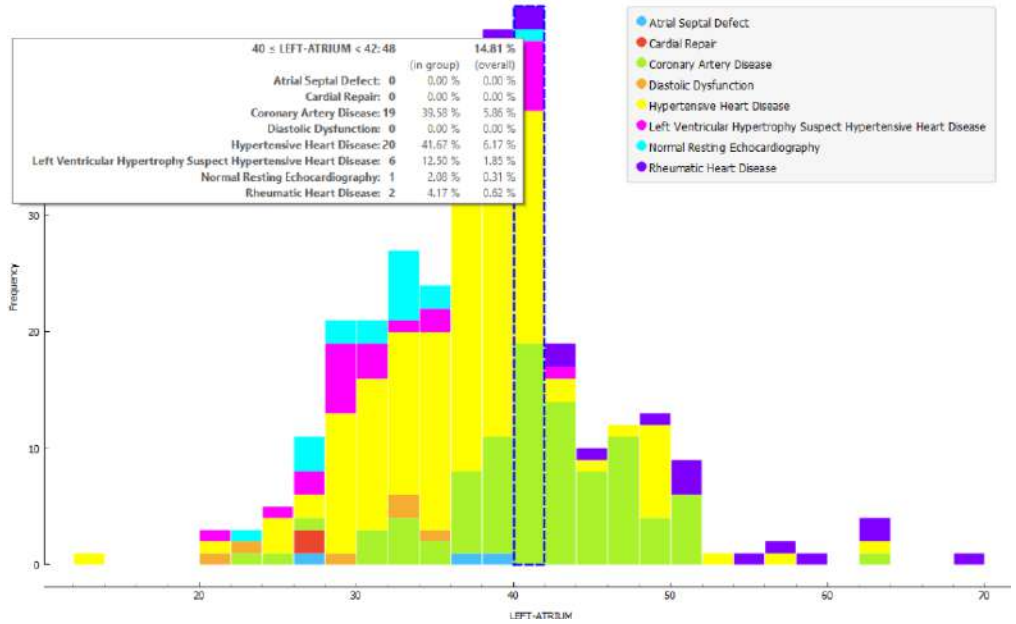



Figure 1. Left-Atrium Variable Value Range Distribution for Disease Types

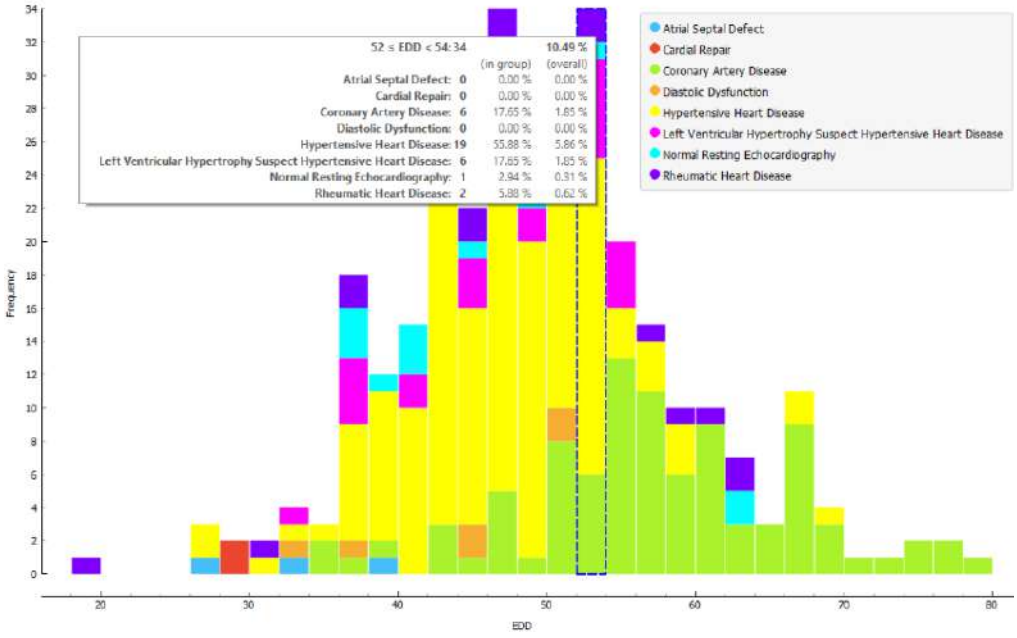



Figure 2. The range of End-Diastolic Diameter (EDD) values for different kinds of disease

p-ISSN: 2528-1682
e-ISSN: 2527-9165

Following a physician's diagnosis, 354 patient medical record files comprising eight types of heart disease were first obtained. The process of selecting attributes and purifying the data occurs during the data comprehension step. The data purification technique yielded 324 useable data instances with eight class labels corresponding to disorder types. The eight categories are as follows: atrial septal defect, cardiac repair, coronary artery disease, diastolic dysfunction, hypertensive heart disease, left ventricular hypertrophy indicative of hypertensive heart disease, normal resting echocardiography, and rheumatic heart disease. The distribution of heart disease categories throughout the sample is seen in Figure 3. The distribution of heart disease categories throughout the sample is seen in Figure 3.

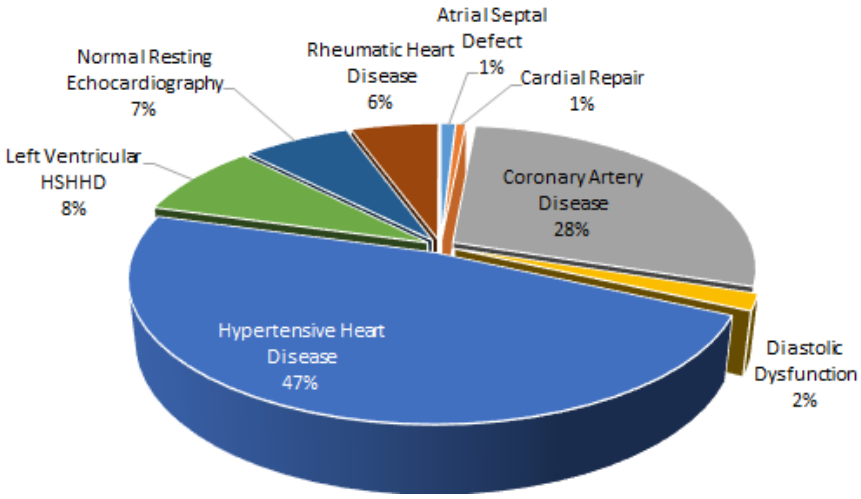



Figure 3. Distribution of types of heart disease in the dataset

The goal of the data preparation step is to create datasets that are useable and analyzable. Data tabularization with columns representing attributes and rows representing data instances. To simplify later analysis, the data is saved in *.csv files.

### *3.1.2. Building a classification model*

The difficulty of constructing a classification model is part of data mining. The multilayer perceptron (MLP) technique is employed as a learning algorithm in this stage. To determine the best accurate MLP with activation, three activation functions are utilized. There are two main possibilities for model creation. The current scenario is primarily concerned with how the dataset is divided into training and testing data before being incorporated in the algorithm. The first case employed k-fold cross-validation (k-FCV), whereas the second used Bootstrap.

#### *3.1.2.1 Classification model with k-fold cross-validation division*

Because the k-FCV approach has a value of 10, the dataset is divided into ten parts, and ten iterations of training and accuracy tests are done until the model's final average accuracy is obtained. Training data is often separated into 291 training data sets divided into nine divisions and 33 testing data sets (with a separate section for model performance testing). The model was created using the multilayer perceptron (MLP) method. Training data are used to train the MLP algorithm. Logistic, Relu, and Tanh are examples of activation functions that have been employed. The purpose of comparing the three activation functions is to determine which one has the highest degree of accuracy, so that it may be utilized as the most accurate model for predicting heart disease.

The model is then evaluated using test data. According to the model test results, the logistic activation function and Relu have the same level of classification accuracy (CA), which is 0.758, while the Tanh activation function has a higher level of CA, which is 0.788. Despite having the same accuracy as Logistic, Relu has a superior activation function in this scenario. The fact that Relu has a greater accuracy rating than logistics confirms this. This precision grade shows the correctness of the predicted findings in relation to the actual data. Figure 4 displays an in-depth examination of the CA, F1, accuracy, and recall component qualities.

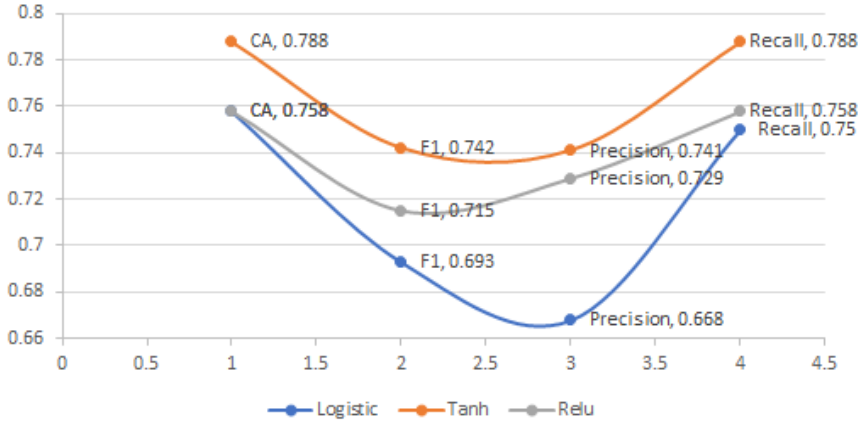



Figure 4. Comparison of CA, F1, Precision, and Recall by Dividing the k-fold Cross Validation Dataset

### 3.1.2.2 Classification model with Bootstrap

When constructing a training set, Bootstrap splits the data into random samples. Random sampling is employed on the dataset. Orange Data Mining separates the dataset into training and testing data using the Bootstrap option. For each occurrence of data in the dataset, the proportion estimated from training data is 32:81. The great majority of the data is utilized for training, with the remainder being used for testing. The training data is then utilized to train the MLP algorithm with three distinct activation functions, as in the k-fold cross-validation scenario. Data testing is used to validate the model that has been created. The Tanh activation function has a greater classification accuracy (CA) than the other two activation functions, according to the accuracy test results. The Logistic, Tanh, and Relu activation functions had classification accuracy scores of 0.664, 0.672, and 0.688, respectively. Tanh has a higher accuracy value than logistics and relu by default. Figure 5 shows a comparison of the three activation functions' accuracy.

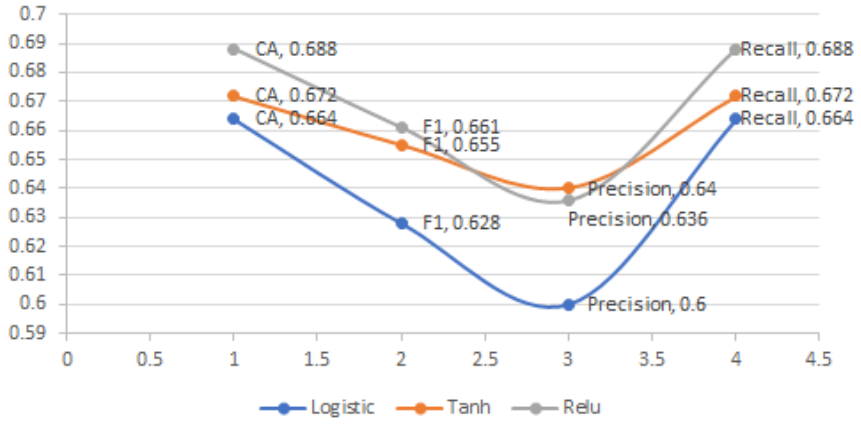



Figure 5. Comparison of CA, F1, precision, and recall by dividing the Bootstrap dataset

### 3.1.3 Model evaluation

During this stage, it is determined which activation function-based model will be used to forecast the kind of heart disease. Classification accuracy (CA), F1, precision, recall, and AUC data are used to assess models. comparing the evaluation component values for the two instances According to the results of the first scenario model, the MLP with the Tanh activation function achieves the highest degree of accuracy when compared to the other two activation functions. Tanh's activation function provides superior classification accuracy than Logistic and Relu in the second scenario outcome model.

Tanh's MLP model is often not better than Relu's MLP model in the first scenario, despite having a greater degree of classification accuracy than other activation functions based on the area under the receiver operating characteristic (AUC) value. AUC may have values ranging from 0 to 1. The closer the model is to 1, the better its performance. In this case, Relu's accuracy and AUC results are inconsistent.

Relu has the greatest AUC value among the three activation functions, although the degree of accuracy between predicted and actual data is the same as Tanh's.

In the second situation, the MLP using the Tanh activation function has the maximum classification accuracy (CA). Tanh outperforms Logistics and Relu in AUC, accuracy, and recall. Based on the results of model testing, the MLP with the Tanh activation function is the best classification model for both the first and second instances. Table 1 compares the evaluation of models based on AUC, CA, F1, accuracy, and recall values for the first and second situations.

Table 1. Comparison of MLP for the First and Second Scenarios

| | K-fold Cross Validation | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | Logistic | Tanh | Relu | Logistic | Tanh | Relu |
| AUC | 0.832 | 0.864 | 0.868 | 0.845 | 0.857 | 0.843 |
| CA | 0.758 | 0.788 | 0.758 | 0.664 | 0.672 | 0.688 |
| F1 | 0.693 | 0.742 | 0.715 | 0.628 | 0.655 | 0.661 |
| Precision | 0.668 | 0.741 | 0.729 | 0.6 | 0.64 | 0.636 |
| Recall | 0.75 | 0.788 | 0.758 | 0.664 | 0.672 | 0.688 |

### *3.2 Discusion*

In this research, the activation function of the best model was used to predict the type of heart disease. Twenty patient data points are supplied in order to assess the patient's heart disease classification. We use physician-identified data from current medical records to confirm the classification findings. Prediction using MLP with the Tanh activation function According to the prediction findings for the extra patient data, up to fifteen patients accurately recognized the disease type that matches the actual data and predicted outcomes, while up to five patients were categorized incorrectly. This shows that the classification accuracy of the prediction model on extra data is 75%. Table 2 shows the results of the heart disease category for new data on twenty individuals.

Table 2. Prediction results for types of heart disease for additional data

| **Patient** | **Actual (Doctor's Diagnosis)** | **Predicted** |
|---|---|---|
| PSJ-484 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-489 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-491 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-492 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-495 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-496 | Coronary Artery Disease | Hypertensive Heart Disease |
| PSJ-480 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-482 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-483 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-486 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-497 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-485 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-487 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-490 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-493 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-478 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-479 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-488 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-494 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-481 | Rheumatic Heart Disease | Rheumatic Heart Disease |

In Table 3, the probability column displays the likelihood of the expected result based on MLP using the Tanh activation function. Patients with the identities PSJ-496, PSJ-485, PSJ-487, PSJ-490, and PSJ-493 had a discrepancy between actual data and predicted results, with probability values of 0.46, 0.65, 0.64, 0.46, and 0.85. The patient with the code PSJ-493 had a higher projected probability value than the other four patients whose predictions did not match.

Table 3. Probability of MLP Prediction Results with the Tanh Activation Function

| **Patient** | **CAD** | **HHD** | **Left Ventricular HSHHD** | **NRE** | **RHD** |
|---|---|---|---|---|---|
| PSJ-484 | 0.97 | 0.00 | 0.00 | 0.00 | 0.03 |
| PSJ-489 | 0.83 | 0.09 | 0.06 | 0.00 | 0.01 |
| PSJ-491 | 0.82 | 0.10 | 0.02 | 0.02 | 0.02 |
| PSJ-492 | 0.94 | 0.03 | 0.00 | 0.00 | 0.02 |
| PSJ-495 | 0.97 | 0.01 | 0.00 | 0.00 | 0.01 |
| PSJ-496 | 0.00 | 0.46 | 0.27 | 0.16 | 0.06 |

| Patient | CAD | HHD | Left Ventricular HSHHD | NRE | RHD |
|---|---|---|---|---|---|
| PSJ-480 | 0.00 | 0.94 | 0.05 | 0.00 | 0.00 |
| PSJ-482 | 0.35 | 0.40 | 0.02 | 0.00 | 0.22 |
| PSJ-483 | 0.05 | 0.84 | 0.08 | 0.00 | 0.02 |
| PSJ-486 | 0.12 | 0.71 | 0.07 | 0.05 | 0.03 |
| PSJ-497 | 0.00 | 0.95 | 0.02 | 0.01 | 0.00 |
| PSJ-485 | 0.01 | 0.65 | 0.27 | 0.02 | 0.01 |
| PSJ-487 | 0.08 | 0.64 | 0.26 | 0.00 | 0.01 |
| PSJ-490 | 0.02 | 0.46 | 0.41 | 0.02 | 0.00 |
| PSJ-493 | 0.01 | 0.85 | 0.09 | 0.01 | 0.03 |
| PSJ-478 | 0.02 | 0.45 | 0.04 | 0.47 | 0.01 |
| PSJ-479 | 0.00 | 0.10 | 0.06 | 0.78 | 0.00 |
| PSJ-488 | 0.03 | 0.22 | 0.03 | 0.66 | 0.01 |
| PSJ-494 | 0.01 | 0.25 | 0.11 | 0.45 | 0.00 |
| PSJ-481 | 0.01 | 0.14 | 0.00 | 0.00 | 0.84 |

Patients with the PSJ-496 code had a 0.46 chance of having hypertensive heart disease, a 0.27 chance of having left ventricular HSHHD, and a 0.16 chance of having a normal resting echocardiogram (NRE). It can also be seen that the likelihood of the real data being reselected as a candidate for the prediction result is 0.00, suggesting that the projected result is very unlikely to match the actual outcome. Patients with PSJ-485, PSJ-487, and PSJ-490 codes show a similar pattern. Table 3 displays the MLP's anticipated probability using the Tanh activation function.

The classification accuracy (CA) of supplementary data prediction results is 0.75, and the area under the curve (AUC) is 0.928%, both of which are near-excellent for a model. Clearly (precision), the model's accuracy in predicting data impacts the value of CA in the prediction outcomes of fresh data. With a precision value of 0.675%, a classification accuracy (CA) of 0.75 is quite satisfactory. Regardless of the kind of heart illness, the MLP model with the Tanh activation function reliably predicts it.

## 4. CONCLUSION

The classification accuracy of a multilayer perceptron (MLP) with several activation functions changes depending on the test data, according to the study. First, the classification accuracy (CA) for the three activation functions used differs. The logistic and Relu activation functions have CA values that are similar. Tanh has more precise activation functions than Logistics and Relu. Relu, on the other hand, maintains the model's quality level in the first scenario based on the AUC value for MLP. The Tanh activation function and the high quality of the developed classification model produce the most exact classification in the second case. In general, the MLP with Tanh activation offers the most accuracy. According to test findings on fresh data, the model can predict cardiovascular disease with 75.0% accuracy. In this work, a comparison of the MLP activation function to the Relu and Logistic activation functions reveals that Tanh is an activation function that may be selected for the prediction of heart disease. Thus, utilizing the MLP with the Tanh activation function, an alternate approach for predicting heart disease is possible.

## REFERENCES


[1] C.A. Hassan, J. Iqbal, R. Irfan, S. Hussain, A. D. Algarni, S.S.H. Bukhari, N. Alturki, and S.S. Ullah, "Effectively Predicti ng the Presence of Coronary Heart Disease Using Machine Learning Classifiers", *Sensors*, Vol. 22, 7227, 2022, https://doi.org/10.3390/s22197227

[2]. Z. He, H. Zhang, X. Chen, J. Shi, L. Bai, Z. Fang, and R. Wang, "Hemorrhagic risk prediction in coronary artery disease patie nts based on photoplethysmography and machine learning," *Scientific Reports*, 12:19190, 2022, https://doi.org/10.1038/s41598-022-22719-7

[3]. H.D. Masethe, and M.A. Masethe, "Prediction of Heart Disease using Classification Algorithms", *Proceedings of the World Congress on Engineering and Computer Science 2014*, Vol II, 22-24 October, 2014

[4]. Anderies, J.A.R.W. Tchin, P.H. Putro, Y.P. Darmawan, A.A.S. Gunawan, "Prediction of Heart Disease UCI Dataset Using Machine Learning Algorithms", *Engineering, Mathematics and Computer Science*, Vol.4, No.3, 2022, pp. 87-93, DOI: 10.21512/emacsjournal.v4i3.8683

[5]. Y. Muhammad, M. Tahir, M. Hayat, and K.T. Chong, "Early and accurate detection and diagnosis of heart disease using intelligent computational model", *Scientific Reports*, 10:19747, 2020, https://doi.org/10.1038/s41598-020-76635-9

[6]. H. Jindal, S. Agrawal, R. Khera, R. Jain and P. Nagrath, "Heart disease prediction using machine learning algorithms", *IOP Conf. Series: Materials Science and Engineering 1022*, pp. 1 - 10, 2021, doi:10.1088/1757-899X/1022/1/012072

[7]. B. Umadevi, and M. Snehapriya, "A Survey on Prediction of Heart Disease Using Data Mining Techniques", *International Journal of Science and Research (IJSR),* Volume 6, Issue 4, pp. 2228 – 2232

[8]. S. Kodati, and R. Vivekanandam, "Analysis of Heart Disease using in Data Mining Tools Orange and Weka", *Global Journal of*

*Computer Science and Technology,* Volume XVIII, Issue I, Version I, pp. 17 - 21, 2018

[9]. S.H. Shadid, A.Shafkat, F. Yasmeen, S.A. Sibli, and M.R.Rafi, "Prediction of Heart Disease Using Data Mining Techniques: A Case Study", *International Journal of Research Publications*, Volume: 41, Issue: 1, 2019, availabe at https://ijrp.org/paper-detail/826

[10]. B.Bahrami, and M.H. Shirvani, "Prediction and Diagnosis of Heart Disease by Data Mining Techniques", *Journal of Multidisciplinary Engineering Science and Technology (JMEST),* Vol. 2, Issue 2, pp. 164 - 168, 2015

[11]. O.Yu. Atkov, S.G. Gorokhova, A.G. Sboev, E.V. Generozov, E.V. Muraseyeva, S.Y. Moroshkina, N.N. Cherniy, "Coronary heart disease diagnosis by artificial neural networks including genetic polymorphisms and clinical parameters", *Journal of Cardiology*, 59, pp. 190—194, 2012, doi:10.1016/j.jjcc.2011.11.005

[12]. R. Chitra, and V. Seenivasagam, "Review of Heart Disease Prediction System Using Data Mining And Hybrid Intelligent Techniques", *ICTACT Journal on Soft Computing*, Vol. 3, No. 4, pp. 605 – 609, 2013, DOI : 10.21917/ijsc.2013.0086

[13]. Taneja, "Heart disease Prediction System Using data Mining Techniques", *Oriental Journal of Computer Science & Technology,* Vol. 6, No. (4): Pp. 457-466, 2013

[14]. C.S. Dangare, and S.S. Apte, "Improved Study of Heart Disease Prediction System using Data Mining Classification Techniques", *International Journal of Computer Applications*, Vol. 47, No.10, 2012

[15]. A.K. Pandey, P. Pandey, K.L. Jaiswal, A.K. Sen, "A Heart Disease Prediction Model using Decision Tree", *IOSR Journal of Computer Engineering (IOSR-JCE)*, Vol. 12, No. 6,pp. 83-86, 2013

[16]. S. Goto, K. Mahara, L. Beussink-Nelson, H. Ikura, Y. Katsumata, J. Endo, H. K. Gaggin, S. J. Shah, Y. Itabashi, C. A. MacRae, and R. C. Deo, "Artificial intelligence-enabled fully automated detection of cardiac amyloidosis using electrocardiograms and echocardiograms", *NATURE COMMUNICATIONS* | (2021) 12:2726, pp. 1-12, 2021, https://doi.org/10.1038/s41467-021-22877-8

[17]. Akansha Jain, Manish Ahirwar, Rajeev Pandey, "A Review on Intutive Prediction of Heart Disease Using Data Mining Techniques", *International Journal of Computer Sciences and Engineering*, 2019, ff10.26438/ijcse/v7i7.109113

[18]. Thamizhiniyal, and A. Vidhya, "Intelligent Risk Analysis and Prediction of Heart Disease Using Data Mining Techniques", *Journal of Information and Computational Science*, Vol. 10, No. 3, pp. 175 - 180, 2020

[19]. R. Fadnavis, K. Dhore, D. Gupta, J. Waghmare, and D. Kosankar, "Heart disease prediction using data mining", *Journal of Physics: Conference Series* 1913, 012099, 2021, doi:10.1088/1742-6596/1913/1/012099

[20]. P. Singh, S. Singh, and G.S. Pandi-Jain, "Effective heart disease prediction system using data mining techniques", *International Journal of Nanomedicine*, Vol. 13, pp. 121 - 124, 2018

[21]. S.Y. Cho, S.H. Kim, S.H. Kang, K.J. Lee, D. Choi, S. Kang, S.J. Park, T.Kim, C.H. Yoon, T.J. Youn, and I.C. Chae, "Pre-existi ng and machine learning-based models for cardiovascular risk prediction", *Scientific Reports*, 11:8886, 2021, https://doi.org/10.1038/s41598-021-88257-w

[22]. C. Krittanawong, H.U.H. Virk, S. Bangalore, Z. Wang, K.W. Johnson, R. Pinotti, H. Zhang, S. Kaplin, B. Narasimhan, T. Kitai, U. Baber, J.L.Halperin and W.H.W. Tang, "Machine learning prediction in cardiovascular diseases: a meta-analysis", *Scientific ReportS*, 10:16057, 2020, https://doi.org/10.1038/s41598-020-72685-1

[23]. R. Alizadehsani, M. Roshanzamir, M. Abdar, A. Beykikhoshk, A. Khosravi, M. Panahiazar, A. Koohestani, F. Khozeimeh, S. Nahavandi, and N. Sarrafzadegan, "A Database For Using Machine Learning and Data Mining Techniques for Coronary Artery Disease Diagnosis", *Scientific Data* | (2019) 6:227, pp. 1 -13, 2019, https://doi.org/10.1038/s41597-019-0206-3

[24]. C. Balakrishnan, and V.D.A. Kumar, IoT-Enabled Classification of Echocardiogram Images for Cardiovascular Disease Risk Prediction with Pre-Trained Recurrent Convolutional Neural Networks, Diagnostics 2023, 13, 775. https://doi.org/10.3390/ diagnostics13040775

[25]. R. Nedadur, B. Wang, and W. Tsang, Artificial intelligence for the echocardiographic assessment of valvular heart disease Heart 2022;108:1592-1599.

[26]. N. Kumar, and D. Kumar, Machine Learning based Heart Disease Diagnosis using Non- Invasive Methods: A Review, Journal of Physics: Conference Series 1950, ICMAI 2021, pp. 1 - 14, doi:10.1088/1742-6596/1950/1/012081

[27]. M. B. Abubaker and B. Babayiğit, "Detection of Cardiovascular Diseases in ECG Images Using Machine Learning and Deep Learning Methods," in IEEE Transactions on Artificial Intelligence, vol. 4, no. 2, pp. 373-382, April 2023, doi: 10.1109/TAI.2022.3159505.

[28]. T. Dhamdhere, S. Bhutambere, A. Bansode, and S. Umare, Heart Disease Detection Using ECG Waves: A Survey, Journal of Emerging Technologies and Innovative Research (JETIR), Vol. 7, Issue 4, pp. 1761 - 1764

[29]. A. S. . Sharma and D. H. . Hota, "ECG Analysis-Based Cardiac Disease Prediction Using Signal Feature Selection with Extraction Based on AI Techniques", Int. j. commun. netw. inf. secur., vol. 14, no. 3, pp. 73–85, Dec. 2022.

[30]. M.H. Vafaie, M. Ataei, and H.R. Koofigar, Heart diseases prediction based on ECG signals' classification using agenetic-fuzzy system and dynamical model of ECG signals, Biomedical Signal Processing and Control 14, 2014, pp. 291–296

JOIN
JURNAL ONLINE INFORMATIKA
ISSN: 2528-1682 (PRINTED) | 2527-9165 (ONLINE)
PUBLISHED BY:



# Vol. 8 No. 1 (2023)


This issue has been available online since 28 June 2023. All articles in this issue (15 original research articles) were authored/co-authored by 2 countries (Indonesia and Malaysia).

**DOI:** https://doi.org/10.15575/join.v8i1

**PUBLISHED:** 2023-06-28

## ARTICLE

### Regression Analysis for Crop Production Using CLARANS Algorithm

**Arie Vatresia,** 1) Research Center for Computing, The National Research and Innovation Agency, Bogor, Indonesia 2) Informatics, Engineering Faculty, Universitas Bengkulu, Indonesia, Indonesia
https://orcid.org/0000-0001-9789-3498
**Ruvita Faurina,** Informatics, Engineering Faculty, Universitas Bengkulu, Indonesia, Indonesia
**Yanti Simanjuntak,** Informatics, Engineering Faculty, Universitas Bengkulu, Indonesia, Indonesia

1-10
DOI : 10.15575/join.v8i1.1031 Abstract View : 563 PDF downloads: 644
PDF

### Scalability Testing of Land Forest Fire Patrol Information Systems

**Ahmad Khusaeri,** Department of Computer Science, IPB University, Bogor, Indonesia, Indonesia
**Imas Sukaesih Sitanggang,** Department of Computer Science, IPB University, Bogor, Indonesia, Indonesia
**Hendra Rahmawan,** Department of Computer Science, IPB University, Bogor, Indonesia, Indonesia

11-18
DOI : 10.15575/join.v8i1.977 Abstract View : 234 PDF downloads: 350
PDF

### Social Network Analysis: Identification of Communication and Information Dissemination (Case Study of Holywings)

**Umar Aditiawarman,** Department of Computer Science, Universitas Nusa Putra, Indonesia
**Mega Lumbia,** Department of Computer Science, Universitas Nusa Putra, Indonesia
**Teddy Mantoro,** Department of Computer Science, Sampoerna University, Indonesia
**Adamu Abubakar Ibrahim,** Information and Communication Technology, International Islamic University Malaysia, Indonesia

19-26
DOI : 10.15575/join.v8i1.911 Abstract View : 368 PDF downloads: 432
PDF

### Run Length Encoding Compresion on Virtual Tour Campus to Enhance Load Access Performance

MAKE A SUBMISSION

ACCREDITED


EDITORIAL TEAM
REVIEWER
PEER REVIEW PROCESS
FOCUS AND SCOPE
AUTHOR GUIDELINES
AUTHOR FEES
ARTICLE WITHDRAWAL
PUBLICATION ETHICS
COPYRIGHT NOTICE
PLAGIARISM CHECK
REFERENCES MANAGEMENT
JOURNAL HISTORY

TOOLS

MANUSCRIPT TEMPLATE

**Ade Bastian,** Department of Informatics, Faculty of Engineering,Universitas Majalengka, Indonesia, Indonesia
https://orcid.org/0000-0001-7257-1185
**Ardi Mardiana,** Department of Informatics, Faculty of Engineering,Universitas Majalengka, Indonesia, Indonesia
**Mega Berliani,** Department of Informatics, Faculty of Engineering,Universitas Majalengka, Indonesia, Indonesia
**Mochammad Bagasnanda Firmansyah,** Department of Informatics, Faculty of Engineering,Universitas Majalengka, Indonesia, Indonesia
27-35
DOI : 10.15575/join.v8i1.1000 Abstract View : 225 PDF downloads: 198
PDF

## The Implementation of Restricted Boltzmann Machine in Choosing a Specialization for Informatics Students

**Vinna Rahmayanti Setyaning Nastiti,** Department of Informatics, Universitas Muhammadiyah Malang, Indonesia, Indonesia
**Zamah Sari,** Department of Informatics, Universitas Muhammadiyah Malang, Indonesia, Indonesia
**Bella Chintia Eka Merita,** Department of Informatics, Universitas Muhammadiyah Malang, Indonesia, Indonesia
36-43
DOI : 10.15575/join.v8i1.917 Abstract View : 169 PDF downloads: 204
PDF

## Implementation of Generative Adversarial Network to Generate Fake Face Image

**Jasman Pardede,** Department of Informatics, Faculty of Industry, Institut Teknologi Nasional Bandung, Indonesia, Indonesia
**Anisa Putri Setyaningrum,** Department of Informatics, Faculty of Industry, Institut Teknologi Nasional Bandung, Indonesia, Indonesia
44-51
DOI : 10.15575/join.v8i1.790 Abstract View : 274 PDF downloads: 438
PDF

## Catbreedsnet: An Android Application for Cat Breed Classification Using Convolutional Neural Networks

**Anugrah Tri Ramadhan,** Department of Informatics Engineering, Universitas Dian Nuswantoro, Indonesia, Indonesia
**Abas Setiawan,** Department of Computer Science, Faculty of Mathematics and Natural Science, Universitas Negeri Semarang, Indonesia, Indonesia
52-60
DOI : 10.15575/join.v8i1.1007 Abstract View : 432 PDF downloads: 321
PDF

## Malware Image Classification Using Deep Learning InceptionResNet-V2 and VGG-16 Method

**Didih Rizki Chandranegara,** Department of Informatics, University of Muhammadiyah Malang, Indonesia, Indonesia
**Jafar Shodiq Djawas,** Department of Informatics, University of Muhammadiyah Malang, Indonesia, Indonesia
**Faiq Azmi Nurfaizi,** Department of Informatics, University of Muhammadiyah Malang, Indonesia, Indonesia
**Zamah Sari,** Department of Informatics, University of Muhammadiyah Malang, Indonesia, Indonesia
61-71
DOI : 10.15575/join.v8i1.1051 Abstract View : 302 PDF downloads: 240
PDF

## Comparative Analysis of Machine Learning-based Forest Fire Characteristics in Sumatra and Borneo

**Ayu Shabrina,** School of Computing, Telkom University, Bandung, Indonesia, Indonesia
**Intan Nuni Wahyuni,** Reseach Center for Computing, The National Research and Innovation Agency of Indonesia, Indonesia
**Arnida L Latifah,** 1) Reseach Center for Computing, The National Research and Innovation Agency of Indonesia 2) School of Computing, Telkom University, Bandung, Indonesia, Indonesia
72-80
DOI : 10.15575/join.v8i1.1035 Abstract View : 273 PDF downloads: 370
PDF

## Implementation of Ant Colony Optimization – Artificial Neural Network in Predicting the Activity of Indenopyrazole Derivative as Anti-Cancer Agent

**Isman Kurniawan,** School of Computing, Telkom University, Bandung, Indonesia, Indonesia
**Nabilla Kamil,** School of Computing, Telkom University, Bandung, Indonesia, Indonesia
**Annisa Aditsania,** School of Computing, Telkom University, Bandung, Indonesia, Indonesia
**Erwin Budi Setiawan,** School of Computing, Telkom University, Bandung, Indonesia, Indonesia
81-90
DOI : 10.15575/join.v8i1.1055 Abstract View : 217 PDF downloads: 146
PDF

## Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data

**Tb Ai Munandar,** Department of Informatics, Universitas Bhayangkara Jakarta Raya, Indonesia, Indonesia
91-98
DOI : 10.15575/join.v8i1.1027 Abstract View : 263 PDF downloads: 357

PDF

### Classification of Stunting in Children Using the C4.5 Algorithm

**Muhajir Yunus,** Master Program of Informatics, Universitas Ahmad Dahlan, Indonesia , Indonesia
**Muhammad Kunta Biddinika,** Master Program of Informatics, Universitas Ahmad Dahlan, Indonesia , Indonesia
**Abdul Fadlil,** Electrical Engineering, Universitas Ahmad Dahlan, Indonesia, Indonesia

99-106

DOI : 10.15575/join.v8i1.1062 Abstract View : 521 PDF downloads: 464

PDF

### Multi-Step Vector Output Prediction of Time Series Using EMA LSTM

**Mohammad Diqi,** Department of Informatics, Universitas Respati Yogyakarta, Indonesia, Indonesia
https://orcid.org/0000-0002-9012-9080
**Ahmad Sahal,** Department of Information Technology, Universitas Respati Yogyakarta, Indonesia, Indonesia
https://orcid.org/0000-0001-6771-4233
**Farida Nur Aini,** Department of Information Technology, Universitas Respati Yogyakarta, Indonesia, Indonesia

107-114

DOI : 10.15575/join.v8i1.1037 Abstract View : 278 PDF downloads: 256

PDF

### Texture Analysis of Citrus Leaf Images Using BEMD for Huanglongbing Disease Diagnosis

**Sumanto,** 1) Department of Computer Science, IPB University, Indonesia 2) Department of Information System, Universitas Bina Sarana Informatika, Indonesia, Indonesia
**Agus Buono,** Department of Computer Science, IPB University, Indonesia, Indonesia
**Karlisa Priandana,** Department of Computer Science, IPB University, Indonesia, Indonesia
**Bib Paruhum Silalahi,** Department of Mathematics, IPB University, Indonesia, Indonesia
**Elisabeth Sri Hendrastuti,** Department of Plant Protection, IPB University, Indonesia, Indonesia

115-121

DOI : 10.15575/join.v8i1.1075 Abstract View : 236 PDF downloads: 198

PDF

### Digital Image Processing Using YCbCr Colour Space and Neuro Fuzzy to Identify Pornography

**Beki Subaeki,** Department of Information System, Faculty of Engineering, Sangga Buana University Bandung, Indonesia, Indonesia
**Yana Aditia Gerhana,** Department of Informatics, UIN Sunan Gunung Djati Bandung, Indonesia, Indonesia
**Meta Barokatul Karomah Rusyana,** Department of Informatics, UIN Sunan Gunung Djati Bandung, Indonesia, Indonesia
**Khaerul Manaf,** Department of Information System, Faculty of Engineering, Sangga Buana University Bandung, Indonesia, Indonesia

122-130

DOI : 10.15575/join.v8i1.1070 Abstract View : 245 PDF downloads: 187

PDF

Jurnal Online Informatika, p-ISSN: 2528-1682 | e-ISSN: 2527-9165

JOIN
JURNAL ONLINE INFORMATIKA
ISSN: 2528-1682 (PRINTED) | 2527-9165 (ONLINE)
Register Log
PUBLISHED BY:



# Editorial Team






JOIN STATS


Platform & workflow by OJS / PKP

JOIN has been indexed by :













Jurnal Online Informatika, p-ISSN: 2528-1682 | e-ISSN: 2527-9165

JOIN
JURNAL ONLINE INFORMATIKA
ISSN: 2528-1682 (PRINTED) | 2527-9165 (ONLINE)
Register Log
PUBLISHED BY:



## REVIEWER

1. Muhammad Ali Ramdhani, (Scopus ID: 57209454522, H-Index: 20), UIN Sunan Gunung Djati Bandung, Indonesia
2. Giacomo Cabri, (Scopus ID: 35511410700, H-Index: 22), Department FIM, University of Modena and Reggio Emilia, Italy.
3. Cepy Slamet, (Scopus ID: 57191840769, H-Index: 8), UIN Sunan Gunung Djati Bandung, Indonesia
4. Mohamad Irfan, (Scopus ID: 57191849732, H-Index: 5), Asia e-University, Malaysia
5. Mohamed Osman Suliman Omara, (Scopus ID: 55953537200, H-Index: 1), International College of Semiconductor Technology National Yang Ming Chiao Tung University, Taiwan
6. Chan Voeun, (Scopus ID: 55953537200, H-Index: 1), National Polytechnic Institue of Cambodia, Cambodia
7. Cecep Nurul Alam, (Scopus ID: 57191842037, H-Index: 4), Asia e-University, Malaysia
8. Dian Nuraiman, (Scopus ID: 57190939062, H-Index: 1), RMIT University, Australia, Australia
9. Tanweer Alam, (Scopus ID: 57189067051, H-Index: 6), Islamic University of Madinah, Saudi Arabia
10. Satrya Fajri Pratama, (Scopus ID: 43061455200, H-Index: 3), Universiti Teknikal Malaysia Melaka, Malaysia
11. Undang Syaripudin, (Scopus ID: 57203461493, H-Index: 1), Asia e-University, Malaysia
12. Wisnu Uriawan, (Scopus ID: 57191844379, H-Index: 2), University of Lyon (INSA de Lyon), France
13. Mailasan Jayakrishnan, (Scopus ID: 57203164887; H-Index: 7), Xiamen University Malaysia., Malaysia
14. Aldy Rialdy Atmadja, (Scopus ID: 57189266962, H-Index: 4), UIN Sunan Gunung Djati Bandung, Indonesia
15. Ayu Purwarianti, (Scopus ID: 13104011100, H-Index: 9), Institut Teknologi Bandung, Indonesia
16. A'ang Subiyakto, (Scopus ID: 56105360200, H-Index: 9), UIN Syarif Hidayatullah Jakarta, Indonesia
17. Ana Hadiana, (Scopus ID: 57217981864, H-Index: ), Research Center for Informatics, LIPI, Indonesia
18. Rinaldi Munir, (Scopus ID: 35176324300, H-Index: 5), Institut Teknologi Bandung, Indonesia
19. Aulia Akhrian Syahidi, (Scopus ID: 57204180035, H-Index: 8), Smart City Information System Study Program, Politeknik Negeri Banjarmasin, Indonesia
20. Husni Teja Sukmana, (Scopus ID: 23398706200, H-Index: 5), UIN Syarif Hidayatullah Jakarta, Indonesia
21. Riyan Naufal Hay's, (Scopus ID: 57217116508, H-Index: 1), Universitas Serang Raya, Indonesia
22. Maisevli Harika, (Scopus ID: 57209461103, H-Index: 1), Politeknik Negeri Bandung, Indonesia
23. Popon Dauni, (Scopus ID: 57212214494), Universitas Kebangsaan, Indonesia
24. Nunik Destria Arianti, (Scopus ID: 57203169098, H-Index: 1), Universitas Nusaputra, Indonesia
25. Anjar Wanto, (Scopus ID: 57200091869, H-Index: 4), STIKOM Tunas Bangsa Pematangsiantar, Indonesia
26. Yana Aditia Gerhana, (Scopus ID: 57191836144, H-Index: 5), Asia e-University, Malaysia
27. Faiz M. Kaffah, (Scopus ID: 57203459275, H-Index: 1), Universitas Bisnis dan Informatika, Indonesia
28. Beki Subaeki, (Scopus ID: 57189524427, H-Index: 1), Universitas Sangga Buana, Indonesia
29. Esa Firmansyah, (Scopus ID: 57208283428, H-Index: 1), STMIK Sumedang, Indonesia
30. Moch Arif Bijaksana, (Scopus ID: 55339249800, H-Index: 3), Telkom University, Indonesia
31. Elis Ratna Wulan, (Scopus ID: 57192402404, H-Index: 1), UIN Sunan Gunung Djati Bandung, Indonesia
32. Khaerul Manaf, (Scopus ID: 57191846660, H-Index: 1), Universitas Sangga Buana, Indonesia
33. Arini Arini, (Scopus ID: 50660979000; H-Index: 2), UIN Syarif Hidayatullah Jakarta, Indonesia
34. Setio Basuki, (Scopus ID: 57190070688; H-Index: 2), Universitas Muhammadiyah Malang, Indonesia
35. Daniel Silli Bataona, (Scopus ID: 56623092500, H-Index: 2), Politeknik Negeri Kupang, Indonesia
36. Jumadi Jumadi, (Scopus ID: 57191839150, H-Index: 3), Institut Teknologi Bandung, Indonesia
37. Muhammad Irwan Padli Nasution, (Scopus ID: 57204839772, H-Index: 2), UIN Sumatera Utara, Indonesia
38. Ahmad Ashraf Abdul Halim, (Scopus ID: 57200985251, H-Index: 4), Faculty of Electronic Engineering & Technology (FKTEN), Universiti Malaysia Perlis (UniMAP), Malaysia.
39. Abdelaaziz Hessane, (Scopus ID: 57807939900, H-Index: 2), Department of Computer Sciences, FSTE, Moulay Ismail University of Meknès, Morocco.
40. Areeg Alfouri, (Scopus ID: 58164968500, H-Index: 1), Faculty of Medicine Al-Balqa Applied University, Jordan.
41. Santosh Gore, (Scopus ID: 58541297500, H-Index: 3), Director, Sai Info Solution, India.
42. G Vinoda Reddy, (Scopus ID: 58541297500, H-Index: 1), Department CSE(AI&ML), CMR Technical Campus, medchal Hyderabad, India.

MAKE A SUBMISSION

ACCREDITED


EDITORIAL TEAM
REVIEWER
PEER REVIEW PROCESS
FOCUS AND SCOPE
AUTHOR GUIDELINES
AUTHOR FEES
ARTICLE WITHDRAWAL
PUBLICATION ETHICS
COPYRIGHT NOTICE
PLAGIARISM CHECK
REFERENCES MANAGEMENT
JOURNAL HISTORY

TOOLS




MANUSCRIPT TEMPLATE


JOIN STATS


Platform & workflow by OJS / PKP

JOIN has been indexed by :













Jurnal Online Informatika, p-ISSN: 2528-1682 | e-ISSN: 2527-9165

Gmail Tb Ai Munandar <tbaimunandar@gmail.com>

# [JOIN] Submission Acknowledgement

1 pesan

**Ichsan Budiman** <join@uinsgd.ac.id> 12 Februari 2023 pukul 10.04
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>

Tb Ai Munandar:

Thank you for submitting the manuscript, "Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data" to Jurnal Online Informatika. With the online journal management system that we are using, you will be able to track its progress through the editorial process by logging in to the journal web site:

Manuscript URL: http://join.if.uinsgd.ac.id/index.php/join/authorDashboard/submission/1027
Username: tbaimunandar

If you have any questions, please contact me. Thank you for considering this journal as a venue for your work.

Ichsan Budiman
JOIN (Jurnal Online Informatika)

Gmail Tb Ai Munandar <tbaimunandar@gmail.com>

# [JOIN] New notification from Jurnal Online Informatika

1 pesan

**Diena Rauda** <join@uinsgd.ac.id> 13 Februari 2023 pukul 15.41
Balas Ke: Ichsan Budiman <ichsanbudiman@uinsgd.ac.id>
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>

You have a new notification from Jurnal Online Informatika:

You have been added to a discussion titled "[JOIN] Pre review Discussion" regarding the submission "Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data".

Link: https://ichsanbudiman.website/index.php/join/authorDashboard/submission/1027

Ichsan Budiman
JOIN (Jurnal Online Informatika)

Gmail Tb Ai Munandar <tbaimunandar@gmail.com>

# [JOIN] Editor Decision

6 pesan

**Diena Rauda** <join@uinsgd.ac.id> 19 Mei 2023 pukul 10.51
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>

Tb Ai Munandar:

We have reached a decision regarding your submission to Jurnal Online Informatika, "Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data".

Our decision is to: Accept Submission

Please revise your article based on the reviewer's comments through the system if any revision (within a week). We will inform you for the copyediting and publication process.

The fee for publication of original papers in this journal is USD 110.00 (for abroad Authors) or IDR 1.500.000.00 (for local Authors). Accepted manuscripts will not be published until payment has been received. The mode of payment is through Direct Deposit from any bank to our bank account with the following details:

This is the name and bank account to transfer the fee:
Bank account Number : 6395502305
Bank Name : Bank Central Asia
Name : Eva Nurlatifah

*Please email your copy of the publication fee deposit slip and mention your ID Article to:
join@uinsgd.ac.id and evanurlatifah@uinsgd.ac.id

JOIN (Jurnal Online Informatika)

**2 lampiran**

**A-join-review-assignment-1027-Article+Text-3282.docx**
184K

**B-join-review-assignment-1027-Article+Text-3282-JW.docx**
183K

**Tb Ai Munandar** <tbaimunandar@gmail.com> 21 Mei 2023 pukul 19.50
Kepada: Diena Rauda <join@uinsgd.ac.id>

Dear Editorial Team,
I sent the revised file according to the reviewer's comments, and it's already in the latest template.

In addition, based on the reviewer's input, there was a change in the title of the manuscript, which was originally "Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data" to "Multi Layer Perceptron for Classification of Heart Disease Based on Electrocardiogram and Echocardiogram Data", but I can't update it on my OJS account.

Revised manuscript files and answer comments for reviewers are in separate files. In response to the reviewer's comments, I have included a file with the *.PDF extension.

I also want to confirm: can the payment for manuscript publication be made?

Regards.

[Kutipan teks disembunyikan]

--
Tb. Ai Munandar
Prodi Informatika, Fakultas Ilmu Komputer
Universitas Bhayangkara Jakarta Raya
e-mail : tbaimunandar@gmail.com
CP : +62 81384512710

**2 lampiran**

**Author's Revision JOIN.pdf**
160K

**Rev-Fix-3-Tb Ai Munandar JOIN Template 2023.docx**
303K

---

**JOIN (Jurnal Online Informatika)** <join@uinsgd.ac.id> 23 Mei 2023 pukul 13.06
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>

Yes, you can do that.

Pada tanggal Min, 21 Mei 2023 pukul 20.51 Tb Ai Munandar <tbaimunandar@gmail.com> menulis:
[Kutipan teks disembunyikan]

---

**Tb Ai Munandar** <tbaimunandar@gmail.com> 23 Mei 2023 pukul 21.42
Kepada: "JOIN (Jurnal Online Informatika)" <join@uinsgd.ac.id>, evanurlatifah@uinsgd.ac.id

Dear Journal Manager (JOIN UIN Sunan Gunung Jati).

In this email, I sent proof of payment for article publication with ID number 1027. Please check the file attachments.

Regards.

[Kutipan teks disembunyikan]

**Bukti Transfer JOIN Tb Ai Munandar.jpeg**
104K

**JOIN (Jurnal Online Informatika)** <join@uinsgd.ac.id> 30 Mei 2023 pukul 18.52
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>
Cc: evanurlatifah@uinsgd.ac.id

Dear Tb Ai Munandar,

Received with thanks.
Please prepare your manuscript based on review results and use the new JOIN's template. We will inform you about the copy editing process next.
Thank you.

Regards,
JOIN Team

Pada tanggal Sel, 23 Mei 2023 pukul 22.43 Tb Ai Munandar
[Kutipan teks disembunyikan]

---

**JOIN (Jurnal Online Informatika)** <join@uinsgd.ac.id> 20 Juni 2023 pukul 11.49
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>

Thank you, we have been received your payment, here we include your LoA and invoice

Pada tanggal Sel, 30 Mei 2023 pukul 19.52 JOIN (Jurnal Online
[Kutipan teks disembunyikan]

**2 lampiran**

**8_1-1027-INVOICE.pdf**
168K

**8_1-1027-LOA.pdf**
149K

Gmail Tb Ai Munandar <tbaimunandar@gmail.com>

# [JOIN] CopyEdit

2 pesan

**JOIN (Jurnal Online Informatika)** <join@uinsgd.ac.id> 24 Juni 2023 pukul 05.11
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>

Dear Author.

Your Article has entered copy edit stage. We found differences in your article metadata in JOIN and the manuscript.

This is your manuscript title in the docx file."Multi Layer Perceptron for Classification of Heart Disease Based on Electrocardiogram and Echocardiogram Data"

This is your manuscript title in JOIN metadata. "Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data"

Please, inform us which title you choose.

---

**Tb Ai Munandar** <tbaimunandar@gmail.com> 24 Juni 2023 pukul 05.16
Kepada: "JOIN (Jurnal Online Informatika)" <join@uinsgd.ac.id>

Dear editorial team
I prefer to choose "Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data" because the LoA says the title.
Thank you in advance.

Best regards,

[Kutipan teks disembunyikan]

--
Tb. Ai Munandar
Prodi Informatika, Fakultas Ilmu Komputer
Universitas Bhayangkara Jakarta Raya
e-mail : tbaimunandar@gmail.com
CP : +62 81384512710

Gmail Tb Ai Munandar <tbaimunandar@gmail.com>

# [JOIN] Urgent Request: Update Metadata for Your Article

5 pesan

**JOIN (Jurnal Online Informatika)** <join@uinsgd.ac.id> 25 Juni 2023 pukul 13.23
Kepada: Arie Vatresia <arie.vatresia@unib.ac.id>, Ahmad Khusaeri <khusaerikhusaeri@apps.ipb.ac.id>, Umar Aditiawarman <umar.aditiawarman@nusaputra.ac.id>, Ade Bastian <adebastian@unma.ac.id>, Ardi Mardiana <aim@unma.ac.id>, Mega Berliani <berlianimega3@gmail.com>, Mochammad Bagasnanda Firmansyah <mochammadbagasnandafirmansyah@gmail.com>, Vinna Rahmayanti Setyaning Nastiti <vinastiti@umm.ac.id>, Jasman Pardede <jasmanpardede78@gmail.com>, Anisa Putri Setyaningrum <anisaputrisetyaningrum@gmail.com>, Anugrah Tri Ramadhan <111201811540@mhs.dinus.ac.id>, Abas Setiawan <abas.setiawan@mail.unnes.ac.id>, Didih Rizki Chandranegara <didihrizki@umm.ac.id>, Jafar Shodiq Djawas <jafardjawas@webmail.umm.ac.id>, Faiq Azmi Nurfaizi <faiqazmi123@webmail.umm.ac.id>, Zamah Sari <zamahsari@umm.ac.id>, Arnida L Latifah <arnidalatifah@telkomuniversity.ac.id>, Isman Kurniawan <ismankrn@telkomuniversity.ac.id>, Nabilla Kamil <nabillakamil@gmail.com>, Annisa Aditsania <aaditsania@telkomuniversity.ac.id>, Erwin Budi Setiawan <erwinbudisetiawan@telkomuniversity.ac.id>, Tb Ai Munandar <tbaimunandar@gmail.com>, Muhajir Yunus <muhajiryunus@gmail.com>, Muhammad Kunta Biddinika <muhammad.kunta@mti.uad.ac.id>, Abdul Fadlil <fadlil@mti.uad.ac.id>, MOHAMMAD DIQI <diqi@respati.ac.id>, Ahmad Sahal <ihza_asm@respati.ac.id>, Farida Nur Aini <farida_mi@respati.ac.id>, Sumanto Sumanto <sto_sumanto@apps.ipb.ac.id>, Agus Buono <agusbuono@apps.ipb.ac.id>, Karlisa Priandana <karlisa@apps.ipb.ac.id>, Bib Paruhum Silalahi <bibparuhum@gmail.com>, Elisabeth Sri Hendrastuti <srihendrastuti@apps.ipb.ac.id>

Dear Authors,

I hope this email finds you well. I am writing to bring an urgent matter to your attention regarding the metadata of your published articles. It has come to our attention that certain information requires IMMEDIATE updates to ensure accuracy and optimal visibility.

As you may know, metadata plays a crucial role in facilitating discoverability and search engine optimization for online content. It helps users find your article more effectively and enhances its visibility within relevant platforms. Therefore, it is essential to keep this information up to date.

We'd like to ask for your help in providing us with the updated metadata for your article. Specifically, we need the following details:

TITLE: Please confirm if the current title accurately reflects the article's content. If any changes are necessary, kindly provide the revised title.

KEYWORDS: Review the existing keywords associated with your article and suggest additional or alternative keywords that accurately represent its main themes and subject matter. These keywords are vital for improving search results and attracting the right audience.

ABSTRACTS: If there have been any substantial changes or updates to the content since its initial publication, please provide an updated abstract that succinctly summarizes the article's key points.

AUTHOR AFFILIATIONS: Ensure that your current affiliation details are correct. If there have been any changes, please provide the updated information, including your institutional affiliation, department, and contact details.

Please review and provide the updated metadata as soon as possible to ensure the accuracy and visibility of your article. I would greatly appreciate your quick attention to this matter.

Please update metadata in JOIN WEBSITE (https://join.if.uinsgd.ac.id/) NO LATER THAN June 27, 2023. If you have any questions or need further clarification, please feel free to let me know.

I appreciate your cooperation on this. We value your contribution to our publication and look forward to ensuring your article gets the attention it needs.

Best regards,

Ichsan Budiman, M.T
JOIN Editor in Chief
ichsanbudiman@uinsgd.ac.id

---

**Tb Ai Munandar** <tbaimunandar@gmail.com> 26 Juni 2023 pukul 08.35
Kepada: "JOIN (Jurnal Online Informatika)" <join@uinsgd.ac.id>

Dear Budiman,

Thank you for the information. For the title of the article, I confirm that it will still use the title according to what was recorded in OJS. As for the title change according to input from the reviewer, it has been confirmed in the previous email, that it will still use the original title according to the LoA I received.

Regarding other metadata, such as abstracts and bibliography, the OJS system is still locked so I can't update the metadata. For this reason, we request that the editorial team be able to open access to editing the metadata.

Best regards,
[Kutipan teks disembunyikan]
--
Tb. Ai Munandar
Prodi Informatika, Fakultas Ilmu Komputer
Universitas Bhayangkara Jakarta Raya
e-mail : tbaimunandar@gmail.com
CP : +62 81384512710

---

**JOIN (Jurnal Online Informatika)** <join@uinsgd.ac.id> 26 Juni 2023 pukul 13.05
Kepada: Tb Ai Munandar <tbaimunandar@gmail.com>

Thank you for your information. Please provide the data in a docx file and send it here. We will do the rest.

Pada tanggal Sen, 26 Jun 2023 pukul 09.35 Tb Ai Munandar <tbaimunandar@gmail.com> menulis:
[Kutipan teks disembunyikan]

---

**Tb Ai Munandar** <tbaimunandar@gmail.com> 27 Juni 2023 pukul 08.26
Kepada: "JOIN (Jurnal Online Informatika)" <join@uinsgd.ac.id>

Dear JOIN team editorial

I submit the file in *.doc format which contains the latest article metadata.

Best regards,

[Kutipan teks disembunyikan]

**Metadata Update.docx**
15K

---

**Vinna Rahmayanti S , S.Si., M.Si .** <vinastiti@umm.ac.id> 27 Juni 2023 pukul 10.01
Kepada: "JOIN (Jurnal Online Informatika)" <join@uinsgd.ac.id>
Cc: Arie Vatresia <arie.vatresia@unib.ac.id>, Ahmad Khusaeri <khusaerikhusaeri@apps.ipb.ac.id>, Umar Aditiawarman <umar.aditiawarman@nusaputra.ac.id>, Ade Bastian <adebastian@unma.ac.id>, Ardi Mardiana <aim@unma.ac.id>, Mega Berliani <berlianimega3@gmail.com>, Mochammad Bagasnanda Firmansyah <mochammadbagasnandafirmansyah@gmail.com>, Jasman Pardede <jasmanpardede78@gmail.com>, Anisa Putri Setyaningrum <anisaputrisetyaningrum@gmail.com>, Anugrah Tri Ramadhan <111201811540@mhs.dinus.ac.id>, Abas Setiawan <abas.setiawan@mail.unnes.ac.id>, Didih Rizki Chandranegara <didihrizki@umm.ac.id>, Jafar Shodiq Djawas <jafardjawas@webmail.umm.ac.id>, Faiq Azmi Nurfaizi <faiqazmi123@webmail.umm.ac.id>, Zamah Sari <zamahsari@umm.ac.id>, Arnida L Latifah <arnidalatifah@telkomuniversity.ac.id>, Isman Kurniawan <ismankrn@telkomuniversity.ac.id>, Nabilla Kamil <nabillakamil@gmail.com>, Annisa Aditsania <aaditsania@telkomuniversity.ac.id>, Erwin Budi Setiawan <erwinbudisetiawan@telkomuniversity.ac.id>, Tb Ai Munandar <tbaimunandar@gmail.com>, Muhajir Yunus <muhajiryunus@gmail.com>, Muhammad Kunta Biddinika <muhammad.kunta@mti.uad.ac.id>, Abdul Fadlil <fadlil@mti.uad.ac.id>, MOHAMMAD DIQI <diqi@respati.ac.id>, Ahmad Sahal <ihza_asm@respati.ac.id>, Farida Nur Aini <farida_mi@respati.ac.id>, Sumanto Sumanto <sto_sumanto@apps.ipb.ac.id>, Agus Buono <agusbuono@apps.ipb.ac.id>, Karlisa Priandana <karlisa@apps.ipb.ac.id>, Bib Paruhum Silalahi <bibparuhum@gmail.com>, Elisabeth Sri Hendrastuti <srihendrastuti@apps.ipb.ac.id>

Dear JOIN Editor,

We have updated our article in revisions tab JOIN website.
Thankyou for your support for our article.

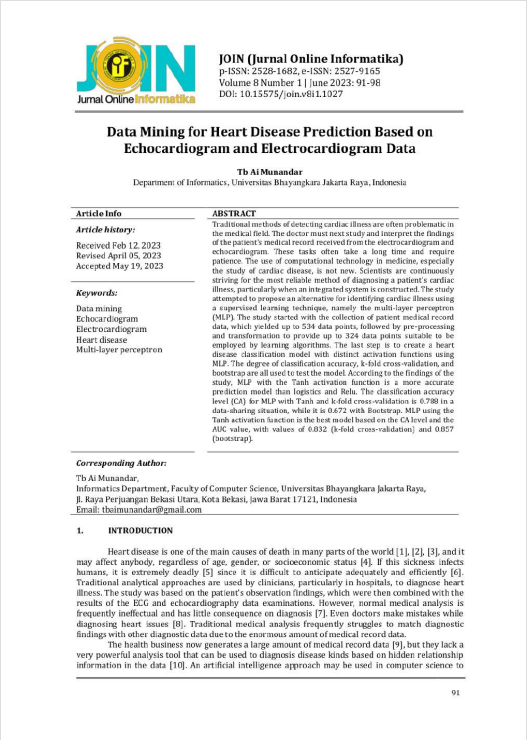
Best Regards,
Vinna Rahmayanti Setyaning Nastiti
[Kutipan teks disembunyikan]

# Digital Receipt

This receipt acknowledges that Turnitin received your paper. Below you will find the receipt information regarding your submission.

The first page of your submissions is displayed below.

| | |
|---|---|
| Submission author: | Tb Ai Munandar |
| Assignment title: | Quick Submit |
| Submission title: | Plagiarism Check JOIN V8N1 |
| File name: | 91-98_1027-fix.pdf |
| File size: | 499.16K |
| Page count: | 8 |
| Word count: | 4,647 |
| Character count: | 25,478 |
| Submission date: | 19-Mar-2024 01:39AM (UTC-0400) |
| Submission ID: | 2324535833 |



JOIN (Jurnal Online Informatika)
p-ISSN: 2528-1682, e-ISSN: 2527-9165
Volume 8 Number 1 | June 2023: 91-98
DOI: 10.15575/join.v8i1.1027

Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data

Tb Ai Munandar
Department of Informatics, Universitas Bhayangkara Jakarta Raya, Indonesia

Article Info

*Article history:*

Received Feb 12, 2023
Revised April 05, 2023
Accepted May 19, 2023

*Keywords:*

Data mining
Echocardiogram
Electrocardiogram
Heart disease
Multi-layer perceptron

ABSTRACT

Traditional methods of detecting cardiac illness are often problematic in the medical field. The doctor must next study and interpret the findings of the patient's medical record received from the electrocardiogram and echocardiogram. These tasks often take a long time and require patience. The use of computational technology in medicine, especially the study of cardiac disease, is not new. Scientists are continuously striving for the most reliable method of diagnosing a patient's cardiac illness, particularly when an integrated system is constructed. The study attempted to propose an alternative for identifying cardiac illness using a supervised learning technique, namely the multi-layer perceptron (MLP). The study started with the collection of patient medical record data, which yielded up to 534 data points, followed by pre-processing and transformation to provide up to 324 data points suitable to be employed by learning algorithms. The last step is to create a heart disease classification model with distinct activation functions using MLP. The degree of classification accuracy, k-fold cross-validation, and bootstrap are all used to test the model. According to the findings of the study, MLP with the Tanh activation function is a more accurate prediction model than logistics and Relu. The classification accuracy level (CA) for MLP with Tanh and k-fold cross-validation is 0.788 in a data-sharing situation, while it is 0.672 with Bootstrap. MLP using the Tanh activation function is the best model based on the CA level and the AUC value, with values of 0.832 (k-fold cross-validation) and 0.857 (bootstrap).

*Corresponding Author:*

Tb Ai Munandar,
Informatics Department, Faculty of Computer Science, Universitas Bhayangkara Jakarta Raya,
Jl. Raya Perjuangan Bekasi Utara, Kota Bekasi, Jawa Barat 17121, Indonesia
Email: tbaimunandar@gmail.com

1. INTRODUCTION

Heart disease is one of the main causes of death in many parts of the world [1], [2], [3], and it may affect anybody, regardless of age, gender, or socioeconomic status [4]. If this sickness infects humans, it is extremely deadly [5] since it is difficult to anticipate adequately and efficiently [6]. Traditional analytical approaches are used by clinicians, particularly in hospitals, to diagnose heart illness. The study was based on the patient's observation findings, which were then combined with the results of the ECG and echocardiography data examinations. However, normal medical analysis is frequently ineffectual and has little consequence on diagnosis [7]. Even doctors make mistakes while diagnosing heart issues [8]. Traditional medical analysis frequently struggles to match diagnostic findings with other diagnostic data due to the enormous amount of medical record data.

The health business now generates a large amount of medical record data [9], but they lack a very powerful analysis tool that can be used to diagnosis disease kinds based on hidden relationship information in the data [10]. An artificial intelligence approach may be used in computer science to

# Plagiarism Check JOIN V8N1

*by* Tb Ai Munandar

**Submission date:** 19-Mar-2024 01:39AM (UTC-0400)
**Submission ID:** 2324535833
**File name:** 91-98_1027-fix.pdf (499.16K)
**Word count:** 4647
**Character count:** 25478

JOIN (Jurnal Online Informatika)
p-ISSN: 2528-1682, e-ISSN: 2527-9165
Volume 8 Number 1 | June 2023: 91-98
DOI: 10.15575/join.v8i1.1027

# Data Mining for Heart Disease Prediction Based on Echocardiogram and Electrocardiogram Data

**Tb Ai Munandar**
Department of Informatics, Universitas Bhayangkara Jakarta Raya, Indonesia

**Article Info**

***Article history:***

Received Feb 12, 2023
Revised April 05, 2023
Accepted May 19, 2023

***Keywords:***

Data mining
Echocardiogram
Electrocardiogram
Heart disease
Multi-layer perceptron

**ABSTRACT**

Traditional methods of detecting cardiac illness are often problematic in the medical field. The doctor must next study and interpret the findings of the patient's medical record received from the electrocardiogram and echocardiogram. These tasks often take a long time and require patience. The use of computational technology in medicine, especially the study of cardiac disease, is not new. Scientists are continuously striving for the most reliable method of diagnosing a patient's cardiac illness, particularly when an integrated system is constructed. The study attempted to propose an alternative for identifying cardiac illness using a supervised learning technique, namely the multi-layer perceptron (MLP). The study started with the collection of patient medical record data, which yielded up to 534 data points, followed by pre-processing and transformation to provide up to 324 data points suitable to be employed by learning algorithms. The last step is to create a heart disease classification model with distinct activation functions using MLP. The degree of classification accuracy, k-fold cross-validation, and bootstrap are all used to test the model. According to the findings of the study, MLP with the Tanh activation function is a more accurate prediction model than logistics and Relu. The classification accuracy level (CA) for MLP with Tanh and k-fold cross-validation is 0.788 in a data-sharing situation, while it is 0.672 with Bootstrap. MLP using the Tanh activation function is the best model based on the CA level and the AUC value, with values of 0.832 (k-fold cross-validation) and 0.857 (bootstrap).

***Corresponding Author:***

Tb Ai Munandar,
Informatics Department, Faculty of Computer Science, Universitas Bhayangkara Jakarta Raya,
Jl. Raya Perjuangan Bekasi Utara, Kota Bekasi, Jawa Barat 17121, Indonesia
Email: tbaimunandar@gmail.com

## 1. INTRODUCTION

Heart disease is one of the main causes of death in many parts of the world [1], [2], [3], and it may affect anybody, regardless of age, gender, or socioeconomic status [4]. If this sickness infects humans, it is extremely deadly [5] since it is difficult to anticipate adequately and efficiently [6]. Traditional analytical approaches are used by clinicians, particularly in hospitals, to diagnose heart illness. The study was based on the patient's observation findings, which were then combined with the results of the ECG and echocardiography data examinations. However, normal medical analysis is frequently ineffectual and has little consequence on diagnosis [7]. Even doctors make mistakes while diagnosing heart issues [8]. Traditional medical analysis frequently struggles to match diagnostic findings with other diagnostic data due to the enormous amount of medical record data.

The health business now generates a large amount of medical record data [9], but they lack a very powerful analysis tool that can be used to diagnosis disease kinds based on hidden relationship information in the data [10]. An artificial intelligence approach may be used in computer science to

extract hidden information from data for decision-making purposes. Artificial intelligence is not a new concept, particularly in the detection of cardiovascular disease. A decade ago, several research on the application of artificial intelligence to the difficulty of diagnosing heart illness were conducted [11], [12], [13], [14], and [15]. Data mining is a branch of artificial intelligence that is frequently used to detect heart illness.

Data mining is the process of detecting patterns and correlations in data for data analytic purposes such as trend forecasting, classification, and grouping [9]. Furthermore, it has the potential to predict heart disease and identify unique illnesses such as cardiac amyloidosis (CA) [16]. Several other studies have used data mining to diagnose cardiac illness, including [17], [18], [19], and [20]. The bulk of researchers execute data mining tasks using machine learning [21], [22], and [23].

Several studies have been conducted to diagnose cardiac disease using simply echocardiography or electrocardiogram (ECG) data. Echocardiogram parameters have been used in studies [24], [25], and [26] to identify heart disease and other conditions. Meanwhile, [27], [28], [29], and [30] employ ECG characteristics to detect cardiac disease and other conditions. The present study employs a data mining method to integrate these two factors in order to generate more accurate identification results.

Despite significant research into using data mining and machine learning techniques to predict heart disease, it remains difficult for health practitioners and academics to use data mining to aid in research and diagnose illnesses based on patient medical record data. This work contributes to a comprehensive understanding of the stages of data mining in the health industry, particularly in the prediction of heart disease. The discussion chapter uses ECG data to show how a multilayer perceptron technique with three activation functions may be utilized to forecast heart disease. This work employs training and testing data sharing approaches such as k-fold cross-validation and bootstrapping to assess the accuracy of the three MLP activation functions utilized to test the MLP model. The metrics area under the curve (AUC), classification accuracy (CA), F1, precision, and recall are used to determine the optimum activation function of MLP.

## 2. METHOD

This study starts with identifying the issue and ends with the collection of patient medical data from one of Banten Province's government general hospitals. The information was gathered manually by collecting patient medical records, which were then combined into a single file to aid in the analytic process. There were 354 data occurrences in the initial data collection results. Following data cleaning and preprocessing, 324 valid datasets were retrieved. There are fifteen predictor variables and one response variable in the dataset. The fifteen prediction criteria were established based on echocardiography and ECG data gathered from the medical records of heart disease patients. The data is ready for use after the preparation step. The *.csv file extension is associated with data analysis. The data is then separated into training data and testing data. For training data, there are two distribution possibilities. The first example uses k-fold cross-validation, whereas the second uses bootstrapping. After that, the training data is sent into the MLP algorithm, which generates a model. Three activation functions are used for training the algorithm using training data. The three roles of activation are logistics, Tanh, and Relu. Validation of the model is performed using scenario-specific test data. The last step is model selection. The chosen model is then used to predict new data, which is then examined. This study also used Orange Data Mining (ODM), a visual programming tool. Several widgets are used to facilitate analysis. The *.xls extension is changed to *.csv for simpler display on ODM work screens.

## 3. RESULT AND DISCUSSION

### *3.1. Result*

#### *3.1.1. Business and data understanding and preparation*

Data mining begins with business knowledge and progresses to data comprehension. In the first phase, we define research objectives, which are subsequently translated into issue descriptions and handled by data mining. We also created a research goal at this time, which was to create an MLP-based model for predicting cardiac illness.

Following the identification of objectives and impediments, the next stage of data understanding is data gathering. The data was gathered from the medical records of heart disease patients at one of Banten Province's regional public facilities. There are fifteen predictor factors and one response variable. The fifteen characteristics were generated from the medical records of individuals who had undergone echocardiogram (ECHO) and electrocardiogram (ECG). Echocardiography data comprises cardiac functions, EDD (end-diastolic diameter), ESD (end-systolic diameter), IVS Diastole, IVSSystole, PW (posterior wall) Diastole, and PW (posterior wall) Systole. HR (heart rate in pulses per minute), PR (PQ), QRS, QT, QTC, and P waves are ECG variables.

Each characteristic has its own heart disease distribution. In the LEFT-ATRIUM variable, for example, the greatest distribution of disease types occurs between 40 and 42:48, with hypertensive heart disease (41.67%), coronary artery disease (39.58%), left ventricular HSHHD (12.50%), rheumatic heart disease (4.17%), and normal resting echocardiography (2.07%) dominating the distribution. Numerous kinds of cardiovascular illness have varying distributions as well. Figures 1 and 2 show the distribution and relative percentages of the LEFT-ATRIUM and end-diastolic diameter (EDD) variables for all forms of heart disease.

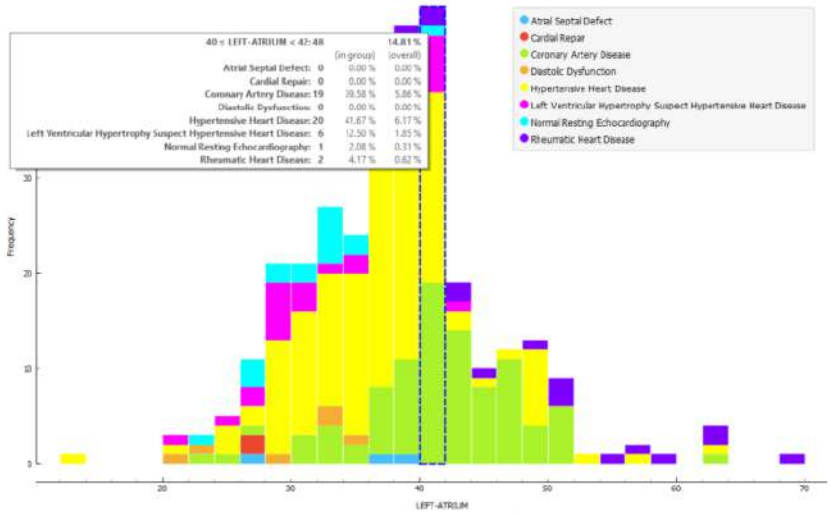



Figure 1. Left-Atrium Variable Value Range Distribution for Disease Types

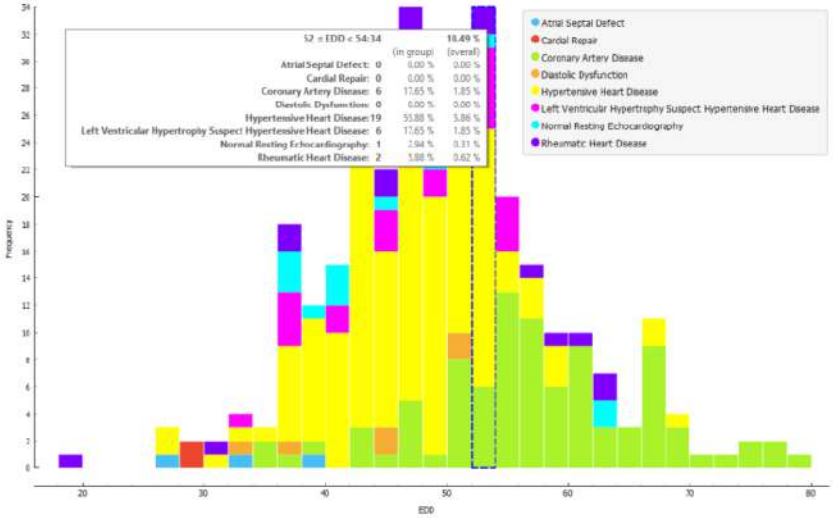



Figure 2. The range of End-Diastolic Diameter (EDD) values for different kinds of disease

Following a physician's diagnosis, 354 patient medical record files comprising eight types of heart disease were first obtained. The process of selecting attributes and purifying the data occurs during the data comprehension step. The data purification technique yielded 324 useable data instances with eight class labels corresponding to disorder types. The eight categories are as follows: atrial septal defect, cardiac repair, coronary artery disease, diastolic dysfunction, hypertensive heart disease, left ventricular hypertrophy indicative of hypertensive heart disease, normal resting echocardiography, and rheumatic heart disease. The distribution of heart disease categories throughout the sample is seen in Figure 3. The distribution of heart disease categories throughout the sample is seen in Figure 3.

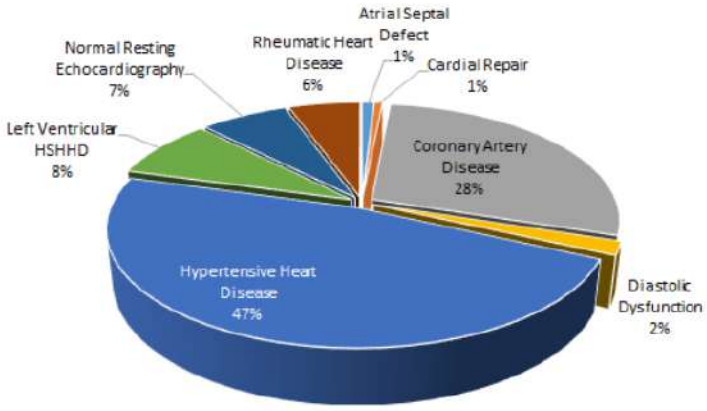



Figure 3. Distribution of types of heart disease in the dataset

The goal of the data preparation step is to create datasets that are useable and analyzable. Data tabularization with columns representing attributes and rows representing data instances. To simplify later analysis, the data is saved in *.csv files.

### *3.1.2. Building a classification model*

The difficulty of constructing a classification model is part of data mining. The multilayer perceptron (MLP) technique is employed as a learning algorithm in this stage. To determine the best accurate MLP with activation, three activation functions are utilized. There are two main possibilities for model creation. The current scenario is primarily concerned with how the dataset is divided into training and testing data before being incorporated in the algorithm. The first case employed k-fold cross-validation (k-FCV), whereas the second used Bootstrap.

#### *3.1.2.1 Classification model with k-fold cross-validation division*

Because the k-FCV approach has a value of 10, the dataset is divided into ten parts, and ten iterations of training and accuracy tests are done until the model's final average accuracy is obtained. Training data is often separated into 291 training data sets divided into nine divisions and 33 testing data sets (with a separate section for model performance testing). The model was created using the multilayer perceptron (MLP) method. Training data are used to train the MLP algorithm. Logistic, Relu, and Tanh are examples of activation functions that have been employed. The purpose of comparing the three activation functions is to determine which one has the highest degree of accuracy, so that it may be utilized as the most accurate model for predicting heart disease.

The model is then evaluated using test data. According to the model test results, the logistic activation function and Relu have the same level of classification accuracy (CA), which is 0.758, while the Tanh activation function has a higher level of CA, which is 0.788. Despite having the same accuracy as Logistic, Relu has a superior activation function in this scenario. The fact that Relu has a greater accuracy rating than logistics confirms this. This precision grade shows the correctness of the predicted findings in relation to the actual data. Figure 4 displays an in-depth examination of the CA, F1, accuracy, and recall component qualities.

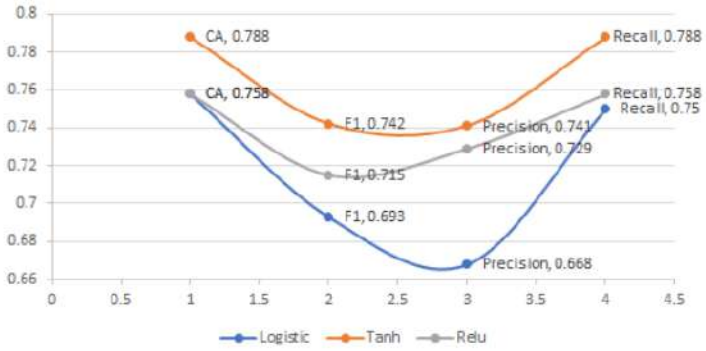



Figure 4. Comparison of CA, F1, Precision, and Recall by Dividing the k-fold Cross Validation Dataset

#### 3.1.2.2 Classification model with Bootstrap

When constructing a training set, Bootstrap splits the data into random samples. Random sampling is employed on the dataset. Orange Data Mining separates the dataset into training and testing data using the Bootstrap option. For each occurrence of data in the dataset, the proportion estimated from training data is 32:81. The great majority of the data is utilized for training, with the remainder being used for testing. The training data is then utilized to train the MLP algorithm with three distinct activation functions, as in the k-fold cross-validation scenario. Data testing is used to validate the model that has been created. The Tanh activation function has a greater classification accuracy (CA) than the other two activation functions, according to the accuracy test results. The Logistic, Tanh, and Relu activation functions had classification accuracy scores of 0.664, 0.672, and 0.688, respectively. Tanh has a higher accuracy value than logistics and relu by default. Figure 5 shows a comparison of the three activation functions' accuracy.

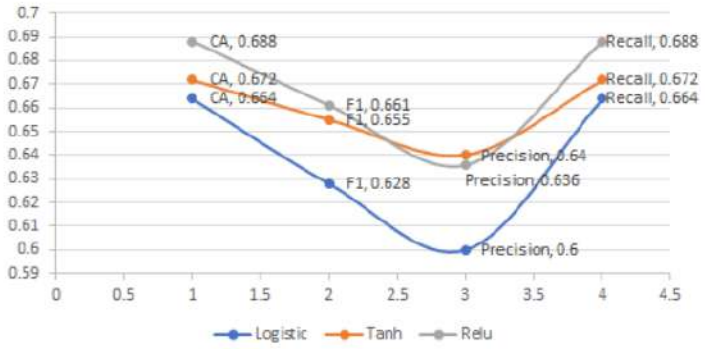



Figure 5. Comparison of CA, F1, precision, and recall by dividing the Bootstrap dataset

### 3.1.3 Model evaluation

During this stage, it is determined which activation function-based model will be used to forecast the kind of heart disease. Classification accuracy (CA), F1, precision, recall, and AUC data are used to assess models. comparing the evaluation component value for the two instances According to the results of the first scenario model, the MLP with the Tanh activation function achieves the highest degree of accuracy when compared to the other two activation functions. Tanh's activation function provides superior classification accuracy than Logistic and Relu in the second scenario outcome model.

Tanh's MLP model is often not better than Relu's MLP model in the first scenario, despite having a greater degree of classification accuracy than other activation functions based on the area under the receiver operating characteristic (AUC) value. AUC may have values ranging from 0 to 1. The closer the model is to 1, the better its performance. In this case, Relu's accuracy and AUC results are inconsistent.

Relu has the greatest AUC value among the three activation functions, although the degree of accuracy between predicted and actual data is the same as Tanh's.

In the second situation, the MLP using the Tanh activation function has the maximum classification accuracy (CA). Tanh outperforms Logistics and Relu in AUC, accuracy, and recall. Based on the results of model testing, the MLP with the Tanh activation function is the best classification model for both the first and second instances. Table 1 compares the evaluation of models based on AUC, CA, F1, accuracy, and recall values for the first and second situations.

Table 1. Comparison of MLP for the First and Second Scenarios

| | K-fold Cross Validation | | | Bootstrap | | |
|---|---|---|---|---|---|---|
| | Logistic | Tanh | Relu | Logistic | Tanh | Relu |
| AUC | 0.832 | 0.864 | 0.868 | 0.845 | 0.857 | 0.843 |
| CA | 0.758 | 0.788 | 0.758 | 0.664 | 0.672 | 0.688 |
| F1 | 0.693 | 0.742 | 0.715 | 0.628 | 0.655 | 0.661 |
| Precision | 0.668 | 0.741 | 0.729 | 0.6 | 0.64 | 0.636 |
| Recall | 0.75 | 0.788 | 0.758 | 0.664 | 0.672 | 0.688 |

### *3.2 Discusion*

In this research, the activation function of the best model was used to predict the type of heart disease. Twenty patient data points are supplied in order to assess the patient's heart disease classification. We use physician-identified data from current medical records to confirm the classification findings. Prediction using MLP with the Tanh activation function According to the prediction findings for the extra patient data, up to fifteen patients accurately recognized the disease type that matches the actual data and predicted outcomes, while up to five patients were categorized incorrectly. This shows that the classification accuracy of the prediction model on extra data is 75%. Table 2 shows the results of the heart disease category for new data on twenty individuals.

Table 2. Prediction results for types of heart disease for additional data

| Patient | Actual (Doctor's Diagnosis) | Predicted |
|---|---|---|
| PSJ-484 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-489 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-491 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-492 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-495 | Coronary Artery Disease | Coronary Artery Disease |
| PSJ-496 | Coronary Artery Disease | Hypertensive Heart Disease |
| PSJ-480 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-482 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-483 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-486 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-497 | Hypertensive Heart Disease | Hypertensive Heart Disease |
| PSJ-485 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-487 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-490 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-493 | Left Ventricular HSHHD | Hypertensive Heart Disease |
| PSJ-478 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-479 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-488 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-494 | Normal Resting Echocardiography | Normal Resting Echocardiography |
| PSJ-481 | Rheumatic Heart Disease | Rheumatic Heart Disease |

In Table 3, the probability column displays the likelihood of the expected result based on MLP using the Tanh activation function. Patients with the identities PSJ-496, PSJ-485, PSJ-487, PSJ-490, and PSJ-493 had a discrepancy between actual data and predicted results, with probability values of 0.46, 0.65, 0.64, 0.46, and 0.85. The patient with the code PSJ-493 had a higher projected probability value than the other four patients whose predictions did not match.

Table 3. Probability of MLP Prediction Results with the Tanh Activation Function

| Patient | CAD | HHD | Left Ventricular HSHHD | NRE | RHD |
|---|---|---|---|---|---|
| PSJ-484 | 0.97 | 0.00 | 0.00 | 0.00 | 0.03 |
| PSJ-489 | 0.83 | 0.09 | 0.06 | 0.00 | 0.01 |
| PSJ-491 | 0.82 | 0.10 | 0.02 | 0.02 | 0.02 |
| PSJ-492 | 0.94 | 0.03 | 0.00 | 0.00 | 0.02 |
| PSJ-495 | 0.97 | 0.01 | 0.00 | 0.00 | 0.01 |
| PSJ-496 | 0.00 | 0.46 | 0.27 | 0.16 | 0.06 |

| Patient | CAD | HHD | Left Ventricular HSHHD | NRE | RHD |
|---|---|---|---|---|---|
| PSJ-480 | 0.00 | 0.94 | 0.05 | 0.00 | 0.00 |
| PSJ-482 | 0.35 | 0.40 | 0.02 | 0.00 | 0.22 |
| PSJ-483 | 0.05 | 0.84 | 0.08 | 0.00 | 0.02 |
| PSJ-486 | 0.12 | 0.71 | 0.07 | 0.05 | 0.03 |
| PSJ-497 | 0.00 | 0.95 | 0.02 | 0.01 | 0.00 |
| PSJ-485 | 0.01 | 0.65 | 0.27 | 0.02 | 0.01 |
| PSJ-487 | 0.08 | 0.64 | 0.26 | 0.00 | 0.01 |
| PSJ-490 | 0.02 | 0.46 | 0.41 | 0.02 | 0.00 |
| PSJ-493 | 0.01 | 0.85 | 0.09 | 0.01 | 0.03 |
| PSJ-478 | 0.02 | 0.45 | 0.04 | 0.47 | 0.01 |
| PSJ-479 | 0.00 | 0.10 | 0.06 | 0.78 | 0.00 |
| PSJ-488 | 0.03 | 0.22 | 0.03 | 0.66 | 0.01 |
| PSJ-494 | 0.01 | 0.25 | 0.11 | 0.45 | 0.00 |
| PSJ-481 | 0.01 | 0.14 | 0.00 | 0.00 | 0.84 |

Patients with the PSJ-496 code had a 0.46 chance of having hypertensive heart disease, a 0.27 chance of having left ventricular HSHHD, and a 0.16 chance of having a normal resting echocardiogram (NRE). It can also be seen that the likelihood of the real data being reselected as a candidate for the prediction result is 0.00, suggesting that the projected result is very unlikely to match the actual outcome. Patients with PSJ-485, PSJ-487, and PSJ-490 codes show a similar pattern. Table 3 displays the MLP's anticipated probability using the Tanh activation function.

The classification accuracy (CA) of supplementary data prediction results is 0.75, and the area under the curve (AUC) is 0.928%, both of which are near-excellent for a model. Clearly (precision), the model's accuracy in predicting data impacts the value of CA in the prediction outcomes of fresh data. With a precision value of 0.675%, a classification accuracy (CA) of 0.75 is quite satisfactory. Regardless of the kind of heart illness, the MLP model with the Tanh activation function reliably predicts it.

## 4. CONCLUSION

The classification accuracy of a multilayer perceptron (MLP) with several activation functions changes depending on the test data, according to the study. First, the classification accuracy (CA) for the three activation functions used differs. The logistic and Relu activation functions have CA values that are similar. Tanh has more precise activation functions than Logistics and Relu. Relu, on the other hand, maintains the model's quality level in the first scenario based on the AUC value for MLP. The Tanh activation function and the high quality of the developed classification model produce the most exact classification in the second case. In general, the MLP with Tanh activation offers the most accuracy. According to test findings on fresh data, the model can predict cardiovascular disease with 75.0% accuracy. In this work, a comparison of the MLP activation function to the Relu and Logistic activation functions reveals that Tanh is an activation function that may be selected for the prediction of heart disease. Thus, utilizing the MLP with the Tanh activation function, an alternate approach for predicting heart disease is possible.

## REFERENCES


[1] C.A. Hassan, J. Iqbal, R. Irfan, S. Hussain, A. D. Algarni, S.S.H. Bukhari, N. Alturki, and S.S. Ullah, "Effectively Predicting the Presence of Coronary Heart Disease Using Machine Learning Classifiers", *Sensors*, Vol. 22, 7227, 2022, https://doi.org/10.3390/s22197227

[2]. Z. He, H. Zhang, X. Chen, J. Shi, L. Bai, Z. Fang, and R. Wang, "Hemorrhagic risk prediction in coronary artery disease patients based on photoplethysmography and machine learning," *Scientific Reports*, 12:19190, 2022, https://doi.org/10.1038/s41598-022-22719-7

[3]. H.D. Masethe, and M.A. Masethe, "Prediction of Heart Disease using Classification Algorithms", *Proceedings of the World Congress on Engineering and Computer Science 2014*, Vol II, 22-24 October, 2014

[4]. Anderies, J.A.R.W. Tchin, P.H. Putro, Y.P. Darmawan, A.A.S. Gunawan, "Prediction of Heart Disease UCI Dataset Using Machine Learning Algorithms", *Engineering, Mathematics and Computer Science*, Vol.4, No.3, 2022, pp. 87-93, DOI: 10.21512/emacsjournal.v4i3.8683

[5]. Y. Muhammad, M. Tahir, M. Hayat, and K.T. Chong, "Early and accurate detection and diagnosis of heart disease using intelligent computational model", *Scientific Reports*, 10:19747, 2020, https://doi.org/10.1038/s41598-020-76635-9

[6]. H. Jindal, S. Agrawal, R. Khera, R. Jain and P. Nagrath, "Heart disease prediction using machine learning algorithms", *IOP Conf. Series: Materials Science and Engineering 1022*, pp. 1 - 10, 2021, doi:10.1088/1757-899X/1022/1/012072

[7]. B. Umadevi, and M. Snehapriya, "A Survey on Prediction of Heart Disease Using Data Mining Techniques", *International Journal of Science and Research (IJSR)*, Volume 6, Issue 4, pp. 2228 – 2232

[8]. S. Kodati, and R. Vivekanandam, "Analysis of Heart Disease using in Data Mining Tools Orange and Weka", *Global Journal of*

*Computer Science and Technology*, Volume XVIII, Issue I, Version I, pp. 17 - 21, 2018

[9]. S.H. Sajid, A.Shafkat, F. Yasmeen, S.A. Sibli, and M.R.Rafi, "Prediction of Heart Disease Using Data Mining Techniques: A Case Study", *International Journal of Research Publications*, Volume: 41, Issue: 1, 2019, availabe at https://ijrp.org/paper-detail/826

[10]. B.Bahrami, and M.H. Shirvani, "Prediction and Diagnosis of Heart Disease by Data Mining Techniques", *Journal of Multidisciplinary Engineering Science and Technology (JMEST)*, Vol. 2, Issue 2, pp. 164 - 168, 2015

[11]. O.Yu. Atkov, S.G. Gorokhova, A.G. Sboev, E.V. Generozov, E.V. Muraseyeva, S.Y. Moroshkina, N.N. Cherniy, "Coronary heart disease diagnosis by artificial neural networks including genetic polymorphisms and clinical parameters", *Journal of Cardiology*, 59, pp. 190—194, 2012, doi:10.1016/j.jjcc.2011.11.005

[12]. R. Chitra, and V. Seenivasagam, "Review of Heart Disease Prediction System Using Data Mining And Hybrid Intelligent Techniq *ICTACT Journal on Soft Computing*, Vol. 3, No. 4, pp. 605 – 609, 2013, DOI : 10.21917/ijsc.2013.0086

[13]. Taneja, "Heart disease Prediction System Using data Mining Techniques", *Oriental Journal of Computer Science & Technology*, Vol. 6, No. (4): Pp. 457-466, 2013

[14]. C.S. Dangare, and S.S. Apte, "Improved Study of Heart Disease Prediction System using Data Mining Classification niques", *International Journal of Computer Applications*, Vol. 47, No.10, 2012

[15]. A.K. Pandey, P. Pandey, K.L. Jaiswal, A.K. Sen, "A Heart Disease Prediction Model using Decision Tree", *IOSR Journal of Computer Engineering (IOSR-JCE)*, Vol. 12, No. 6,pp. 83-86, 2013

[16]. S. Goto, K. Ihara, L. Beussink-Nelson, H. Ikura, Y. Katsumata, J. Endo, H. K Gaggin, S. J. Shah, Y. Itabashi, C. A. MacRae, and R. C. Deo, "Artificial intelligence-enabled fully automated detection of cardiac amyloidosis using electrocardiograms and echocardiograms", *NATURE COMMUNICATIONS* | (2021) 12:2726, pp. 1-12, 2021, https://doi.org/10.1038/s41467-021-22877-8

[17]. Akansha Jain, Manish Ahirwar, Rajeev Pandey, "A Review on Intutive Prediction of Heart Disease Using Data Mining Techniques", *International Journal of Computer Sciences and Engineering*, 2019, ff10.26438/ijcse/v7i7.109113

[18]. Thamizhiniyal, and A. Vidhya, "Intelligent Risk Analysis and Prediction of Heart Disease Using Data Mining Techniques", *Journal of Information and Computational Science*, Vol. 10, No. 3, pp. 175 - 180, 2020

[19]. R. Fadnavis, K. Dhore, D. Gupta, J. Waghmare, and D. Kosankar, "Heart disease prediction using data mining", *Journal of Physics: Conference Series* 1913, 012099, 2021, doi:10.1088/1742-6596/1913/1/012099

[20]. P. Singh, S. Singh, and G.S. Pandi-Jain, "Effective heart disease prediction system using data mining techniques", *International Journal of Nanomedicine*, Vol. 13, pp. 121 - 124, 2018

[21]. S.Y. Cho, S.H. Kim, S.H. Kang, K.J. Lee, D. Choi, S. Kang, S.J. Park, T.Kim, C.H. Yoon, T.J. Youn, and I.C. Chae, "Pre-existing and machine learning-based models for cardiovascular risk prediction", *Scientific Reports*, 11:8886, 2021, https://doi.org/10.1038/s41598-021-88257-w

[22]. C. Krittanawong, H.U.H. Virk, S. Bangalore, Z. Wang, K.W. Johnson, R. Pinotti, H. Zhang, S. Kaplin, B. Narasimhan, T. Kitai, U. Baber, J.L. Halperin and W.H.W. Tang, "Machine learning prediction in cardiovascular diseases: a meta-analysis", *Scientific Reports*, 10:16057, 2020, https://doi.org/10.1038/s41598-020-72685-1

[23]. R. Alizadehsani, M. Roshanzamir, S. Abdar, A. Beykikhoshk, A. Khosravi, M. Panahiazar, A. Koohestani, F. Khozeimeh, S. Nahavandi, and N. Sarrafzadegan, "A Database For Using Machine Learning and Data Mining Techniques for Coronary Artery Disease Diagnosis", *Scientific Data* (2019) 6:227, pp. 1 -13, 2019, https://doi.org/10.1038/s41597-019-0206-3

[24]. C. Balakrishnan, and V.D.A. Kumar, IoT-Enabled Classification of Echocardiogram Images for Cardiovascular Disease Risk Prediction with Pre-Trained Recurrent Convolutional Neural Networks, Diagnostics 2023, 13, 775. https://doi.org/10.3390/diagnostics13040775

[25]. R. Nedadur, B. Wang, and W. Tsang, Artificial intelligence for the echocardiographic assessment of valvular heart disease Heart 2022;108:1592-1599.

[26]. N. Kumar, and D. Kumar, Machine Learning based Heart Disease Diagnosis using Non-Invasive Methods: A Review, Journal of Physics: Conference Series 1950, ICMAI 2021, pp. 1 - 14, doi:10.1088/1742-6596/1950/1/012081

[27]. M. B. Abubaker and B. Babayiğit, "Detection of Cardiovascular Diseases in ECG Images Using Machine Learning and Deep Learning Methods," in IEEE Transactions on Artificial Intelligence, vol. 4, no. 2, pp. 373-382, April 2023, doi: 10.1109/TAI.2022.3159505.

[28]. T. Dhamdhere, S. Bhutambere, A. Bansode, and S. Umare, Heart Disease Detection Using ECG Waves: A Survey, Journal of Emerging Technologies and Innovative Research (JETIR), Vol. 7, Issue 4, pp. 1761 - 1764

[29]. A.S.. Sharma and D. H.. Hota, "ECG Analysis-Based Cardiac Disease Prediction Using Signal Feature Selection with Extraction Based on AI Techniques", Int. j. commun. netw. inf. secur., vol. 14, no. 3, pp. 73–85, Dec. 2022.

[30]. M.H. Vafaie, M. Ataei, and H.R. Koofigar, Heart diseases prediction based on ECG signals' classification using agenetic-fuzzy system and dynamical model of ECG signals, Biomedical Signal Processing and Control 14, 2014, pp. 291–296

# Plagiarism Check JOIN V8N1

ORIGINALITY REPORT

| 15% | 10% | 6% | 9% |
|---|---|---|---|
| SIMILARITY INDEX | INTERNET SOURCES | PUBLICATIONS | STUDENT PAPERS |

PRIMARY SOURCES

| | | |
|---|---|---|
| 1 | Submitted to Al Zaytoonah University<br>Student Paper | <1% |
| 2 | portal.awkum.edu.pk<br>Internet Source | <1% |
| 3 | www.igi-global.com<br>Internet Source | <1% |
| 4 | www.jestr.org<br>Internet Source | <1% |
| 5 | Faraz S. Ahmad, Yuan Luo, Ramsey M. Wehbe, James D. Thomas, Sanjiv J. Shah. "Advances in Machine Learning Approaches to Heart Failure with Preserved Ejection Fraction", Heart Failure Clinics, 2022<br>Publication | <1% |
| 6 | Submitted to Mountain Lakes High School<br>Student Paper | <1% |
| 7 | Submitted to Universidad Internacional de la Rioja<br>Student Paper | <1% |

| | | |
|---|---|---|
| 8 | www.hrpub.org<br>Internet Source | <1% |
| 9 | Ashima Kukkar, Yugal Kumar, Jasminder Kaur Sandhu, Manjit Kaur, Tarandeep Singh Walia, Mohammed Amoon. "DengueFog: A Fog Computing-Enabled Weighted Random Forest-Based Smart Health Monitoring System for Automatic Dengue Prediction", Diagnostics, 2024<br>Publication | <1% |
| 10 | Submitted to Northcentral<br>Student Paper | <1% |
| 11 | www.coursehero.com<br>Internet Source | <1% |
| 12 | www.ijarcs.info<br>Internet Source | <1% |
| 13 | Run Zong Liu, Yuan Yan Tang, Bin Fang. "Automatic decision support by information energy decision tree algorithm", 2014 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2014<br>Publication | <1% |
| 14 | Submitted to Washington University in St. Louis<br>Student Paper | <1% |
| 15 | Submitted to Deakin University<br>Student Paper | |

| | | |
|---|---|---|
| | | <1 % |
| 16 | Edgar M. Hidalgo, Leah Wright, Mats Isaksson, Gavin Lambert, Thomas H. Marwick. "Current Applications of Robot-Assisted Ultrasound Examination", JACC: Cardiovascular Imaging, 2023<br>Publication | <1 % |
| 17 | Submitted to Harvard Medical School<br>Student Paper | <1 % |
| 18 | Submitted to Berlin School of Business and Innovation<br>Student Paper | <1 % |
| 19 | Submitted to Universitas Sebelas Maret<br>Student Paper | <1 % |
| 20 | Submitted to University of Bedfordshire<br>Student Paper | <1 % |
| 21 | Submitted to University of Exeter<br>Student Paper | <1 % |
| 22 | www.jsr.org<br>Internet Source | <1 % |
| 23 | Shrivathsa Thokur Vasudeva, Shrikantha Sasihithlu Rao, Navin Karanth Panambur, Chakrapani Mahabala et al. "Diagnostic classification of undifferentiated fevers using artificial neural network", AIP Publishing, 2020 | <1 % |

| | Publication | |
|---|---|---|
| 24 | Submitted to Sveučilište Sjever- University North<br>Student Paper | <1 % |
| 25 | Submitted to Curtin University of Technology<br>Student Paper | <1 % |
| 26 | Submitted to Universitas Airlangga<br>Student Paper | <1 % |
| 27 | doaj.org<br>Internet Source | <1 % |
| 28 | Submitted to University of Lancaster<br>Student Paper | <1 % |
| 29 | Submitted to University of Maryland, University College<br>Student Paper | <1 % |
| 30 | mdpi-res.com<br>Internet Source | <1 % |
| 31 | patents.google.com<br>Internet Source | <1 % |
| 32 | www.ijraset.com<br>Internet Source | <1 % |
| 33 | academic.oup.com<br>Internet Source | <1 % |
| 34 | dc.tsinghuajournals.com<br>Internet Source | <1 % |

| | | |
|---|---|---|
| 35 | knepublishing.com<br>Internet Source | <1 % |
| 36 | vdocuments.site<br>Internet Source | <1 % |
| 37 | www.science.org<br>Internet Source | <1 % |
| 38 | ijpeds.iaescore.com<br>Internet Source | <1 % |
| 39 | journals.ssu.ac.ir<br>Internet Source | <1 % |
| 40 | www.ijaresm.com<br>Internet Source | <1 % |
| 41 | Transactions on Engineering Technologies, 2015.<br>Publication | <1 % |
| 42 | eprints.iums.ac.ir<br>Internet Source | <1 % |
| 43 | ia902508.us.archive.org<br>Internet Source | <1 % |
| 44 | pure-oai.bham.ac.uk<br>Internet Source | <1 % |
| 45 | journals.lww.com<br>Internet Source | <1 % |

| | | | |
|---|---|---|---|
| Exclude quotes | Off | Exclude matches | Off |
| Exclude bibliography | Off | | |