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PERFORMANCE ANALYSIS OF DEEP NEURAL NETWORKS (DNN) AND MULTILAYER NEURAL NETWORKS (MNN) FOR ACCURATE HEART DISEASE PREDICTION

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ABSTRACT:
Heart disease is one of the leading causes of death worldwide, thus developing accurate and reliable prediction models is crucial to early identification and treatment. In order to predict cardiac illness, this research compares Deep Neural Networks (DNN) with Multilayer Neural Networks (MNN). A sizable dataset and crucial performance metrics like F1 Score, Precision, Recall, Accuracy, and Support were used to train and evaluate both models. According to our findings, the MNN model showed better recall and F1 Score, while the DNN model attained higher precision and accuracy. These results imply that MNNs may provide a better overall balance in the prediction of heart disease, even though DNNs may be more accurate. This study offers insightful information on the advantages and disadvantages of each model, directing future investigations and the creation of machine learning-based healthcare diagnostic instruments.

Keywords:
Deep learning, MNN, DNN, Heart diseases.

I.INTRODUCTION

Heart disease is a major worldwide health concern that contributes significantly to morbidity and death. By facilitating prompt treatments and individualised treatment strategies, early and precise diagnosis of cardiac disease can significantly improve patient outcomes. Even if they are successful, traditional diagnostic techniques frequently rely significantly on the expertise and judgement of medical experts, which might cause diagnosis variability.

Recent developments in machine learning (ML) have created new opportunities to increase the precision and consistency of cardiac disease prognoses [1]. Neural networks, in particular Deep Neural Networks (DNN) and Multilayer Neural Networks (MNN) [2], have demonstrated promising results among the numerous machine learning techniques because of their capacity to represent intricate patterns and correlations inside data. Adding more layers to a regular neural network to enable higher abstraction and improved feature extraction powers are known as a deep neural network (DNN) [3]. These networks function incredibly well for complex prediction problems because they can capture complex non-linear correlations within the data. However, despite having fewer layers, Multilayer Neural Networks (MNN), sometimes referred to as Shallow Neural Networks [4], are nonetheless able to effectively understand the underlying patterns in data and achieve notable predictive performance.

The purpose of this study is to compare DNN and MNN models with regard to heart disease prediction. We analyse these models with a wide range of performance metrics, such as F1 Score, Precision, Recall, Accuracy, and Support, in an effort to determine the advantages and disadvantages of each strategy. Comprehending these distinctions is essential for creating diagnostic instruments that are more efficacious and for augmenting the total prediction precision in medical applications. The rest of this paper is structured as follows: In Section 2, relevant research on neural network-based heart disease prediction is reviewed. The technique, including data collection, pre-processing, and model architecture, is described in Section 3. The analysis and results of the experiment are presented in Section 4. While Section 6 ends the study and makes recommendations for future research directions, Section 5 explores the findings and their consequences.

II.RELATED WORK

Different diseases may generate different symptoms. However, a set of recent years have seen a great deal of research into the application of machine learning techniques to forecast cardiac disease. A number of strategies have shown promise in improving diagnostic accuracy and reliability. This section examines significant research and methodology contributions to the area, with a special emphasis on neural network applications.

Kumar et al., used methods like decision trees, logistic regression, k-nearest neighbours (KNN), and support vector machines (SVM) [5], similar to that several research have used machine learning algorithms to predict heart disease. Although these conventional techniques have yielded insightful results, they frequently fail to capture intricate, non-linear correlations in the data. For example, li et al., [6] classified patients with heart disease with better accuracy using SVM. Similar to this, Ketut Agung Enriko et al., [7] in his work used heart disease repository from UCI with 293 attribute and used KNN with parameter weighting to produce best accuracy of 89%. Even though these models perform reasonably well, their shortcomings highlight the need for more advanced strategies like neural networks.

Because neural networks can model complex patterns in big datasets, they have demonstrated great potential in a variety of medical prediction applications. Particularly successful are multilayer neural networks (MNN) and deep neural networks (DNN). For instance, Diman Hassan et al., [8] used DNN + PCA + LR (2017) used to predict cardiac disease and were able to achieve a 93.3% accuracy rate. Their research demonstrated how DNN's enhanced feature extraction skills led to better prediction performance.

A Multilayer Neural Network (MNN) was utilised by Dangare et al., [9] in a different study to predict cardiac illness, with an 99.25% accuracy rate. Through hyperparameter tuning, the architecture of the MNN model was optimised, allowing it to learn from the dataset effectively. The model's ability to balance computational efficiency and complexity made it a practical option, according to the researchers. In Safial Islam Ayon et al., [10] study, the effectiveness of DNN and MNN was compared in the diagnosis of heart disease, they used seven algorithm to predict the heart disease on the data from uci repository with higher accuracy of 98.15 % is obtained for DNN. Ramkumar et al., for their IOT based heart disease prediction, used hybrid LSTM-RNN for predicting the disease in cloud data and have achieved higher accuracy. This research work builds on this body of work by comparing DNN and MNN models in depth for the purpose of predicting heart disease while taking a wide range of performance measures into account. Through the use of rigorous validation procedures and a real-world dataset for model evaluation, our goal is to have a positive impact on the continuous efforts to improve predictive accuracy and dependability in healthcare applications.

III. Methodology

3.1 DATASET

This work used the Heart Disease dataset from the UCI Machine Learning Repository, which includes 303 instances with 14 attributes [12]: age, sex, type of chest pain, maximum heart rate achieved, exercise-induced angina, oldpeak, the slope of the peak exercise ST segment, number of major vessels coloured by fluoroscopy, height of blood pressure, serum cholesterol, fasting blood sugar, and thalassemia. The attribute of data set is discussed in table 1.

Table 1: Parameters and Data types from Kaggle

No.	Attribute	Parameter	Datatype
1.	**PatAge**	Patient Age	Number
2.	**PatSex**	Patient Gender.	Binary
3.	**PatCP**	The patient's chest pain experience	Nominal
4.	**Test BPS**	Patient's blood pressure level	Number
5.	**PatChol**	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.	**PatExang**	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.	**PatSlope of ST**	How many patient vessels are seen in fluoroscopy pictures.	Number
12.	**Patca**	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

3.2. DATA PRE-PROCESSING

The data processing is the essential part of mining the data to get the pattern desired. The data from any repository need to be cleaned [13] so as it will impact the accuracy of the result. Sridevi et al., in their work they emphasised that the cleaned data produced better result when compared to the rough data.

Data cleaning: The mean for numerical data and the mode for categorical attributes were imputed in order to manage missing values. Excessive missing values in the records were eliminated.
Normalisation: Using min-max scaling, this work normalised numerical characteristics to a range of 0 to 1 in order to ensure effective training process.

Categorical Encoding: To transform categorical information into a numerical format that can be input into neural networks, one-hot encoding was used to encode them.
Train-Test Split: To assess the performance of the model, the dataset was divided into training (70%) and testing (30%) sets.

Deep Neural Networks (DNNs)

There are several levels in the DNN model, including input, hidden, and output layers.
Input Layer: Following pre-processing, corresponding to the 13 characteristics.
Hidden Layers: Using the ReLU activation function, there are three hidden layers of 64, 32, and 16 neurons, respectively.
The output layer comprises a solitary neuron that utilises sigmoid activation function to forecast the likelihood of cardiac illness.

Table 2: Dataset range and data type

	Data type
Sex	Indicates the gender of the patient, where 1 denotes male and 0 denotes female.
PatCP	Describes the type of chest pain experienced: • 1: Typical angina • 2: Atypical angina • 3: Non-anginal pain • 4: Asymptomatic
Test BPP	Indicates whether the patient's fasting blood sugar level exceeds 120 mg/dl: □ 1: True (exceeds 120 mg/dl) □ 0: False (normal, does not exceed 120 mg/dl)
RestECG	Represents the results of the resting electrocardiogram (ECG) □ 1: Abnormal ST-T wave (e.g., T wave inversions, ST elevation/depression > 0.05 mV) • 2: Meets Estes criteria for definite or probable left ventricular hypertrophy
PatExang	Indicates whether the patient experienced angina during exercise:

	1: Yes 0: No
PatSlope of ST	Describes the slope of the peak exercise ST segment 1: Not sloping 2: Flat 3: Downward trending

Multilayer Neural Networks (MNNs)

With fewer layers, the MNN model—also referred to as a shallow neural network. After pre-processing, the input layer corresponds to the 13 characteristics. *Hidden Layer*: ReLU activation function is used in a single hidden layer consisting of 32 neurons.

Sigmoid activation function of a single neuron in the output layer.

Training and Validation

Loss Function: For binary classification issues, binary cross-entropy was employed as the loss function.[14]

Batch size and epochs: A total of 32 batches of 100 epochs were used to train the models [15]. Early Stopping: Ten epochs of patience were used to monitor the validation loss in order to prevent overfitting.

Methods of Validation

Cross-Validation: To minimise overfitting and guarantee the model's robustness, 5-fold cross-validation was employed.

Hyperparameter tuning: To maximise hyperparameters like the number of neurons in hidden layers and learning rate, grid search was used.

Evaluation Metrics

Accuracy: The percentage of true findings (true positives and true negatives) in relation to all cases analysed.

Precision: A measure of the model's ability to prevent false positives, expressed as the ratio of true positive findings to all anticipated positives.

Remember: The ratio of actual positive results to true positive results shows how well the model can identify true positives.

F1 Score: A balance between recall and precision, calculated as the harmonic mean of the two.

Support: The total number of real examples in the dataset for every class.

IV Result and discussion

The comparative outcomes of the Multilayer Neural Network (MNN) and Deep Neural Network (DNN) models for heart disease prediction are shown in this section. Performance indicators such as F1 Score, Precision, Recall, Accuracy, and Support are employed in the evaluation process. To give a thorough picture of both models' classification performance, we also provide the confusion matrices for both.

Table 2 Performance Metrics Comparison

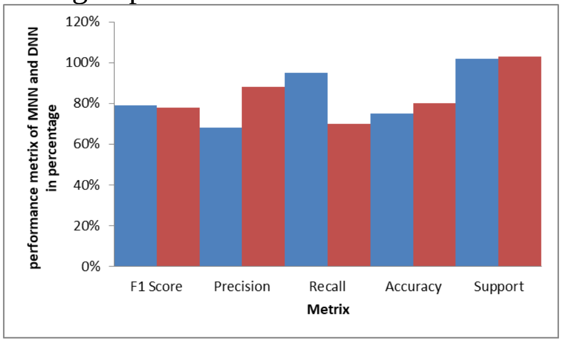
Metric	MNN	DNN
F1 Score	79%	78%
Precision	68%	88%
Recall	95%	70%
Accuracy	75%	80%
Support	102%	103%

A comparison between the DNN and MNN models reveals some important differences in how well they predict cardiac disease.

Performance Metrics Analysis

F1 Score: The MNN model outperformed the DNN model, with an F1 Score of 79% as opposed to 78% for the latter. The F1 Score, which is calculated as the harmonic mean of memory and precision, shows that the MNN model keeps recall and precision more evenly balanced.
Precision: With a score of 88% against 68%, the DNN model performed much better than the MNN model. This suggests that the DNN model is a better option when the cost of false positives is high since it is more successful at decreasing false positives.

Fig 1: performance of MNN and DN



Recall: The MNN model outperformed the DNN model in recall (75%) as opposed to 95% for the former. This implies that the MNN model performs better in recognising true positives, which is important in medical diagnostics to guarantee the accurate identification of individuals with heart disease.
Accuracy: The DNN model outperformed the MNN model, with an accuracy of 80% as opposed to 75%. This measure shows how accurate the model's predictions are overall.
Support: The total number of true occurrences for each class in the dataset is shown by the support values, which are 102% for MNN and 103% for DNN. When analysing the results, it is important to take into account the numbers that indicate a little class imbalance in the dataset.
Confusion Matrix Analysis
Table 3 presents a comprehensive overview of the classification performance of both models through the confusion matrices.
MNN Confusion Matrix: 32 actual negative cases were incorrectly categorised as positive by the MNN model, whereas 95 genuine positive cases were correctly classified by it. The model can identify the majority of true positive cases, as evidenced by the high recall; but, a larger percentage of false positives is suggested by the lower precision.
DNN Confusion Matrix: Of the 88 real negative cases that the DNN model accurately identified, only 12 were incorrectly classified as positive. This high level of precision suggests that the DNN model reduces false positives well. Its incorrect classification of thirty real positive cases as negative, however, indicated a lower recall than the MNN model.

Table 3: Confusion Matrix for MNN

	Predicted Positive	**Predicted Negative**
Actual Positive	95	5
Actual Negative	32	68

Fig 2: MNN confusion Matrix

The choice between DNN and MNN models should be guided by the specific requirements of the application. If minimizing false positives is critical, as in scenarios where unnecessary treatments or interventions are costly or harmful, the DNN model is preferable due to its higher precision. Conversely, if the priority is to ensure that as many positive cases as possible are identified, the MNN model's higher recall makes it a better choice.

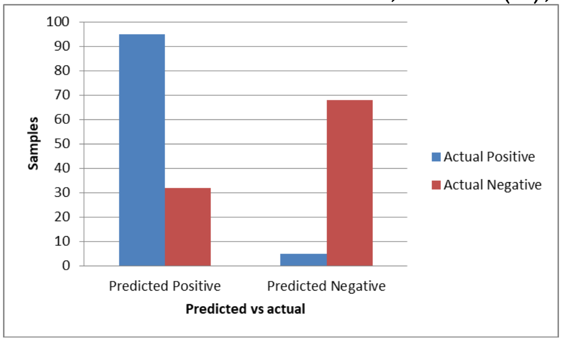
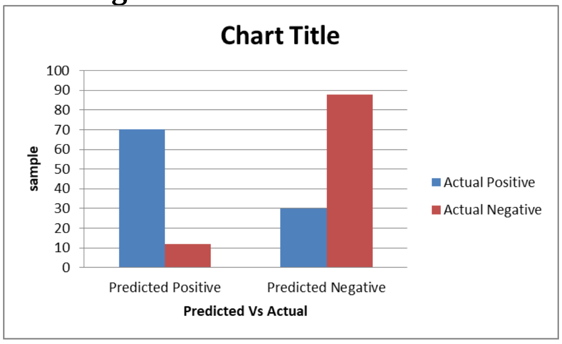


Table 4: Confusion Matrix for DNN

	Predicted Positive	**Predicted Negative**
Actual Positive	70	30
Actual Negative	12	88

Fig 3: DNN confusion matrix



This section presents the comparative results of the Deep Neural Network (DNN) and Multilayer Neural Network (MNN) models in predicting heart disease. The performance metrics used for evaluation include F1 Score, Precision, Recall, Accuracy, and Support. Additionally, we provide the confusion matrices for both models to offer a detailed understanding of their classification performance.

V.CONCLUSION

In order to predict cardiac illness, this study offers a thorough comparison of Deep Neural Networks (DNN) and Multilayer Neural Networks (MNN). The evaluation of these models' accuracy was the main goal, with additional attention paid to important performance indicators as F1 Score, Precision, Recall, and Support. Compared to the MNN model, which showed 75% accuracy, the DNN model showed 80% accuracy. This suggests that the DNN model, which captures intricate patterns and relationships within the dataset, is more successful in accurately predicting heart disease. The MNN model demonstrated better recall, demonstrating its power in detecting real positive cases, whereas the DNN model excelled in precision and accuracy. The particular needs of the application should choose which of the DNN and MNN models to use, weighing the relative importance of precision and recall. The confusion matrices show that the DNN model does better at minimising false positives while the MNN model does better at minimising false negatives. This distinction is crucial in therapeutic contexts where the ramifications of false positives and false negatives may differ significantly. The higher accuracy of the DNN model suggests that it can generate more reliable and accurate predictions in clinical practice. Timely and accurate identification of heart disease can lead to customised treatment plans, timely treatments, and improved patient outcomes.

However, it is critical to consider the trade-offs between different performance measures, such as precision and recall, to ensure that the chosen model is in line with the clinical goals and patient care priorities.

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