

OPTIMIZED MACHINE LEARNING MODELS FOR ACCURATE HEART DISEASE PREDICTION

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Abstract— Enhanced predictive models are necessary for the early identification and intervention of heart disorders, which continue to be a major global health concern. In order to anticipate cardiac sickness, this research suggests a deep learning-based method based on a sizable patient data set. By employing a deep neural network and a multi-layered neural network to identify intricate patterns in the data, the architecture improves forecast accuracy. The 14-attribute data set used in this investigation was taken from Kaggle. The long short-term memory (LSTM) and gated recurrent unit (GRU) deep learning models will be the main focus of this investigation. These models are put through a thorough review process with established performance measures, demonstrating their ability to discriminate between individuals with and without cardiac problems. The technique of deep learning outperforms conventional techniques and has encouraging prediction skills, according to the results. Including interpretable components increases the clinical value of the model and helps medical practitioners make more informed decisions.

Keywords- Machine learning, GRU, Heart diseases, LSTM.

I. INTRODUCTION

Preventive and accurate prediction models are critical for early management of cardiovascular diseases (CVDs), which are a leading cause of death and morbidity worldwide. Given the intricacy of cardiovascular health, using sophisticated deep-learning algorithms is a thorough method of examining a variety of patient data, such as clinical symptoms, medical history, and demographic data. The exponential growth of data over time limits the forecast accuracy of machine learning systems. To get more accurate data, the researcher plans to improve this conventional approach. This work evaluates and enhances the accuracy of cardiovascular disease prediction using a GRU and an LSTM. GRU and LSTM were used to assess the effectiveness of the model that accurately predicts the existence or lack of heart disease [1].

The F1 score, recall, accuracy, and precision of the deep learning models LSTM and GRU are examined in this study. Consequently, it suggests the best model among them all. This study makes use of the cardiovascular data set from Kaggle. The data set is then ready for deep learning model training. Ultimately, the review process suggests the best model among all of them. To begin the heart disease prediction process, the variables are first taken out of the dataset and separated into training and testing data sets. The architecture, depicted in Figure 1, enumerates the six fundamental components that make up the proposed work.

Each has a distinct function. Training data can be pre-processed using the GRU and LSTM algorithms, and then the data can be categorized for analysis of the patient's potential for heart disease. The outcome was generated with remarkable precision. By evaluating how well an LSTM and GRU recognize patterns in the dataset, this work seeks to enhance heart disease prediction models. Through the application of sophisticated deep learning algorithms, this work aims to improve early detection and preventative techniques for cardiovascular diseases by offering insights into the intricate relationships and interactions within the data. The results must also be analyzed, and new and enhanced models must be used in upcoming studies to increase accuracy. This study is divided into four sections: related work in Chapter 2, technique and methodology in Chapter 3, result and discussion in Chapter 4, and conclusion.

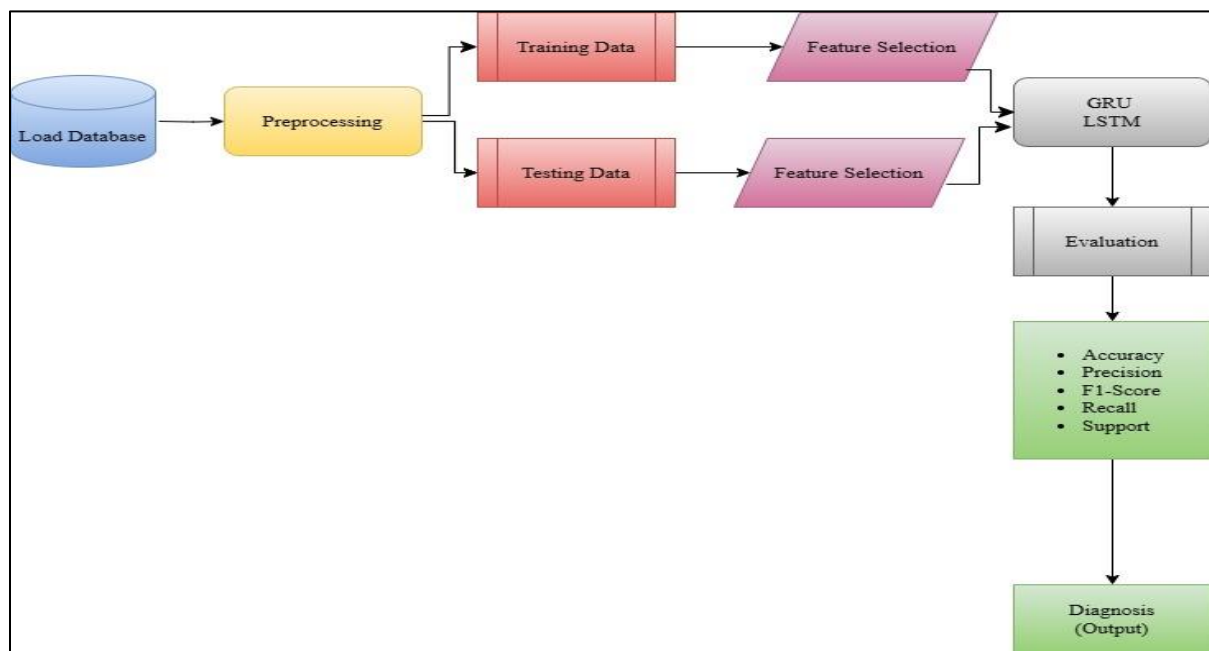


Figure 1: Heart disease pre-processing flow method

II. RELATED WORK

Symptoms can vary depending on the ailment. However, the symptoms of certain heart and blood vessel disorders are typically similar. Heart disease prediction is one of the many sectors where deep learning techniques are widely used. Using deep learning algorithms improves accuracy when compared to traditional methods. An ensemble classifier with a BiLSTM or BiGRU model with a DNN model offers accuracy and F1-score between 91% and 96% for the different types of heart disease, with 17% of records having hypertensive heart disease, 16% having ischemic heart disease, 7% having mixed heart disease, and 8% having valvular heart disease, according to the study by Asma Baccouche et al. [2].

Irfan Javid et al.'s work [3] aims to apply deep learning models (like LSTM and GRU), machine learning algorithms (like RF, SVM, and KNN), and suggested methodology. The Hard Voting Ensemble Model, which has an accuracy of 85.71% and outperforms all other models in terms of prediction accuracy, was used to maintain this ensemble approach.

Five traditional machine learning models—LR, RF, K-NN, DT, NB, and hybrid models (i.e., CNN-LSTM and CNN-GRU)—were compared by author Ahmed Almulihi et al. [4]. CNN-LSTM and CNN-GRU, two pre-trained and optimized deep hybrid models, yielded a score of 98.41. A hybrid deep learning model for heart disease prediction employing recurrent neural networks (RNNs) with multiple gated recurrent units (GRU), long short-term memory (LSTM), and Adam optimizer is proposed in the work of Surenthiran Krishnan et al. [5]. Recent RNN models have achieved 98.23% accuracy, whereas deep neural networks (DNNs) have achieved 98.5% accuracy in their suggested RNN model, yielding 98.6876%.

In order to create a new hybrid deep learning model for heart disease prediction, Omankwu et al. [6] used a recurrent neural network (RNN) that incorporates several gated recurrent units (GRUs), long short-term memory (LSTM), and the Adam optimizer. An outstanding accuracy of 98.6876% was obtained by this suggested model. Convolution Neural Network and Gate Recurrent Unit (CNN GRU) offers a novel approach that yields great accuracy, according to Abdelmegeid Amin Ali et al. [7]. Essential characteristics are extracted from the data set using the Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) feature selection algorithms, which reach 94.5 percent accuracy.

III. METHOD AND METHODOLOGY

The purpose of this research is to use computerized cardiac prediction systems to estimate the risk of heart disease. Both patients and healthcare practitioners can benefit from the automated tools. The approaches and techniques utilized for CVD prediction are covered in this area of the research effort. These include the data collection procedure, data pre-processing, classification strategy, and metrics used to assess the approaches.

3.1 Dataset

The data set used in this work comes from the Kaggle database and includes a total of 14 attributes. The dataset is further divided into 80-20 train to test split is used however no specific optimizer is used for this work.

The learning rate applied during training 0.001 and batch size is used in 64 and Epoch is 50.

For the age distribution attribute, Fig. 2 represents the people with CVDs and people with no CVDs commonly. It can be viewed that maximum measurements exist between 40- 52 years old. It is also realized that if age has a relation to having CVDs, then people in the age range from 50-52 and 40-41 had a dominant consolidation with heart diseases. Furthermore, to depict the possibility of any relation, Fig. 1 represents the maximal correlated discrete feature (thalach) devised adjacent to age. It is observed that heart rate is commonly higher for people with heart disease as compared to people with no heart disease. Moreover, maximal heart rate decreased noted to a -ve correlated value of -0.3 as age increased. It is represented previously in Fig. 1.

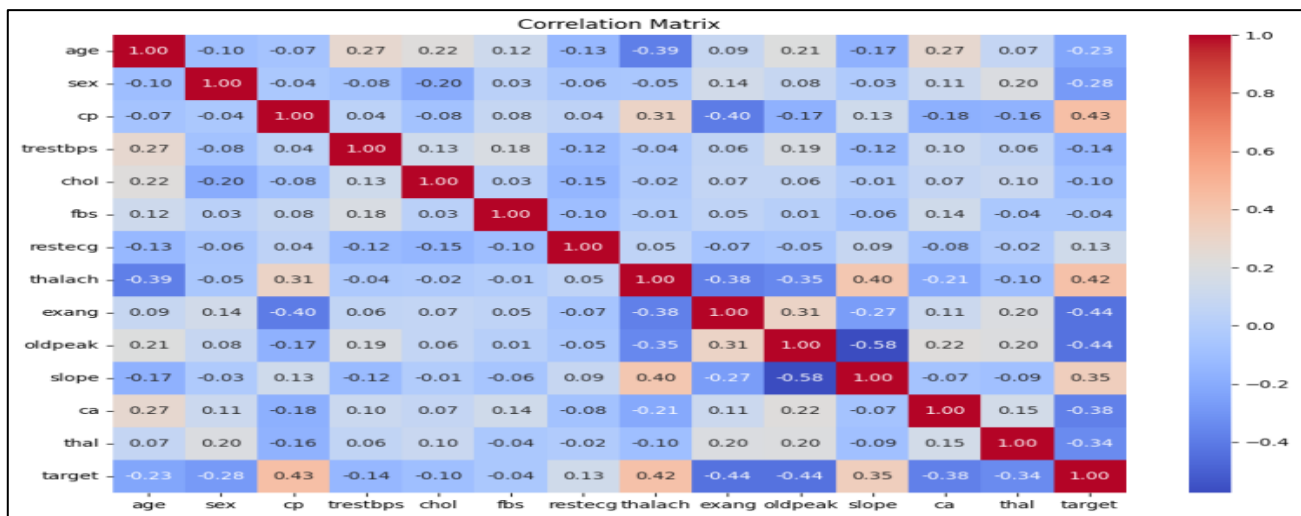


Figure 2: Correlation of matrix values

3.3 Statistical Analysis

To perform a thorough statistical analysis and determine the mean, max, min, and standard deviation for each attribute in the dataset, this study used Python code[9]. The arithmetic mean was found using the `mean()` technique from the `statistics` module, and the standard deviation was computed more easily with the help of `numpy` functions. The statistical analysis is presented in Figure 3, with a focus on high-accuracy measures for certain qualities such as ST Depression during Exercise (Oldpeak), Thal, Chest Pain (CP), Resting Blood Pressure (Trestbps), and the Slope of the ST segment (PSlope of ST). With accurate mean, max, and min values included in this study, attribute distributions can be understood in more detail.

The Python Standard Library included modules such as assays that enabled file operations. Boolean data, 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 find the least and greatest values. In conclusion, the rigorous statistical analysis, which includes mean, maximum, minimum, and standard deviation, provides a thorough examination of the dataset. This method assists in identifying patterns and insights related to heart disease diagnosis (Target).

3.4 The Heart Disease Prediction System Based On Deep Learning

This research program aims to create a decision support system that can forecast a person's risk of heart disease. The methodology makes use of two deep-learning models designed specifically for diagnosing cardiovascular disorders (CVD). GRUs (Gated Recurrent Units) and LSTMs (Long Short-Term Memory networks) outperform conventional RNNs (Recurrent Neural Networks) due to their ability to handle long-term dependencies and avoid the gradient vanishing problem. LSTMs capturing complex dependencies, while GRUs are faster and use fewer parameters. However, for natural

language processing (NLP) tasks that require managing parallelization and long-range dependencies, Transformers generally perform better.

For structured data, multilayer perceptron (MLPs) are effective, while convolutional neural networks (CNNs) excel in image tasks. LSTMs and GRUs are still recommended for time-series forecasting and speech recognition, especially with short datasets where Transformers may be too resource-intensive. In the following section of the paper, we provide an in-depth analysis of the GRU and LSTM models used in CVD classification. The analysis that follows provides light on the nuances of these approaches and how each improves the accuracy and effectiveness of heart disease evaluations in the context of a decision support system.

3.4.1 GRU

A type of recurrent neural network (RNN) called the Gated Recurrent Unit (GRU) was created to effectively capture long-range dependencies in sequential data and solve the vanishing gradient problem. GRU units are made up of gating mechanisms, such as update and reset gates, which control the retention and updating of information over time and regulate the flow of information within the network. GRU networks mitigate the problems of vanishing gradients found in classic RNN architectures and are capable of efficiently capturing temporal dependencies in sequential data by adaptively updating the hidden state based on input and previous hidden states. Because of this, GRUs work well in applications where it's critical to simulate long-term dependencies, like natural language processing, time series analysis, and sequence generation.

Here are the steps involved in the GRU algorithm:

Step 1: Define the parameters for the data.

Step 2: Predefined parameters serve as the foundation for the models.

Step 3: Data are saved and submitted to begin pre-processing.

Step 4: Key phases include encoding categorical data, scaling features, missing values, and clean data.

Step 5: Cross-validation k-fold to data is conducted.

Step 6: The classifier's trained data.

Step 7: The use of GRU classifiers

Step 8: Repeat step 5 till step 7 through the end of training data

3.4.2 LSTM

Recurrent neural network (RNN) architecture with the Long Short-Term Memory (LSTM) type was created expressly to solve the vanishing gradient issue and capture long-range dependencies in sequential data[11]. Long-term storage memories (LSTMs) are made up of memory cells that can store data for a long time in addition to input, output, and forget gates that control the information flow in the network. LSTMs can efficiently capture temporal patterns and dependencies in sequences because of these gates, which allow them to selectively update and retain information over numerous time steps. For tasks like speech recognition, natural language processing, and time series prediction, where correct modelling depends on a grasp of context and long-term interdependence, LSTMs are hence well-suited.

Here are the steps involved in the LSTM algorithm:

Step 1: Gather data from the length of the sequence LSTM, with each input provided as a respectable vector.

Step 2: Initialise the hidden state and cell state to zeros or tiny random values. The LSTM requires the initialization of a set of weights and biases.

Step 3: Determine how much of the earlier cell state to forget by calculating the forget gate. The sigmoid function, the bias, and the weight matrix for the forget gate are calculated as sigma.

Step 4: Determine the input gate's value, which establishes the amount of newly acquired data that should be stored in the cell state. To determine the bias and weight matrix for the input gate.

Step 5: Determine the candidate cell state, which is the new cell state that is being proposed. The weight matrix for the bias and candidate cell state.

Step 6: Use the input and output gates to combine the desired cell state with the prior cell state to update the cell state. Where it indicates element-wise multiplication, it is calculated.

Step 7: Determine how much of the cell state to output as the concealed state by calculating the output gate. Sigma is computed along with the bias and the weight matrix of the output gate.

Step 8: Output: Apply the output gate to the cell state to calculate the hidden state.

Step 9: To obtain the final hidden states, repeat steps 3 through 8 for each time step in the input sequence. The final hidden states of the neural network can be transferred to additional layers or utilized for prediction.

3.5 Metrics Used

According to the dataset table, metrics are used to optimize the dataset to achieve high data accuracy. F1-Score, Recall, Precision, and support are used in the evaluation process to make sure that the data is accurately assessed and refined[12]. The metrics for classification performance that are most frequently employed are accuracy (ACC), precision (PRE), recall (REC), and F1-score (F1). In contrast to the True Positive (TP), which denotes that the person is ill and the test is positive, the True Negative (TN) shows that the person is healthy and the result is negative. False positives are tests that come back positive even when the subject is healthy (FP). When a test is negative, but the subject is ill, it is known as a false negative (FN).

$$ACC = \frac{TP+TN}{TP+TN+FP+FN} \quad - (1)$$

$$RECALL = \frac{TP}{TP+FN} \quad - (2)$$

$$PRECISION = \frac{TP}{TP+FP} \quad - (3)$$

4. RESULTS AND DISCUSSIONS

In this study, two classification techniques GRU and LSTM are applied to a dataset of cardiac conditions. This section discusses the experiment's outcome and the statistical analysis and assessment metrics used for deep learning algorithms in the research work [13]. The collection contains a total of 1025 patient records. The dataset is used to create two sets: a training set and a testing set. The experiment makes use of Python scripts for assessment, categorization, and statistical analysis. Two-dimensional confusion matrices show the results of using neural networks on training datasets. The confusion matrix makes it easy to understand which classifications are correct.

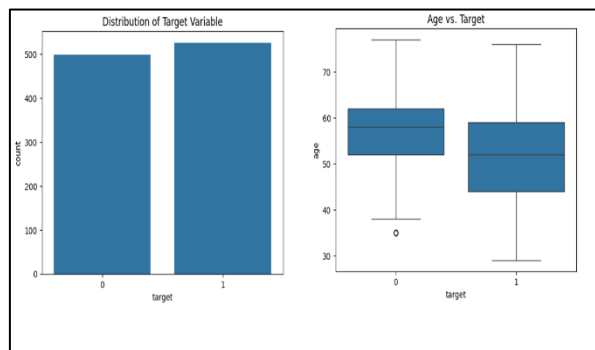


Figure 3: Target value and Age Comparison

Figure 3 depicts the statistical analysis made on the data set used for the research work. The analytics include mean, std, min, max, and count of the attributes involved in the research work.

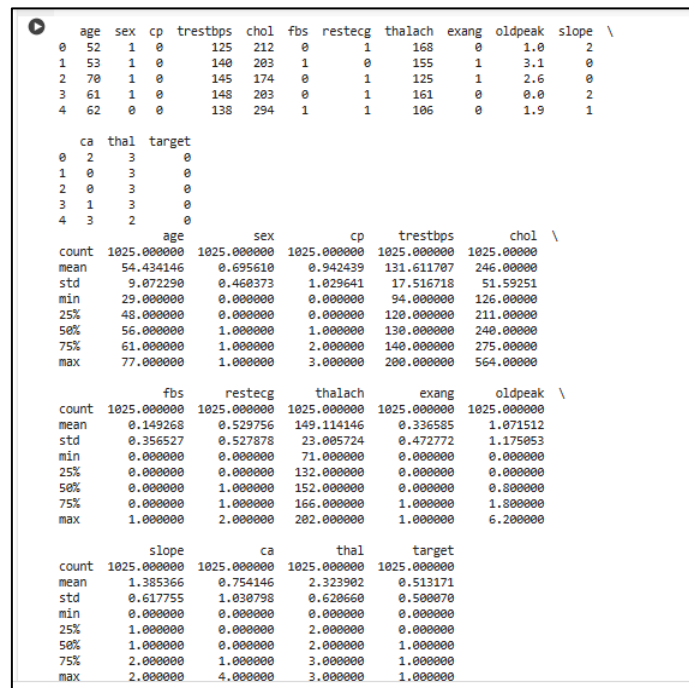


Figure 4: Statistical Analysis of CVD

The result of the deep learning algorithm is displayed in the table 4. The result shows that the accuracy of GRU is 80 % which is 12% more compared to the LSTM model, which has 58 % accuracy. Similar to the accuracy the precision of GRU is 92% whereas for LSTM it is 54%. 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 GRU.

Table 2: LSTM Classification Report

	Precision	Recall	F1-score
NHD	0.54	0.99	0.70
HD	0.94	0.17	0.28
Macro Avg	0.74	0.58	0.49
Weighted Avg	0.74	0.58	0.49

The precision for no heart disease (NHD) is 0.54% and the recall is 0.99% in Table 2, where the LSTM accuracy is 0.58%. Similarly, the F1 score is 0.70%. Regarding heart disease (HD), the F1 score is 0.28%, recall is 0.17%, and precision is 0.94%. In a similar vein, the LSTM achieves an overall accuracy that is 0.58% higher than that of the weighted average (0.74%), recall (0.58%), and F1-score (0.49%).

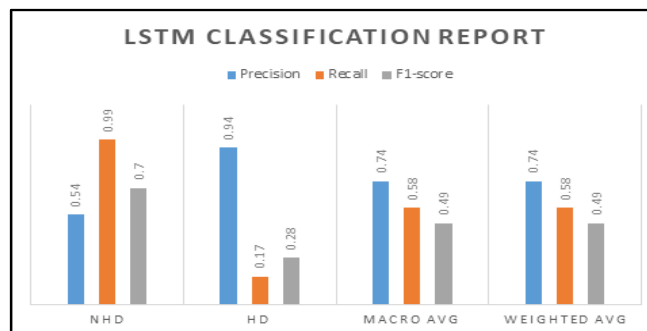


Figure 5: LSTM Classification report

Table 3: GRU classification report

	Precision	Recall	F1-score
NHD	0.92	0.65	0.76
HD	0.73	0.94	0.82
Macro Avg	0.82	0.79	0.79
Weighted Avg	0.82	0.80	0.79

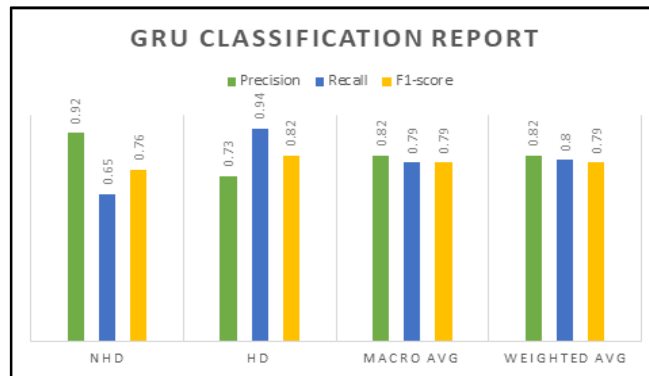


Figure 6: GRU classification report

When we take the heart disease (HD) the precision is 0.73%, recall is 0.94%, and F1 score is 0.82%; similarly, the overall accuracy achieved by the GRU is 0.80% more over when we take the weighted average, which is 0.82%, recall is 0.80%, and F1-score is 0.79%. In Table 3, when we take the GRU accuracy is 80%, hence precision for No heart disease (NHD) is 0.92% and recall is 0.65%, similarly, the F1 score is 0.76%.

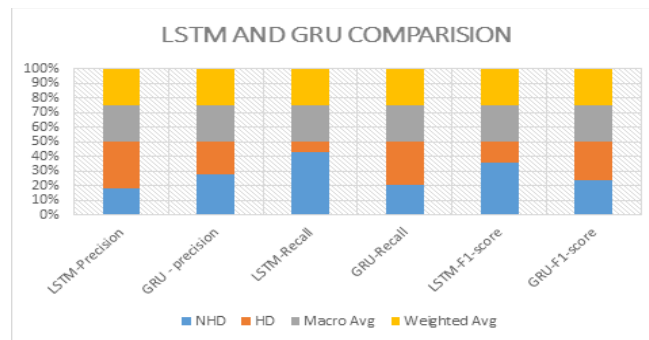


Figure 7: LSTM AND GRU COMPARISON

When we compare the GRU and LSTM, GRU accuracy is 80% and LSTM accuracy is 58%, so, we conclude that the accuracy of GRU is better in this research, similarly, we take the precision of class1 LSTM gives 0.54 and GRU as 0.92, so precision for NHD in GRU is 0.92 which is high compare to LSTM. When we take the heart disease class the precision for LSTM is 0.94% and 0.73% for GRU so the LSTM is high compared with GRU.

Table 4: Result of Deep Learning Model

Metrics	GRU	LSTM
F1 Score	79	49
Precision	82	74
Recall	80	58
Accuracy	80	58

The Table 4 outcomes are plotted on the graph that is available in Figure 6. 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 58 % for LSTM shows that the LSTM model is good in identifying positive instances, however, the GRU lacks in identifying the same with 80%. The F1 score of 79% for GRU shows that the model has a good balance between precision and recall.

As demonstrated in Figure 8 final analysis, our research found that combining GRU and LSTM yields the best classification approach for the dataset on heart disease prediction generated from the graph below for various features.

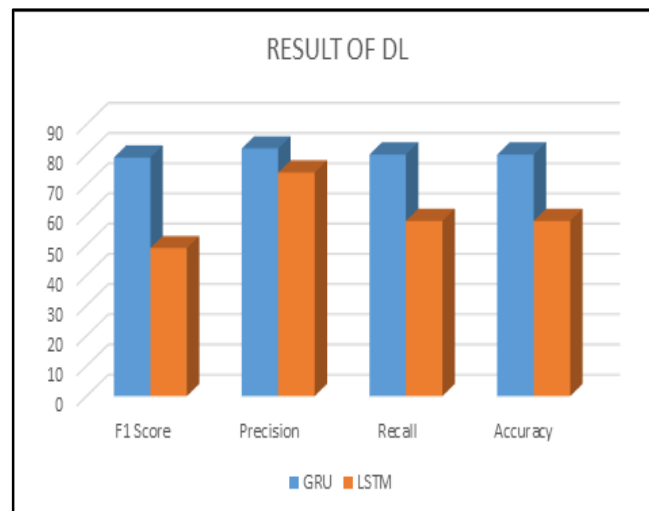


Figure 8: Metrics of Classification Algorithm

The neural network analysis technique given in this research work produced the best results when comparing the GRU and LSTM algorithms, delivering the best results of GRU with 80% and LSTM with 58% accuracy, to predict heart disease using 14 features. As a result, whereas GRU surpasses LSTM in terms of accuracy, precision, and F1 score, MNN performs better in recall. According to the study's findings, one of these two models' hyperparameters may need to be further refined to improve or change the performance of the measures.

CONCLUSION

In summary, the use of deep learning and machine learning algorithms for the prediction of heart attacks holds great potential for the future. Medical collection has been the subject of a great deal of research lately. In this field, a lot has been agreed upon, but considerable work remains. Since there hasn't been much study on the assessment of heart attack prediction using deep learning techniques, the goal of this work is to boost accuracy through the application of deep learning algorithms. This work can open up new avenues for further accuracy improvement using various deep-learning algorithms, such as LSTM and GRU algorithms. Deep learning techniques have been compared.

The dataset is processed into F1-Score, Recall, Precision, and Support vectors using the technique to provide data correctness. When it comes to overall accuracy, the GRU model performs exceptionally well (80%) compared to 58% for the LSTM. These metrics verify our simulation's stability and its capacity to successfully strike a balance between precision and recall. The study's conclusions show that when compared to the GRU, the LSTM performs with greater accuracy and precision. Nonetheless, in terms of Recall, the GRU outperforms the LSTM. Consequently, it can be concluded that further hyperparameter optimization for either of these models may improve or modify the overall performance metrics. A similar procedure will be used in the following work with attribute optimization.

REFERENCES

[1] Ms. Komal S. Jaisinghani, Dr. Sandeep Malik, "Design of an Augmented Varma GRU & LSTM Based Multimodal Feature Analysis Model for Enhancing Heart Disease Preemption Performance", 'International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING', ISSN:2147679921, pp 184-195.

[2] Asma Baccouche, Begonya Garcia-Zapirain, Cristian Castillo Olea and Adel Elmaghraby, "Ensemble Deep Learning Models for Heart Disease Classification: A Case Study from Mexico", Information 2020, 11, 207; doi:10.3390/info11040207.

- [3] Irfan Javid, Ahmed Khalaf Zager Alsaedi, Rozaida Ghazali, "Enhanced Accuracy of Heart Disease Prediction using Machine Learning and Recurrent Neural Networks Ensemble Majority Voting Method", International Journal of Advanced Computer Science and Applications (IJACSA), Vol. 11, No. 3, 2020.
- [4] Ahmed Almulihi, Hager Saleh, Ali Mohamed Hussien, "Ensemble Learning Based on Hybrid Deep Learning Model for Heart Disease Early Prediction", Diagnostics 2022, 12, 3215, <https://doi.org/10.3390/diagnostics12123215>.
- [5] Surenthiran Krishnan, Prithheega Magalingam, Roslina Ibrahim, "Hybrid deep learning model using recurrent neural network and gated recurrent unit for heart disease prediction", International Journal of Electrical and Computer Engineering (IJECE), Vol. 11, No. 6, December 2021, pp. 5467~5476.
- [6] Omankwu, Obinnaya Chinecherem & Ubah, Valentine Ifeanyi, "Hybrid Deep Learning Model for Heart Disease Prediction Using Recurrent Neural Network (RNN)", NIPES Journal of Science and Technology Research 5(2) 2023, pp. 184-194 ISSN-2682-5821.
- [7] Abdelmegeid Amin Ali, Hassan Shaban Hassan, "Heart Diseases Diagnosis based on a Novel Convolution Neural Network and Gate Recurrent Unit Technique", 978-1-7281-3052-1/ 2020, IEEE.
- [8] S.Narmadha, S.Gokulan, M.Pavithra, R.Rajmohan, Dr.T.Ananthkumar, "Determination of various Deep Learning Parameters to Predict Heart Disease for Diabetes Patients", IEEE, ICSCAN, 2020.
- [9] M.Pavithra, Dr.K.Saruladha, K. Sathyabama, "GRU Based Deep Learning Model for Prognosis Prediction of Disease Progression", Proceedings of the Third International Conference on Computing Methodologies and Communication (ICCMC 2019), IEEE Xplore Part Number: CFP19K25-ART; ISBN: 978-1-5386-7808-4.
- [10] Mana Saleh Al Reshan, Samina Amin, Muhammad Ali Zeb, "A Robust Heart Disease Prediction System Using Hybrid Deep Neural Networks", Digital Object Identifier, 10.1109/ACCESS.2023.3328909.
- [11] CMM. Mansoor, Sarat Kumar Chettria, HMM.Naleer, "Efficient Prediction Model for Cardiovascular Disease Using Deep Learning Techniques", Migration Letters Volume: 20, No: S13(2023), pp. 449-459 ISSN: 1741-8984 (Print) ISSN: 1741-8992.
- [12] Randa Shaker Abd-Alhussain, Hadab Khalid Obayes, Farah Al-Shareefi, "Utilizing Synthetic Tabular Data Method to Improve Heart Attack Prediction Accuracy", Al-Salam Journal for Engineering and Technology Journal Homepage, <http://journal.alsalam.edu.iq/index.php/ajest>, e-ISSN: 2790-4822p-ISSN: 2958-0862.
- [13] Pushparaj S, Sanjay N, Sivasankaran M, Thamizh Chem-mal S, "Prediction of Heart Disease Using Hybrid of CNNLSTM Algorithm", Journal of Survey in Fisheries Sciences, 10(1S) 5700-5710.
- [14] <https://www.kaggle.com/datasets/colewelkins/cardiovascular-disease/data>