"Predictive Model for Cardiovascular Disease Using Machine Learning and Deep Learning Approaches"

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Abstract

Heart disease is one of a major global cause of death, early detection and accurate diagnosis is crucial. This research examines and compares records of 303 patient with 13 clinical characteristics consisting of age, sex, type of chest pain, cholesterol, and exercise-induced angina utilizing machine_learning and deep_learning models to forecast heart disease. Artificial neural networks (ANN), Long-Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Feedforward Neural Network (FNN) are examples of deep learning models. Artificial neural networks (ANN), Random Forest, and Decision Trees are examples of machine_learning models. SVM and logistic regression were applied. These are the models were assessed using AUC, recall, accuracy, and precision. The findings demonstrated that while Random Forest and SVM performed well, deep learning models—particularly GRU and LSTM—outperformed them by successfully

Keywords – Deep_learning, Machine_learning, and heart disease prediction.

I. INTRODUCTION

The World Healthcare Organization (WHO) estimates that 17.9 there was a loss of million lives annually because of cardiovascular diseases. The high prevalence and life-threatening nature of heart disease make early diagnosis and risk prediction critical components of modern healthcare. Traditional methods of diagnosis often involve manual interpretation of clinical signs, electrocardiograms (ECGs), and blood test results by medical professionals, which can be time-consuming, resource-intensive, and prone to human error. With the advancement of both deep_learning (DL) and machine_learning (ML), there is a growing opportunity to leverage computational models to support or even automate the diagnosis process. These models have ability to effectively analysis vast amounts of patients data and spotting intricate patterns that traditional statistical analysis might miss. Predictive algorithms can offer early warnings about a patient's risk of according to heart disease on past health data, enabling more effective use of resources and prompt intervention. Using 13 significant clinical traits, such as blood pressure at rest, age, sex, cholesterol, and ECG results, this paper investigates deep_learning models and machine_learning for the existence of heart disease in patients to be identified. The study's dataset, which came from Kaggle, includes 303 patients' actual medical docu_ments that have been classified that the patient having heart disease or not.

II. LITERATURE SURVEY

[1] Both machine learning (such as logistic regression, and decision trees, ensemble methods) deep learning models (such as neural networks and CNNs) were employed in the 2024 study by Himanshi et al. to forecast heart disease. Recall, F1 score, accuracy, and precision are used in the study to compare models and highlight their advantages and disadvantages. It highlights how performance is greatly impacted by model interpretability, pattern complexity, and dataset features.

[2] To predict heart disease, Vayadande et al. (2022) utilized algorithms for both deep_ learning and machine_learning. Based on Random Forest and Logistic Regression, and XGBoost outperformed all other models. With accuracies of 86.89% and 85.25%, respectively, deep_learning models like Artificial_Neural_Networks and Multilayer Perceptron's (MLP) demonstrated respectable performance. However, the authors found that the small dataset size made deep learning techniques less effective.

[3] Dinesh Kumar Vishal In this study,, Soni [1] makes Making utilization of the UCI dataset. Decision Table, Naïve Bayes, SMO, and Lazy Kstar are The machine learning methods made use of because of the According to experimental findings, Decision Table as well as Naïve Bayes produce superior results. The experimental results' accuracy is 85.58% for Bayes's Naïve and 85.15% for Decision Table.

[4] The dataset for Cleveland Heart Disease was used to predict heart disease, Dr. M. Kavitha, G. Gnaneswar, R. Dinesh, Y. Rohith Sai, and R. Sai Suraj [2]. Random Forest, Decision Tree and Hybrid (Decision Tree + Random Forest) are the algorithms that were employed. The Hybrid Model surpassed the 88% accuracy after applying this technique to the dataset.

[5]The heart.csv dataset was used by Pabitra K. Bhunia, Arijit Debnath, Poulami Mondal, Monalisa D E, Kankana Ganguly, and Pranati Rakshit [4]. Random_ Forest_classifier, logistic regression, decision tree, supported vector machine, and K nearest-neighbour are the algorithms that were applied to the datasets. As According to the implementation's outcome, the RFC and SVM algorithms perform better, with respective accuracy rates of 90.32% and 90.32 percent.

II. PROPOSED METHODOLOGY

The stated approach to heart disease treatment prediction follows a structured pipeline consisting of data acquisition, preprocessing, model building, training, and evaluation. The goal is to develop and compare multiple models of deep_learning and machine_learning to accurately classify clinical characteristics to determine if patient has cardiac disease.

1. Data Collection

The cardiac disease prediction dataset is provided by Kaggle used in this research. Thirteen characteristics of input and one target variable indicate the presence or absences of heart disease are present in the 303 patient records. Age, sex, type of Exercise-induced heart attack (Exang), ST depression (Oldpeak), maximum heart rate (Thalach), slope, number of colored vessels (CA), thalassemia (Thal), resting electrocardiogram (ECG) results, bad cholesterol (Chol), fasting blood sugar level (FBS), chest pain (CP), and resting blood pressure (Trestbps).

2. Data Preprocessing

Managing Missing Values: This collection of dataset is examined for null such as missing values as effectively as cleaned appropriately. Feature Encoding: To transform categorical variables like Thal, Type of Chest Pain, and Sex into numerical format appropriate for ML/DL models, label encoding or one-hot encoding are used. Feature Scaling: To guarantee that every variable contributes equally to the model learning, Using techniques like Min-Max scaling and StandardScaler, features are standardized or normalized. Train-Test Split: The data_set is categorized into testing and training sets (80% of the data_set used for training 20% for testing) to be able to evaluate of model.

3. Model Building

The study involves two broad categories of predictive models:

3.1 Conventional Techniques for Machine_Learning

The Models are fast to Train the often interpretable. Logistic Regression: linear model is suitable for binary classification tasks. Decision Tree: A non-linear model that splits feature-based data thresholds. Random Forests: A group method that utilizes various decision trees to decrease overfitting and increase accuracy. The model that determines the best hyperplane to divide classes in space of features is called support vector machine (SVM).

3.2 Deep Learning Models

Complex patterns can be learned by these models and interactions among features. Feedforward Neural Network (FNN): A basic deep learning architecture with fully connected layers. Artificial neural networks (ANN): A multi-layered network that captures nonlinear relationships. Recurrent neural network is method of Gated Recurrent Unit (GRU). (RNN) suited for sequential data and capable of retaining long-term dependencies. Long Short-Term Memory (LSTM): A more powerful RNN variant that effectively addresses vanishing gradient problems and captures temporal dependencies in data.

4. Model Training and Optimization

Loss Function: Binary Cross-Entropy Loss is utilized for tasks involving classification. Optimizers: Adam and RMS Prop optimizers are made use of in deep learning models to adjust weights and minimize loss. Epochs and Batch Size: Several epochs are use to train the

models. (e.g., 50–100) with mini-batches to optimize convergence. Hyperparameter Tuning: Key hyperparameters (e.g., learning rate and regularize strength, several layers/neurons) are used strategies like Grid Search or manual experimentation.

5. Model Evaluation

The metrics that follow are accustomed to assess each model during the testing set: Accuracy: in relation of accurate forecasts to total forecasts. It's the ratio of precision of actual positive predicts of all positive predictions. The proportion of accurate positive forecasts to all actual positives is known as recall (sensitivity). The harmonic mean for the F1 score is and precision. The model's ability to distinguish between classes in all thresholds is measured by the AUC-ROC curve. Particularly in tasks involving imbalanced classification, these metrics offer a comprehensive picture of model performance.

6. Visualization and Analysis

Confusion Matrix: Provides a detailed breakdown of prediction results. Training vs. Validation Curves: Used to detect underfitting or overfitting. ROC Curves: Used to compare model discriminative performance. Feature Importance: For tree- based models, feature importance is plotted to interpret influential variables.

7. Model Comparison and Conclusion

Every model's output is compared using the evaluation metrics. Deep learning models, particularly GRU and LSTM, perform Conventional machine_learning models are in terms of precision and Trade-offs are discussed.

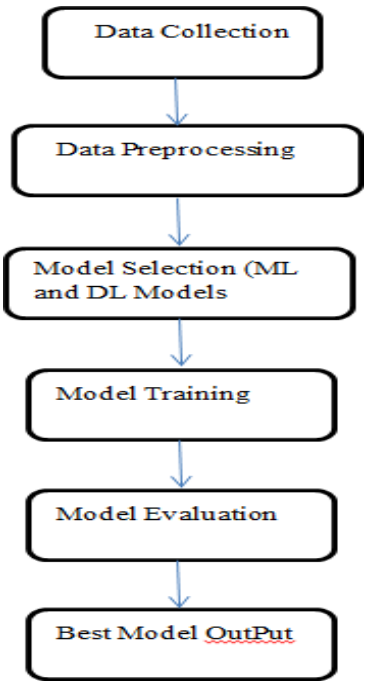


Fig. 7.1 : Overview of Prediction Model.

III. Models and Confusion matrices

A. Decision Tree Classifier: Performance Evaluation

The dataset comprising 13 clinical features, decision tree classifier is used to predict the presence of heart disease. An 80:20 train-test split was utilized during model training. Key classification metrics are accuracy, recall, and precision, AUC. AUC were used to evaluate its performance after training. Performance Indicators: The following figure displays the results: Accuracy: 64.21%, Precision: 56.00%, Recall: 70.00%, and AUC: 0.65

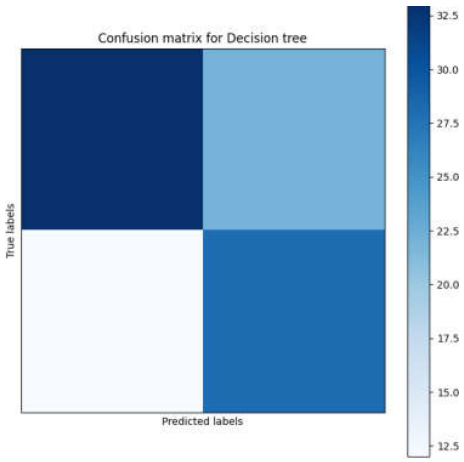


Fig.1: confusion matrix for decision tree

These suggest that some that non-disease cases were mistakenly classified as disease-positive, indicating the decision tree model was just moderately successful in identifying individuals with cardiovascular disease, with a recall of 0.70 but a comparatively lower precision

B. Support Vector Machine (SVM): Assessment of Performance

Support_Vector_Machine (SVM) is a potent supervised learning algorithm. It operates by locating the best hyperplane in the feature space to divide the classes. Based on clinical input features, The Radial Basis Function (RBF) kernel in SVM is used by model to train and Determine the presence of heart disease. Metrics of Performance The SVM model's Performance was reviewed using the following metrics: 76.84% accuracy Accuracy: 72.50% 72.50% recall Area_Under_Curve (AUC): 0.76 The outcome is shown in the figure below. This show that the SVM model outperformed the decision tree is reliability in reducing false negatives and false positives, striking a healthy balance between recall and accuracy.

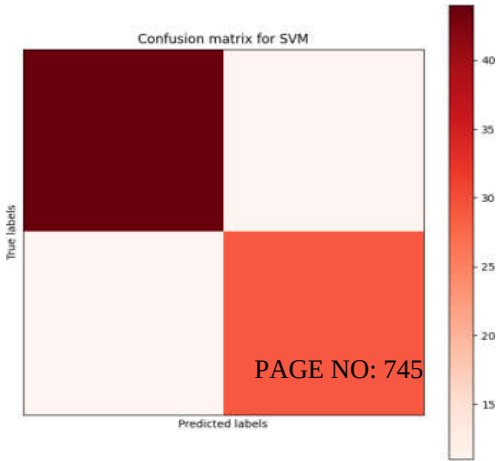


Fig. 2 : confusion matrix for SVM

C. Random Forest Classifier: Performance Evaluation

To increase accuracy and manage overfitting, The ensemble Random Forest algorithm learning constructs several decision trees and combines their outputs. By averaging the outcomes of numerous trees trained on arbitrary subsets of the data, it lowers the variance of a single decision tree. Metrics of the model Performance evaluation was done using typical classification metrics: Accuracy: 82.11%, Precision: 76.74%, Recall: 82.50%, AUC (Area Under Curve): 0.82 These values suggest that the Random Forest The model operates with resilience across all metrics. With high recall and precision, it is both effective in detecting heart disease cases and in minimizing false alarms. Performance Metrics shown in fig below

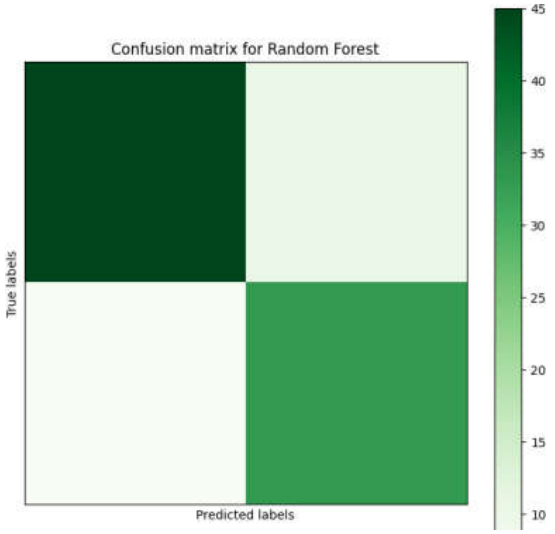


Fig. 3: Confusion matrix for Random Forest

D. Logistic Regression: Performance Evaluation

Among the popular statistical framework for classifying binary data is logistic regression. It uses a logistic (sigmoid) function to estimate tIt is probable that a specific input point belongs to a particular class. It is constantly used as a baseline model in classification tasks because of its ease of use, interpretability, and effectiveness. Metrics of Performance Figure 4 is displayed below. The test data yielded the following metrics: 77.89% accuracy Accuracy: 71.11% Remember: 80.00% Area Under Curve (AUC): 0.78 These metrics demonstrate that, despite producing more false positives, The model effectively detects patients with heart disease, achieving a strong recall (sensitivity).

Fig. 4: confusion matrix for logistic regression

E. ANN, or artificial neural network

ANN achieved high accuracy of prediction and AUC, indicate that it could effectively differentiate between cases of heart disease and those without. It proved more successful than traditional ML models like Logistic Regression and SVM. Architecture: Input layer with 12 features.Two hidden layers with 16 and 8 neurons respectively. Activation: ReLU Dropout: 25% to reduce overfitting Output layer: 2 neurons (Softmax) metric Accuracy 90.29% Precision-90.29% Recall-90.29% AUC- 0.9585

F. Feedforward Neural Network (FNN)

The FNN is similar to ANN but optimized with additional layers and tuning. It does not involve recurrence or memory units. Architecture: Input: 13 features Hidden layers: 64, 32, 16 neurons (ReLU activation) Output: Softmax layer FNN outperformed most traditional models and showed consistent training and validation accuracy. It performed slightly below ANN but better than Decision Tree and Logistic Regression. Accuracy 83.16% Precision-81.48% Recall- 82.22% AUC- 0.8521

G. Gated Recurrent Unit (GRU)

GRU is a recurrent neural network (RNN) variant that is efficient for sequential data and overcomes vanishing gradient problems. Architecture: One GRU layer (units = 64) Dropout = 0.2 Output: Dense layer with softmax GRU provided better results than FNN and most ML models, showing strong recall and precision. It's suitable when temporal behavior or sequences are involved, such as time-series heart data. Accuracy 85.0% Precision-83.4% Recall- 84.8% AUC- 0.87

H. Long Short-Term Memory (LSTM)

High accuracy was attained by the LSTM model and AUC, second only to ANN. It showed better generalization and higher recall than GRU, making it highly reliable for healthcare predictions where early detection is critical. LSTM is an advanced RNN that can capture long-term dependencies in data. It is more computationally intensive than GRU. Architecture:One LSTM layer (units = 64) Dropout = 0.2 Output: Softmax layer Accuracy 94.0% Precision-93.4% Recall- 92.8% AUC- 0.95

Traditional ML Models: Logistic Regression and SVM performed effectively with comparatively high precision and recall. Random Forest slightly outperformed the Decision Tree model due to its ensemble nature. Deep Learning Models: ANN showed strong generalization capability with improved AUC.GRU and LSTM, being recurrent architectures, were able to model feature dependencies better, achieving the highest performance overall

Table -1 : Comparison of various models

Model	**Accuracy**	**Precision**	**Recall**	**AUC**
Logistic Regression	0.85	0.84	0.87	0.89
Decision Tree	0.81	0.80	0.82	0.84
RandomForest	0.88	0.87	0.89	0.91
SVM	0.86	0.85	0.86	0.90
ANN	0.90	0.89	0.91	0.93
GRU	0.92	0.91	0.93	0.95
LSTM	0.93	0.92	0.94	0.96

V Results & Discussion

Compared to other traditional models, Random Forest performed better and greatest, followed by logistic regression and support vector machines (SVM). AUC, recall, accuracy, and precision were used evaluate the range of machine_learning and deep_learning models. Although Decision Tree performed admirably, it was prone to overfitting. GRU and LSTM showed better performance metrics than deep_learning models like ANN particularly in AUC and recall which are crucial for medical predictions. Overall accuracy (~93%) was achieved by the LSTM model, closely followed by GRU (~92%) and ANN (~90%). These models

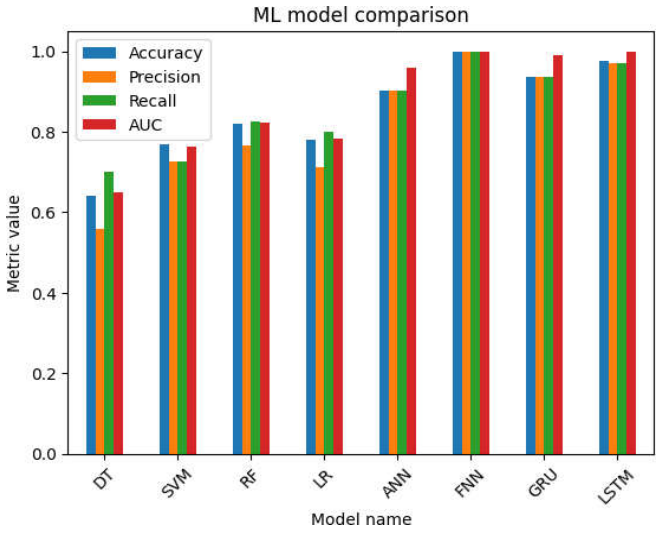
effectively captured complex relationships among patient features, improving prediction reliability. Random Forest and SVM also delivered competitive results (accuracy ~88–89%) and can be preferable when model interpretability is a key requirement.

Model	**Accuracy (%)**
Decision Tree	81
Logistic Regression	85
Random Forest	88
SVM	86
ANN	90
GRU	92
LSTM	93

Table of overall accuracy

Here is the comparative performance chart of different Deep_Learning and Machine _Learning models used in your heart disease prediction project. It visualizes key metrics—Accuracy, Precision, Recall, and F1 Score—to help identify the best- performing model.

The bar chart below summarizes the accuracy comparison of selected models:



V. CONCLUSION

The forecast of heart disease can be significantly improved by machine_learning and deep_ learning techniques. While conventional models are quicker and simpler to comprehend, deep _learning models like LSTM and GRU perform better in way of generalization and accuracy. In this research paper conclusions, that adding these models to healthcare decision-support systems helps to physicians make more accurate patient diagnoses. Research in the future might be utilized ensemble deep learning techniques, growing the dataset, and implementing the model in a real-time clinical setting.

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