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Classification of coronary heart disease using the multi-layer perceptron neural networks

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ABSTRACT

Coronary heart disease (CHD) is one of the leading causes of death worldwide. The complexity of risk factors such as blood pressure, cholesterol, smoking history, and unhealthy lifestyles often makes the diagnosis process less effective. With the increasing need for fast and accurate heart disease prediction systems, the use of artificial intelligence-based methods such as Neural Networks is a promising solution. This study aims to evaluate the ability of the Multi-Layer Perceptron (MLP) algorithm to classify CHD risk using the Framingham Heart Study dataset, while comparing it with other commonly used classification methods. This research used the collection of Framingham heart disease data containing 15 medical features. The data was then processed through cleaning, normalization, and class balancing using the SMOTE method. An MLP model was designed with two hidden layers using 200 and 128 neuron architectures, and tested in three training and testing data split scenarios (70:30, 75:25, and 80:20). The model was trained for 100 epochs and evaluated using accuracy, precision, and recall metrics to assess its classification performance. The experiment results show that MLP is able to produce high performance with 86.20% accuracy. 84.40% precision, and 88.56% recall. Compared to other methods such as Decision Tree and SVM, the experiment results show that MLP demonstrated superior classification accuracy. Thus, MLP has the potential to be an effective tool for supporting early diagnosis of coronary heart disease more intelligently and efficiently.

1. Introduction

Heart disease is a condition that affects heart function and can affect anyone regardless of age, gender, or lifestyle [1]–[3]. This disease is a leading cause of death worldwide, with approximately 17.9 million deaths annually, of which 85% are caused by heart attacks and strokes [4]. In Indonesia, the prevalence of heart disease reached 1.5% of the population according to the 2018 Basic Health Research (Riskesdas). The high incidence of this disease indicates the need for early detection and prompt treatment to reduce the risk of complications.

Plaque, a buildup of fat and cells on the walls of the coronary arteries, can narrow the blood vessels and increase the risk of coronary heart disease [5]. Symptoms range from chest discomfort to a potentially fatal heart attack [6], [7]. In addition to genetic and environmental factors, unhealthy lifestyles such as smoking, poor diet, and lack of physical activity are also major risk factors [8]–[12].

A proper diagnosis of coronary heart disease (CHD) is crucial to prevent fatal complications. Neumann et al. [13] explain that various methods such as ECG, treadmill, angiography, and blood pressure and cholesterol measurements are used to identify symptoms and risk factors. However, the complexity of symptoms and the multitude of risk factors often make a rapid and accurate diagnosis difficult. Therefore, more efficient and precise diagnostic methods are needed.

Artificial intelligence (Artificial Intelligence) is now widely applied in the health sector to support the disease diagnosis process, including the classification of heart disease risk [14]–[19]. Previous research [13] has utilizedFramingham Heart Studyas a dataset to predict the risk of coronary heart disease. This dataset includes various medical and lifestyle variables, such as smoking history, cholesterol, blood pressure, and other relevant factors [20]. The modelNeural Network, specifically Multi Layer Perceptron(MLP), has not been widely used in medical classification research because of its ability to recognize complex non-linear patterns in data.

Therefore, this study aims to classify coronary heart disease using the methodMulti Layer Perceptron(MLP) to produce a diagnostic system that is automatic, efficient, and has a high level of accuracy.

2. Method

2.1. Data Collection

The data used in this study is the Framingham Heart Study obtained from the Kaggle public repository [14]. This dataset consists of 4,240 samples with 15 attributes that include demographic information, lifestyle, and medical parameters relevant to the risk of coronary heart disease.

2.2. Preprocessing Data

The data preprocessing stage is carried out to prepare the data so that it is ready for use in the model training process.preprocessingdata includes:

- HandlingMissing Value :Blank values in the columns are filled using the median of each numeric feature to avoid bias due to missing data.
- Separation of Features and Labels : The TenYearCHD column is used as the label (target class), while all other columns are used as features.
- Data Normalization : StandardScaler is used to standardize the feature scale so that each feature has a distribution with a mean of 0 and a standard deviation of 1.
- Class Balancer : Because the class distribution is unbalanced, the method used isSynthetic Minority Oversampling Technique(SMOTE) to increase the number of samples in the minority class to balance it with the majority class

2.3. MLP Architecture

Model Multi Layer Perceptronused consists ofinput layerwith the number of neurons according to the number of features in the dataset, twohidden layerwith 200 and 128 neurons respectively, andoutput layerwith one neuron for binary classification. Activation functionresume used on hidden layer And sigmoid on output layer. Optimization is done usingAdam Optimizer with loss function binary cross-entropy.

2.4. Model Evaluation

Model performance evaluation is performed using three main metrics, namelyaccuracy, precision, And recall

- Accuracymeasures the percentage of correct predictions out of total predictions, formulated as [21]

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

- Precisionmeasure the proportion of correct positive predictions, with the equation [21]

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

- Recall measuring the model's ability to detect positive cases, formulated as [21]

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

3. Results and Discussion

3.1. Data Preprocessing Results

The dataset used is the Framingham Heart Study in CSV format (framingham.csv). This dataset contains health attributes such asage, sex, totChol, sysBP, glucose, AndTenYearCHDas target label.Stagespreprocessingis done as follows:

- HandlingMissing Value

  Numeric attribute blanks are filled using the median of each column. This process ensures no missing data, allowing the model to train optimally as show in Fig. 1.

	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose	TenYearCHD
0	1	39	4.0	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0	0
1	0	46	2.0	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0	0
2	1	48	1.0	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0	0
3	0	61	3.0	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0	1
4	0	46	3.0	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0	0

Fig. 1. The results of handling missing values show that all columns have been filled with median values

- Separation of Features and Labels

  The features used are all columns exceptTenYearCHDwhich becomes the target label as show in Fig. 2.

Semua Fitur (X):

	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose
0	1	39	4.0	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0
1	0	46	2.0	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0
2	1	48	1.0	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0
3	0	61	3.0	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0
4	0	46	3.0	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0

Label (y):

	TenYearCHD
0	0
1	0
2	0
3	1
4	0

Fig. 2. Displays the results of the separation between features (X) and labels (y)

- Data Normalization

  Features are normalized usingStandardScalerto have a mean of 0 and a standard deviation of 1shown in Table 1.

Table 1. Data Distribution Before and After SMOTE

Feature 1	Feature 2	Feature 3	Feature 4
1.1531	-1.2342	2.0060	-0.9882
0.3429	-0.2012	-0.8672	-0.4176
-0.1593	0.7200	1.5904	-0.2450

- Data Normalization

  The initial data had significant class imbalance. Therefore, it was usedSynthetic Minority Oversampling Technique(SMOTE) to increase the number of samples in the minority class is shown in Table 2.

Table 2. Data Distribution Before and After SMOTE

Class	Amount of Data Before SMOTE	Amount of Data After SMOTE
0 (No PJK)	3.590	3.596
1 (PJK)	648	3.596
Total	4.238	7.192

3.2. Model Training Results

Model Multi Layer PerceptronThe (MLP) used has the following architecture.

- Input Layer: the number of neurons corresponds to the number of features in the dataset.
- Hidden Layer1: 200 neurons with ReLU activation function.
- Hidden Layer 2: 128 neurons with ReLU activation function.
- Output Layer: 1 neuron with sigmoid activation function for binary classification.

Optimization is done using Adam Optimizer withloss functionBinary Cross-Entropy. The training process is carried out until the model reaches optimal accuracy.

3.3. MLP Model Evaluation Results

To determine the best configuration, testing was carried out on 30 model variations.Multi Layer Perceptron (MLP) with different parameter combinations. The parameters varied include the number of neurons in eachhidden layer, mark learning rate, activation function,optimizer, and the amountepoch. Performance evaluation is conducted using accuracy, precision, and reliability metrics.recallon the same proportion of training and test data. Experimental Results of Multi Layer Perceptron (MLP) model configuration on the framingham heart study dataset show in Table 3.

Table 3. Experimental Results of Multi Layer Perceptron (MLP) Model Configuration on the Framingham Heart Study Dataset

No	Amount Hidden Layer	Amount NeuronEveryLayer		Epoch	Accuracy	Precision	Recall
		1	*2*				
1	2	100	100	100	0.8253	0.8284	0.8172
2	2	150	100	100	0.8364	0.7831	0.9271
3	2	125	100	100	0.8292	0.8006	0.8733
4	2	64	64	100	0.7803	0.7543	0.8262
5	2	125	125	100	0.8337	0.8066	0.8744
6	2	150	,150	100	0.8487	0.8081	0.9114
7	2	160	100	100	0.8453	0.8204	0.8811
8	2	160	125	100	0.8426	0.7994	0.9114
9	2	64	32	100	0.7786	0.7720	0.7858
10	2	128	32	100	0.7825	0.7548	0.8318
11	2	128	64	100	0.8259	0.7915	0.8811
12	2	128	50	100	0.80978	0.78586	0.84753
13	2	200	64	100	0.8275	0.7776	0.9136
14	2	200	40	100	0.8164	0.7776	0.8822
15	2	200	122	100	0.8570	0.8216	0.9091
16	2	200	123	100	0.8570	0.8184	0.9147
17	2	163	104	100	0.8426	0.8335	0.8531
18	2	200	10	100	0.7652	0.7117	0.8856
19	2	200	50	100	0.8264	0.7965	0.8922
20	2	200	140	100	0.8581	0.8233	0.9091
21	2	200	130	100	0.8611	0.8321	0.9114
22	2	200	120	100	0.8526	0.8064	0.9248
23	2	200	110	100	0.8617	0.8423	0.8923
24	2	200	100	100	0.8459	0.7994	0.9204
25	2	200	90	100	0.8581	0.8240	0.9080
26	2	200	80	100	0.8459	0.7965	0.9260
27	2	200	70	100	0.8437	0.8039	0.9058
28	2	129	64	100	0.8192	0.7901	0.8654
29	2	129	40	100	0.8036	0.7958	0.8036
30	2	200	128	100	0.8620	0.8440	0.8856

Based on the results in Table 3, the configuration with 200 neuron architecture onhidden layerfirst, 128 neurons in the second hidden layer, ReLU activation function onhidden layer, sigmoid activation function on the output layer, learning rate 0.001, and Adam optimizer shows the best performance with accuracy 86,20%, precision84.40%, andrecall88.56%. This configuration was then used in the main evaluation stage of the model.

Three scenarios of training and test data splits, namely 70:30, 75:25, and 80:20, were tested to evaluate their impact on model performance. The evaluation was performed using the metricaccuracy, precision, And recallcalculated based on the confusion matrix. The 80:20 ratio yields the best performance as shown in Table 4.

Table 4. Test Results of the Multi-Layer Perceptron Neural Network Model

Metric	Mark (%)
Accuracy	86.23
Precision	85.14
Recall	87.56

The proportion of 80:20 produces a valueaccuracy, precision, And recallhighest. Althoughvalidation lossshows little fluctuation, the model performance remains stable so this proportion is used in the main experiment Fig. 3.

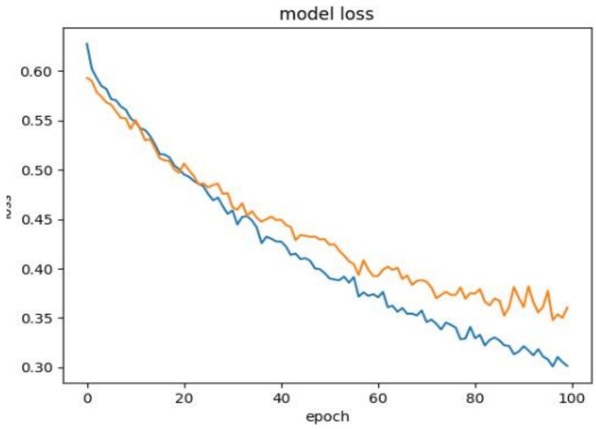

Fig. 3. Graphicsvalidation loss

3.4. MLP Performance Analysis

Based on the evaluation results, the MLP model is able to achieve the levelacuraccywhich is quite high, with a valueprecision And recallbalanced. This shows that the model is not only able to predict positive cases correctly, but can also identify the majority of cases that are truly positive. The applicationpreprocessingsuch as normalization andSMOTEplays an important role in improving model performance, especially in addressing data imbalance

3.4.1. Influence AnalysisActivation

Experiments were conducted with five activation functions (ReLU, LeakyReLU, tanh, ELU, and SELU) using the same architecture. The results show that ReLU provides the best performance (86.20% accuracy, 84.40% precision, 88.56% recall), followed by LeakyReLU with competitive results. The tanh function tends to overfit after the 70th epoch, while ELU and SELU produce lower accuracy (Table 5).

Table 5. Comparison of activation functions

Activation Function	Accuracy	Precision	Recall	Short Notes
resume	86.20%	84.40%	88.56%	Highest and stable performance
LeakyReLU	86,37%	85,51%	8733	Stable, not easyoverfitting
fishy	80,03%	77,27%	7578%	Tendsoverfittingafter the 70th epoch
UP	72,69%	87,10%	86.30%	Smoother, but training takes a little longer
The village	69,74%	67,68%	74,66%	Less stable, low performance, and less suitable for this MLP architecture

3.4.2. Influence AnalysisLearning Rate

Learning ratedetermines the size of the weight update step at each iteration. Testing with values of 0.1, 0.01, 0.001, and 0.0001 shows thatlearning rate0.001 produces the best performance (accuracy 86.20%, precision 84.40%, recall87.53%), in line with the valuedefault Adam optimizer. Too large values (0.01 and 0.1) reduce performance and causeoverfittingor model failure, while too small a value (0.0001) makes training slower and accuracy lower as shown in Table 6.

Table 6. Comparison of learning rate experiment results

Learning Rate	Accuracy	Precision	Recall	Notes
0.001	0.8620	0.8440	0.8856	High recall, quite good performance.
0.01	0.7925	0.7171	0.9607	Tendsoverfittingafter the 70th epoch
0.0001	0.7463	0.7215	0.7959	Smoother, but training takes a little longer
0.1	0.5038	0.0	0.0	Accuracy terkecil

3.4.3. Momentum Influence Analysis

Momentum onoptimizer is used to accelerate training by utilizing information about previous weight changes. Testing with momentum values of 0.5, 0.7, and 0.9 on the SGD optimizer showed lower performance than the Adam optimizer. The best value, namely momentum 0.9, only produced an accuracy of 71.13%, far below the Adam baseline (86.23%). This indicates that in this study, Adam is more effective than SGD with momentum on the data and MLP architecture used, as shown in Table. 7.

Table 7. Comparison of Momentum Effects

No	Momentum	Accuracy	Precision	Recall
1	0.5	0.6840	0.6591	0. 7522
2	0.7	0.6890	0.6590	0.7735
3	0.9	0.7113	0.6805	0.7881
4	0.1	0.6724	0.6504	0.7343

3.4.4. Analysis of the Effect of Feature Reduction

Features aim to reduce model complexity, speed up the training process, and minimize risks.overfittingby using only the features most relevant to the target. However, in this study, using all features provided the most optimal performance compared to the reduced feature combination shown in Table 8.

Table 8. Comparison of the Effect of Feature Reduction

No	Combination Name	Feature List	Accuracy	Precision	Recall	Reason for Selection
1	Combination 1 (Top 4)	age, sysBP, totChol, glucose	0.7107	0.6913	0.7533	Core biometric features, high correlation to CHD
2	Combination 2 (Top 6)	age, sysBP, totChol, glucose, currentSmoker, prevalentHyp	0,7463	0.7229	0.7926	Additional lifestyle factors & disease history. A complete combination of biometrics, behavior, and medical history.
3	Combination 3 (Top 8)	age, sysBP, totChol, glucose,currentSmoker, prevalentHyp, BPMeds, diaBP	0.7508	0.7407	0.7656	A complete combination of biometrics, behavior, and medical history
4	Combination 4(Baseline)	All features in the dataset	0.8681	0.8525	0.8878	Used as a comparison (baseline) for experiments.

3.4.5 Comparison of Classification Methods with other methods

The performance of MLP is compared with several other methods reported in previous studies, namelyDecision Tree, Random Forest, and KNN. In addition, a comparison was made with the MLP from the research of Beunza et al. who used the same dataset and features show in Table 9.

Table 9. Comparison of MLP performance with other classification methods

No	Method	Accuracy	Precision	Recall
1	MLP	0.8620	0.8440	0.8856
2	*Decision Tree*(Raharja et al.)	0.7336	0.5250	0,5300
3	*Random Forest* (Krishnani dkk.)	0,9680	_	_
4	KNN (Krishnani dkk.)	0,9289	_	_

The results in Table 9 show that MLP has higher accuracy compared toDecision Tree, and approaches the performance of Random Forest and KNN, but this study does not showPrecision And recall.

Table 10. Comparison of MLP performance with MLP from Beunza et al. using the same features(sex, age, cigsPerDay, prevalentStroke, prevalentHyp, totChol, sysBP, dan glucose)

No	Method	Accuracy	Precision	Recall
1	MLP	0.7669	0.7518	0.7914
2	MLP (Beunza et al.[22])	0.7100	0.2900	0.7000

Table 10 shows that the MLP in this study producedaccuracy, precision, And recallwhich is better than MLP in the research of Beunza et al., which shows the effectiveness of the architecture optimization and preprocessing stages used.

4. Conclusion

This study shows that the Multi Layer Perceptron (MLP) method is able to classify the risk of coronary heart disease effectively with a high level of accuracy.accuracy, precision, And recallhigh. The training data proportion of 80:20 gave the best performance and was used in the main experiment. The implementationpreprocessingsuch as handlingmissing value, normalization, and class balancing using SMOTE have been shown to improve model performance. Testing of the training parameters shows that the ReLU activation function,learning rate0.001, and using the Adam optimizer yielded the best results. Feature reduction decreases performance, making using all features the best option. Compared to other methods, MLP has competitive performance and outperforms MLP from previous studies with the same features. For further development, it is recommended to test the model on more diverse medical datasets and apply advanced hyperparameter optimization to improve the accuracy and generalization capabilities of the model.

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Data and Software Availability Statements

Dataset Framingham Heart Studyused in this study are publicly available at Kaggle via the following link: https://www.kaggle.com/amanajmera1/framingham-heart-study-dataset. The program code and model training scripts are available upon request to the authors.

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