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Predicting Heart Disease Algorithm Using DNN & MNN in Deep Learning

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Abstract

Heart diseases remain a significant global health concern, necessitating advanced predictive models for early detection and intervention. Based on an extensive collection of patient data, this study suggests a method for predicting cardiac disease using deep learning algorithms. The architecture employs a multi-layered neural network and deep neural network to capture intricate patterns within the data, optimizing predictive accuracy. The data set downloaded from Kaggle with 14 attributes is used in this study. The deep learning model multilayer neural network and deep neural network are chosen for this study. These models undergo rigorous evaluation using standard performance metrics, demonstrating their efficacy in discriminating between individuals with and without heart disease. Results indicate that the deep learning algorithm exhibits promising predictive capabilities, outperforming traditional methods. Integrating interpretable elements contributes to the model's clinical utility, facilitating better-informed decision-making for healthcare professionals.

Keywords: *Deep learning; DNN; Heart diseases; MNN.*

1. Introduction

Cardiovascular diseases (CVDs) are a leading cause of death and morbidity worldwide, hence prediction models that are accurate and proactive are necessary for prompt management. Because cardiovascular health is so complex, using sophisticated deep learning algorithms provides a thorough method of examining a variety of patient data, such as clinical signs, medical history, and demographic data. Because of the rapid growth in data over time, machine learning techniques are not very accurate in their predictions [1]. To get more accurate data, the researcher has to improve this conventional approach. This work evaluates and improves the efficacy of heart disease prediction by utilising the capabilities of a deep neural network and a multi-layer neural network. Using DNN and MNN, the efficacy of the model that accurately forecasts the presence or absence of cardiac disease was investigated. This work aims at comparing the deep learning models MNN and DNN with the metrics like F1 score, recall, precision, accuracy. With the result it suggests the best model among the other. This research work uses the cardio vascular data set derived from the kaggle. The data set is then processed to accommodate the deep learning models. The evaluation process finally, suggests the best model among them. The process of predicting heart disease begins with extracting the variables from the dataset and splitting it into training and testing sets of data. Figure 1 is the architecture, which outlines the six key components that make up the proposed work's building blocks. Each has a distinct function. Training data can be pre-processed by using the DNN and MNN algorithms, which can then be used to classify the data for analyzing whether or not the patient has heart disease. The outcome was generated with great precision. Heart Disease Preprocessing Flow Method is shown in Figure 1. This research aims to evaluate the effectiveness of a multi-layer neural network and DNN in discerning patterns within the dataset, contributing to the refinement of predictive models for heart disease [2].

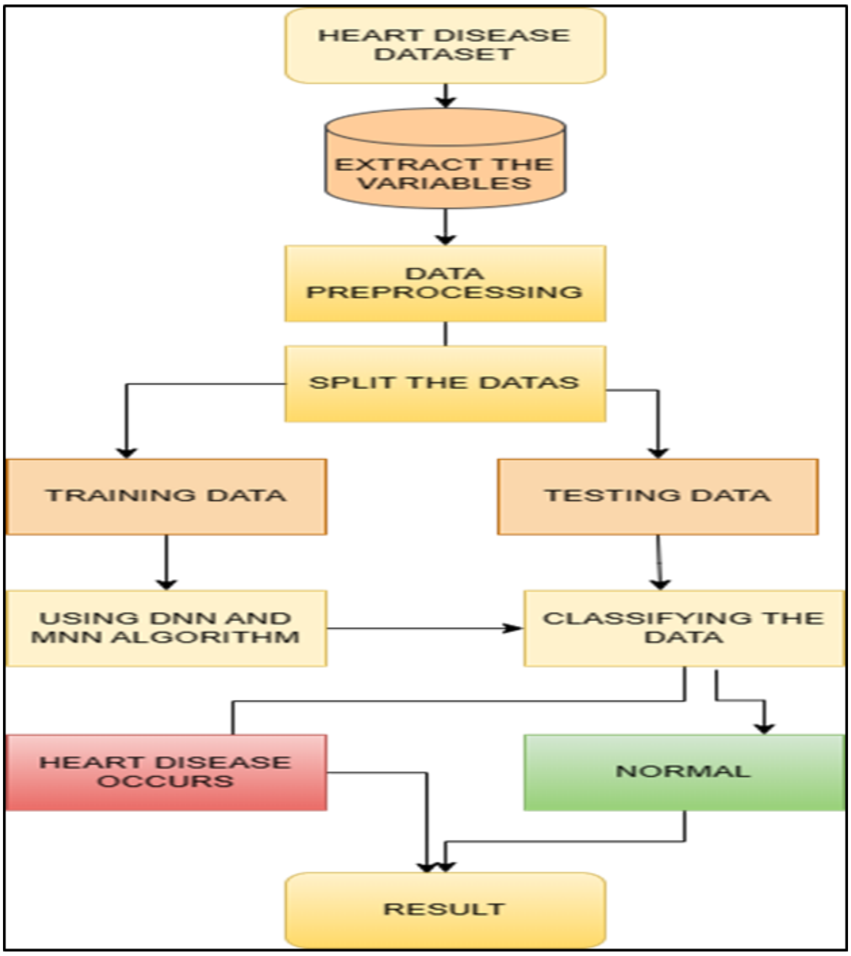

Figure 1 Heart Disease Preprocessing Flow Method

Using advanced deep learning techniques, this work aims to improve early detection and prevention measures for cardiovascular diseases by offering insights into the intricate relationships and dependencies within the data. Further, the result is to be analysed and in forthcoming research work model needs to be enhanced and new models need to be introduced to enhance the accuracy. This paper is segmented into Chapter 2 related work, Chapter 3method and methodology, Chapter 4 result and discussion, and finally, the conclusion.

2. Related Work

Different diseases may generate different symptoms. However, a set of heart and blood vessel disorders frequently share symptoms. Deep learning methods are often used in many different areas, particularly in heart disease prediction. Using deep leering methods improves the accuracy compared to traditional methods. The study described by I KetutAgungEnriko, 2020[3] Using the 450 data from Jakarta's Harapan Kita Hospital's 15 input parameters that were collected. AdaBoost, KNN, Naive Bayes, Bagging Algorithm, C4.5, CART, Random Forest, MLP, Logistic, and SVM algorithms are among the few machine learning algorithms that have been empirically validated with the aid of the dataset. The pre-processed data set produced an accuracy of 78.0% with Random Forest. The goal of the work by SENTHILKUMAR MOHAN et al.,[4] is to use machine learning to create a unique cardiovascular disease (CVD) prediction system. He suggested the HRFLM technique, which yields 90.1% accuracy, using the Kaggle dataset, which includes 297 cases.

According to author C. Beulah Christalin Latha et al.'s study,[5] comparing multiple algorithms performed a study with the primary goal of determining the best effective feature selection strategy for predicting cardiovascular disease using NaïveBayes, Bayes Net, RandomForest and Multilayer Perceptron algorithms were considered and the ensambled method produced 7.26% of improved accuracy. Farman Ali et al. [6] employed the ensemble deep learning model in their work as a smart healthcare monitoring system for heart disease prediction based on feature fusion and ensemble deep learning using a heart disease data set. The work yielded 98.5% outcomes. The work on Improved Heart Disease Prediction Using Deep Neural Networks is proposed by the author Mohd Ashraf et al., [7]. The suggested method yields an automated system for heart attack prediction with an 87.64% DNN algorithm. A number of research tiers and algorithms, including Naïve Bayes, K-Nearest Neighbour Algorithm (KNN), Decision Trees (DT), and Genetic Algorithm (GA), are used for cardiovascular disease prediction using text datasets with 14 attributes. KNN and CNN algorithm are used to produce a feature selection process that offers a high degree of prediction, with 91% accuracy, according to Nilam Harkulkar et al.'s [8] suggestion. In order to predict heart illness with a high degree of accuracy (98.3%), author Dengqing Zhang et al.'s research study [9] advises integrating an embedded feature selection approach and a deep neural network with the linear SVC algorithm. According to Sumit Sharma et al. [10, 11], Talos Hyper-parameter optimisation is 90.78% more efficient than other algorithms when classification is carried out using various techniques as KNN, SVM, Naïve Bayes, and Random Forest.

3. Method And Methodology

The aim of this study is to quantify the risk of heart disease using computerised heart disease prediction systems. The automated tools are useful for both patients and healthcare providers. This section of the research work discuss about the methods and methodology used for CVD prediction, which include data collection process, data pre-processing , classification method and metrics used for evaluating the methods.

3.1. Dataset

This work utilizes the data set from the Kaggle database [17] this data set containg totally about 14 attributes. The attribute of the cardio vascular data(CVD) set is briefed in Table 1 and Table 2. The attribute Page is expanded as age of patient and it is numeric which is a critical data of predicting the CVD. Psex is the gender of the patient and it takes binary value. PChest pain type is experienced by the patient and it is described in nominal value. Bpp is measured for patient blood pressure level and it is in number. PCholesterol is defined as the patient's cholesterol level to be determined based on four types of chest pain, “a” nonanginal pain (nothing), (b) atypical angina (abnang), (c) asymptomatic (asympt), and (d) typical angina (angina), which are considered nominal values. FBPS is the Boolean metric used to determine if fasting blood patient sugar is higher than 120 mg/dl is called the fbs. (0 = False; 1 = true) .ECKG is Patient electrocardiogram results are outcomes of electrocardiography during rest it has three categories of values normal (norm), abnormal (abn), and nominal (hypertrophy, or ST-T wave abnormalities). Max PHRT is the highest heart rate that a patient could reach while undergoing exercise testing is denoted in number. Exercise angina testing is a Boolean measure identifying the presence of exercise-induced angina which takes the value nominal 1 = Yes,0 = No. PST depression when compared to rest, the old peak that exercise-induced ST depression is described by EC. The ST segment's peak exercise-related slope is defined by the PSlope of ST. There are three different kinds of values, nominal, flat, and down sloping defined in numbers. PFluoroscopy vessels are described in number and main vessels (0–3) that are fluoroscopically colored (numeric). Thallium PST is a cardiac condition is normal, permanent defect, and reversible defect are defined in binary values for results. PHD is represented by numerical numbers, regardless of whether the patient has received a heart disease diagnosis.

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Table 1 Parameters and Data types from Kaggle

No.	Attribute	Parameter	Datatype
1.	**PAge**	Patient Age	Number
2.	**PSex**	Patient Gender.	Binary
3.	**PCP**	The patient's chest pain experience	Nominal
4.	**Test BPS**	Patient's blood pressure level	Number
5.	**PChol**	Patient cholesterol level	Number
6.	**FBPS**	The patient's Fasting blood sugar test result is over 120 mg/dl.	Number
7.	**RestECG**	Results of the patient's ECG	Categorical
8.	**Thalach**	The highest heart rate that a patient could reach while undergoing exercise testing.	Number
9.	**PExang**	During the exercise testing, the patient got angina. (Categorial) ST depression in a patient during an ECG.	Binary
10.	**Old peak**	The patient's ECG readings' ST segment slope	Number
11.	**PSlope of ST**	How many patient vessels are seen in fluoroscopy pictures.	Number
12.	**pca**	The results of the stress test on Thallium sufferer.	Number
13.	**Thal**	Whether a heart disease diagnosis has been made for the patient.	Binary
14.	**Target**	Whether or not the patient has been diagnosed with Heart Disease.	Binary

Table 2 Dataset Range and Data Type

Attribute	Data type
Sex	The definition of male=1, female=0 is used.
PCP	Value 1: typical angina Value 2: angina not typical Pain different than angina (value 3) Value 4: absence of symptoms.
Test BPP	The patient's blood sugar levels when fasting exceed 120 mg/dl (1=true; 0=false). Normal is indicated by a value of 0.

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RestECG	Value 1: having anomalies in the ST-T wave (T wave inversions and/or ST elevation or depression greater than 0.05 Mv). Value 2: meeting Estes criteria for definite or probable left ventricular hypertrophy.
PExang	Values are defined as Yes=1 and No=0.
PSlope of ST	Value 1: not sloping Value-2: not curved Value: trending downward

3.2. Data Pre-Processing

To pre-process the CVD dataset, several key steps are required to ensure its suitability for analysis and modelling. The initial step involves handling missing values, wherein a strategy for imputation, removal, or interpolation is chosen based on the nature and extent of missing data in each column. Following this, data type conversion is implemented to ensure that each attribute adheres to the specified data type, as outlined in the attribute table. Categorical variables such as "PSex" and "PExang" are encoded using numerical representations, while nominal variables like "PCP" undergo one-hot encoding to transform them into binary columns for each category. For ordinal variables like "PSlope of ST," a mapping to numerical values is performed according to the specified ordinal scale. Numerical features such as "PAge," "Test BPS," "PChol," "Thalach," "Old peak," and "pca" undergo normalization or standardization to achieve a consistent scale, which is crucial for certain machine learning algorithms. Binary features like "FBPS" may be scaled to prevent dominance during modelling. Dummy variables introduced during one-hot encoding are carefully managed to avoid multi co linearity. Outliers in numerical features are identified and addressed, either through removal or transformation. A thorough verification of data consistency ensures that categorical values align with specified ranges and categories. Target variable analysis is conducted to assess distribution and address any imbalances. Additionally, feature engineering is considered, creating or transforming features based on domain knowledge to enhance predictive capabilities. Finally, if applicable, the dataset is split into training and testing sets for model evaluation. All of these procedures add up to a well-prepared dataset, which provides the groundwork for reliable and accurate modelling results.

3.3. Statistical Analysis

This research employed Python code for a comprehensive statistical analysis, calculating mean, max, min, and standard deviation for various attributes in the dataset. The `mean()` method from the `statistics` module determined the arithmetic mean, while `numpy` functions facilitated standard deviation calculations. Figure 2 visually presents the statistical analysis, emphasizing high-accuracy metrics for specific attributes like Cholesterol (Chol), Chest Pain (CP), Resting Blood Pressure (Trestbps), ST Depression during Exercise (Oldpeak), Thal, and the Slope of the ST segment (PSlope of ST). This analysis includes precise values for mean, max, and min, providing a nuanced understanding of attribute distributions. Within the Python Standard Library, modules like `sys` supported file operations. Boolean values, such as sex (male=1, female=0), Chest Pain (CP), and Fasting Blood Sugar (FBPS), were analyzed using the built-in Python functions `min` and `max` to identify the smallest and largest values. In conclusion, the rigorous statistical analysis, encompassing mean, max, min, and standard deviation, offers a detailed exploration of the dataset. This approach aids in uncovering patterns and insights relevant to heart disease diagnosis (Target).

3.4. The Heart Disease Prediction System Based on Deep Learning

This research initiative focuses on the development of a decision support system designed to predict an individual's risk of heart disease. The methodology leverages the capabilities of two deep learning models specifically tailored for classifying cardiovascular diseases (CVD). In this section of the research, we delve into a comprehensive description of the Deep Neural Network (DNN) and Multilayer Neural Network (MNN) models employed in the classification of CVD. The investigation that follows sheds light on the subtleties of these models and how each one improves the precision and efficacy of heart disease risk assessment in the setting of the decision support system.

3.4.1. Deep Neural Network (DNN)

Deep neural networks, which have multiple layers with a large number of neurons each, use a technique called neural network stacking. Every node amplifies the input value it receives by combining weights and capacities, and an activation function processes the sum that results. The signal is then divided by this function to allow for additional propagation. Layers in deep neural networks can be turned on or off, and the output of one layer becomes the input for a layer that comes after it that is forward-oriented. Typically, an artificial neural network has one input, one output, and a maximum of one hidden layer. Deep neural networks, on the other hand, need several hidden layers to function properly. This approach processes attributes using layers of hidden variables, which improves data accuracy. Deep neural networks differ from other neural networks in this way [12]. Every neuron in the network is trained with a unique set of features that come from the previous layer's output. Increasing the level count of the neural network directly impacts the processing capacity of features, allowing it to recognize more intricate patterns. This phenomenon is referred to as "feature hierarchy" [13], where successive layers collaborate to produce abstract and sophisticated outputs. Deep neural networks are equipped to automatically extract linear features from high-dimensional non-linear datasets and manipulate variables for optimal performance.

DNN Algorithm Used To Process The Dataset Is:

1. Initialize the input layer with the input data.
2. For each hidden layer in the network:
   a. Compute the weighted sum of the inputs to the layer.
   b. Add a bias term to the weighted sum.
   c. Pass the result through an activation function.
3. Compute the weighted sum of the inputs to the output layer.
4. Add a bias term to the weighted sum.
5. Pass the result through an activation function to obtain the output of the network

3.4.2. Multilayer neural network (MNN)

An input layer, an output layer, and at least one hidden layer make up an ANN Node layer. Each node is connected and has a corresponding weight and threshold. To awaken and move the data to the next layer, the node's outcome needs to reach a specific threshold value [9]. The method used to build the system was a Multilayer Perceptron Neural Network (MLPNN) using a Forward Propagation Algorithm (FP). In a neural network, each hidden and output layer node uses forward propagation, pre-activation, and activation to transfer the forward method's characteristics in order to generate the optimised outcome. The pre-activation function is the weighted sum calculation. Bias is utilised to produce a non-linear neural network flow by applying the activation function based on the weighted sum. Data propagates forward in a neural network from the left (input layer) to the right (output layer).

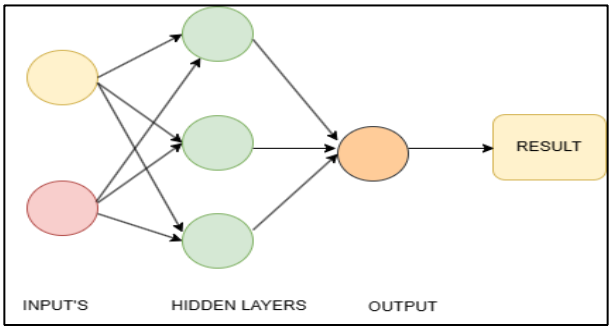

Figure 2 MNN Forward Propagation Flow

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3.5. Metrics Used

Metrics are employed to optimize the dataset for achieving high data accuracy based on the dataset table [1]. The evaluation of the work involves utilizing F1-Score, Recall, Precision, and support to ensure accurate data assessment and refinement.

FI Score: The F1 score is used in a [14] evaluation of a machine learning model's performance in classification tasks. It is computed using the harmonic mean of recall and precision. Precision is the accuracy of positive predictions, whereas recall is a model's capacity to identify actual positive cases. The F1 score is a single number that ranges from 0 to 1, with 1 denoting the highest possible score, and combines precision and recall. The F1 score is determined using the formula.

$$F1 = 2 * \frac{precision * recall}{precision + recall} \quad (1)$$

The F1 score is useful when there is an uneven class distribution or when the sum of the positive and negative examples is not equal. In certain cases, accuracy might be misleading, and the F1 score provides a more true representation of the model's performance. The F1 score is the symmetrical mean of recall and precision. Because it balances recall and precision, this statistic is dependable for binary categorization. A high F1 score indicates that your model's recall and precision are evenly distributed.

Precision: The "precision" [14] of a machine learning model indicates how well it can carry out classification tasks. It displays the accuracy of positive forecasts, that is, the proportion of all positive forecasts that are actual positives.The following formula can be used to determine precision:

$$precision = \frac{Truepositive}{Truepositive + FalsePositive} \quad (2)$$

The number of accurate positive predictions, in this case, is known as true positives, and the number of inaccurate positive predictions is known as false positives. Precision gauges how well the model predicts related outcomes.

Recall: Recall is a statistic [14] that is used to evaluate the performance of a machine learning model in classification tasks. The figure displays the proportion of real positive cases out of all genuine positives that the model successfully identified. The recall formula is as follows:

$$Recall = \frac{Truepositive}{Truepositive + Falsepositive} \quad (3)$$

True positives are the number of accurate positive forecasts in this scenario, whereas false negatives are the number of real positive cases that were incorrectly predicted as negatives.Recall (also known as awareness or true positive rate) is the ratio of correctly expected positive discoveries to the total number of real positives.

Accuracy: The [14] number of actual instances of a class in a given dataset is the measure of accuracy in machine learning. Rebalancing or stratified sampling may be required in response to unbalanced support in the training set, which could indicate underlying problems with the classifier's stated scores.

$$Accuracy = \frac{TP + FN}{TP + FP + TN + FN} \quad (4)$$

Where TP = True Positive
FP = False Positive
TN = True Negative
FN = False Negative

The ratio of accurately anticipated observations to total observations is known as accuracy. It stands for the model's overall accuracy. This research work consumes the mentioned metrics to evaluate the performance of DNN and MNN for cardio vascular disease.

Results and Discussions

This work uses two classification methods, such as DNN and MNN [15] [16], on a data set of heart disorders. This section discuss the result obtained by the experiment carried out for the research work which discuss about the statistical analysis made, the evaluation metrics on deep learning algorithms. There are 1025 patient records altogether in the

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collection. Two sets a training set and a testing set are formed using the dataset. Python code is utilized in the experiment for statistical analysis as well as evaluation and classification. The findings of applying neural networks to training datasets are displayed as two-dimensional confusion matrices. The confusion matrix is simple to comprehend because it shows which classifications are accurate.

	age	sex	cp	trestbps	chol
count	1025.000000	1025.000000	1025.000000	1025.000000	1025.00000
mean	54.434146	0.695610	0.942439	131.611707	246.00000
std	9.072290	0.460373	1.029641	17.516718	51.59251
min	29.000000	0.000000	0.000000	94.000000	126.00000
25%	48.000000	0.000000	0.000000	120.000000	211.00000
50%	56.000000	1.000000	1.000000	130.000000	240.00000
75%	61.000000	1.000000	2.000000	140.000000	275.00000
max	77.000000	1.000000	3.000000	200.000000	564.00000

	fbs	restecg	thalach	exang	oldpeak
count	1025.000000	1025.000000	1025.000000	1025.000000	1025.000000
mean	0.149268	0.529756	149.114146	0.336585	1.071512
std	0.356527	0.527878	23.005724	0.472772	1.175053
min	0.000000	0.000000	71.000000	0.000000	0.000000
25%	0.000000	0.000000	132.000000	0.000000	0.000000
50%	0.000000	1.000000	152.000000	0.000000	0.800000
75%	0.000000	1.000000	166.000000	1.000000	1.800000
max	1.000000	2.000000	202.000000	1.000000	6.200000

	slope	ca	thal	target
count	1025.000000	1025.000000	1025.000000	1025.000000
mean	1.385366	0.754146	2.323902	0.513171
std	0.617755	1.030798	0.620660	0.500070
min	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.000000	2.000000	0.000000
50%	1.000000	0.000000	2.000000	1.000000
75%	2.000000	1.000000	3.000000	1.000000
max	2.000000	4.000000	3.000000	1.000000

Figure 3 Statistical Analysis of Cardio Vascular disease

The figure 3 depicts the statistical analysis made on the data set used for the research work. The analytics include mean, std, min, max, count of the attributes involved in the research work. The result of deep learning algorithm is displayed in the table 3. The result shows that accuracy of MNN is 80 % which is 5% more compared to the DNN model, which has 75 % accuracy. Similar to the accuracy the precision of MNN is 88% whereas for DNN it is 68%. As precision is considered as the accuracy of the positive predictions made by the model so for the given data set the true positive prediction over total positive prediction is high for MNN. The Table 3 outcomes are plotted on the graph that is available in figure 4. Accuracy is shown as a percentage on the y-axis, while the x-axis shows the data pre-processing techniques used for prediction.The recall of 95 % for DNN shows that the DNN model is good in identifying positive instances, however the MNN lack in identifying the same with 75%. The F1 score of 79 % for DNN shows that the model has a good balance between precision and recall.

Table 3 Result of Deep learning Model

Metrics	DNN	MNN
F1 Score	79%	78%
Precision	68%	88%
Recall	95%	70%
Accuracy	75 %	80 %
Support	102%	103%

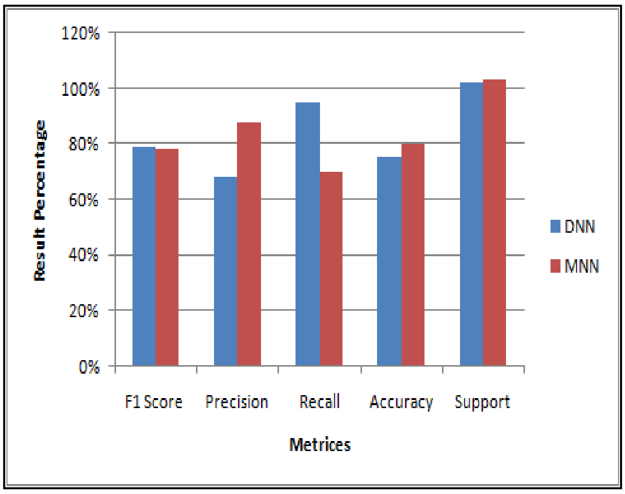

Figure 4 Metrics of Classification Algorithm

The confusion matrix is simple to comprehend because it shows which classifications are accurate and incorrect classification is displayed in the table.

Class A: YES (heart condition)

Class B: Not at all (no cardiac condition)

In confusion matrix, TP (True Positive): It denotes the number of records classified as true while they were true. FN (False Negative): It denotes the number of records classified as false while they were true. FP (False Positive): It denotes the number of records classified as true while they were false. TN (True Negative): It denotes the number of records classified as false while they were false. The confusion matrix provides the result for the patient heart disease occurs or not result analysed in even in the hidden layer propagation. The results of our classification accuracy measurements are shown in the table 4 below.

Table 4 Target Based On Confusion Matrix

	Has HD	No HD
A(Has heart disease)	TP	FN
B(No heart disease)	FP	TN

In the final, analysis, Figure 4 shows, that our research revealed the best classification method for the dataset on heart disease prediction produced from the graph below for different features is a combination of DNN and MNN. To predict heart disease utilizing 14 features, the neural network analysis algorithm presented in this research work generated the greatest results when comparing the deep analysis algorithm and multilayer neural network algorithm, producing the best results of DNN with 75% and MNN with 80% accuracy. So with the result the MNN perform well in accuracy and precision compared to DNN however the Recall and F1 score of DNN outperforms MNN. So this research concludes that further refinement of hyper parameter of one of these two models may lead to adjusted or higher performance of the metrics.

Conclusion

In conclusion, there is a lot of promise for the future in using deep learning and machine learning algorithms to predict heart attacks. Recently, a lot of research has been focused on medical collection. Much has been agreed upon in this field, and much work still needs to be done. This work aims to increase accuracy through the use of deep learning algorithms, bearing in mind that not much research has been done on the evaluation of heart attack prediction using deep learning techniques. This work can pave the way for additional accuracy improvement through the use of different deep-learning algorithms like DNN and MNN algorithms. Comparisons of deep learning methods have been made. Using the algorithm the dataset is processed as F1-Score, Recall, Precision, and Support vectors to provide accuracy of data.The MNN model has excellent performance characteristics, including a 78% F1 score, 88% precision, 70% recall, and 80% total accuracy. These measures confirm the stability of our simulation and its ability to effectively achieve a compromise between recall and precision. The research findings indicate that the MNN exhibits superior accuracy and precision in comparison to the DNN. However, the DNN surpasses the MNN in terms of Recall and F1 score. Therefore, the conclusion drawn is that further optimization of hyperparameters for either of these models could potentially enhance or adjust the overall performance metrics. The same will be carried out in next work with optimization of attributes.

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