Prediction of Cardiac Disease Detection using Optimized Deep Learning Model

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Abstract: Cardiovascular disease (CVD) remains the leading cause of global mortality, necessitating early detection to prevent severe complications such as heart attacks, strokes, and heart failure. Traditional diagnostic methods, including clinical evaluation, laboratory tests, and electrocardiography (ECG), are often time-consuming, subjective, and prone to human error. This study proposes an optimized deep learning framework for cardiac disease prediction, combining Convolutional Neural Networks (CNN) with bidirectional Long Short-Term Memory (Bi-LSTM) layers and the Adam optimizer. The model leverages feature selection and hyperparameter tuning to enhance predictive accuracy and generalization, while explainable AI techniques such as SHAP and LIME ensure interpretability for clinical decision-making. The system was evaluated using benchmark datasets, including the UCI Heart Disease dataset, and compared against traditional machine learning models, including Logistic Regression, Support Vector Machines, Random Forest, and standard LSTM. Experimental results indicate that the proposed CNN-Adam model achieves superior performance with 93.75% sensitivity, 93.10% specificity, 93.44% accuracy, 93.75% precision, and 93.75% F1-score, while maintaining minimal false positive and false negative rates. These findings highlight the model's reliability for early cardiac risk detection and its potential integration into clinical decision-support systems. Future research will focus on real-time deployment using wearable devices, integration with electronic health records, hybrid deep learning architectures, and enhanced interpretability to establish a patient-centered smart cardiac monitoring framework. The study demonstrates that intelligent, optimized deep learning systems can significantly improve proactive cardiac care and preventive healthcare practices.

Keywords: Cardiac Disease Prediction, CNN-BiLSTM, Adam Optimizer, Explainable AI, Smart Healthcare.

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I. INTRODUCTION

Background

Cardiovascular disease (CVD) is the leading cause of mortality globally, accounting for millions of deaths annually. The early detection of heart disease is critical to prevent severe complications and improve patient outcomes. Traditionally, cardiac disease diagnosis relies on clinical evaluations, laboratory tests, and electrocardiogram (ECG) readings (Rubiś, 2022). However, these methods can be time-consuming, subjective, and prone to human error. In recent years, machine learning and deep learning techniques have emerged as powerful tools to automate the detection of cardiac disease, offering higher accuracy, faster predictions, and scalability for large patient datasets. Optimized deep learning models can capture complex nonlinear patterns in clinical and ECG data, thereby improving early diagnostic capabilities (Saikiran et al., 2024).

Motivation

Despite advancements in predictive modeling, many existing approaches face challenges, such as limited datasets, overfitting, and lack of interpretability. Classical machine learning models often fail to capture nonlinear interactions between clinical features, whereas deep learning models require extensive data and hyperparameter tuning (Tafirenyika, 2023). There is also a growing demand for real-time, reliable, and explainable cardiac disease prediction systems that can support clinical decision-making. The motivation for this research is to develop an optimized deep learning framework capable of accurately, efficiently, and interpretably detecting cardiac disease by leveraging feature selection and transfer learning techniques to overcome data limitations and enhance performance (Mall & Singh, 2023).

Main Contributions of Paper

- Development of an optimized deep learning model by combining CNN and bi-LSTM layers for cardiac disease prediction.
- Integration of feature selection and hyperparameter optimization to enhance model accuracy and generalization.
- Application of transfer learning concepts to leverage pre-trained models and reduce training requirements.
- Provision of interpretable predictions using explainable AI tools to support clinical decision-making.
- Extensive evaluation of benchmark datasets (e.g., UCI heart disease) demonstrating improved performance over classical and standard deep learning models.

Objectives

- To design and implement a robust deep learning framework for the prediction of cardiac diseases.
- To optimize model performance using feature selection, hyperparameter tuning, and transfer learning.
- To evaluate the model on benchmark datasets and compare it with traditional machine learning approaches.
- To ensure the interpretability of predictions for clinical usability using explainable AI techniques.
- To provide a framework that can be extended to real-time applications and wearable ECG monitoring.

Organization

The paper is organized into eight sections. Section I introduces a smart monitoring system for the early detection of cardiac disease and outlines the motivation for the study. Section II reviews related work. Section III identifies research gaps, Section IV presents the problem definition and objectives, Section V details the methodology, Section VI presents the results, Section VII concludes, and Section VIII discusses future work.

II. LITERATURE REVIEW

Cardiovascular disease (CVD) continues to be a leading cause of mortality worldwide, accounting for millions of deaths annually. The early detection of cardiac disease is crucial for effective treatment and improving patient outcomes. Traditionally, cardiac disease diagnosis relies on clinical examinations, laboratory tests, and electrocardiogram (ECG) readings, which can be time-consuming and dependent on physician expertise (Flores et al., 2022). With the emergence of machine learning and deep learning, automated prediction models have become increasingly popular, providing clinicians with tools that are both scalable and capable of real-time decision support (Sharma et al., 2025). Early research focused on classical machine learning approaches, such as logistic regression, decision trees, support vector machines, and random forests. Logistic regression provides interpretable models but is limited in handling complex nonlinear relationships in the data. Decision trees improved predictive accuracy but were prone to overfitting, whereas support vector machines and random forests demonstrated better performance on nonlinear and higher-dimensional datasets (Ahlawat, 2025). These traditional models established a baseline for cardiac disease prediction but have gradually been surpassed by deep learning approaches because of the latter's ability to automatically learn complex patterns from data (J & Pandi, 2025).

Deep learning models, including deep neural networks (DNNs), convolutional neural networks (CNNs), and recurrent neural networks such as long short-term memory (LSTM) and bidirectional LSTM, have demonstrated superior predictive capabilities (Basha et al., 2023). DNNs effectively model complex feature interactions, achieving higher accuracy than classical machine learning methods, particularly when combined with dropout and early stopping techniques to reduce overfitting. CNNs, although primarily designed for image data, have been adapted to process ECG and other time-series physiological signals, allowing the extraction of localized feature patterns (Yu, 2023). In particular, LSTM models capture temporal dependencies in ECG data, improving the detection of subtle waveform abnormalities. The integration of attention mechanisms in these recurrent architectures further enhances the model’s ability to focus on critical segments of the data that contribute the most to disease prediction (Mukhtar et al., 2025).

Recent studies have emphasized the importance of combining deep learning with optimization techniques and feature selection strategies. Metaheuristic algorithms, such as genetic algorithms, particle swarm optimization, and ant colony optimization, have been employed to tune model hyperparameters and select the most informative features, which significantly enhances predictive performance (Rakhshani et al., 2020). Ensemble deep learning methods that combine multiple models, such as CNN-LSTM hybrids, have been demonstrated to improve model robustness and stability, leading to higher accuracy and better generalization on unseen data (Tamanna et al., 2024). Explainable artificial intelligence (XAI) tools, including SHAP and LIME, have also been incorporated to interpret model decisions and identify key clinical features, such as age, cholesterol levels, and resting blood pressure, that influence predictions. This integration of explainability is crucial for clinical adoption, as it provides transparency and trustworthiness in model outputs (Reddy & Annamalai, 2025).

III. RESEARCH GAP

- Most existing models rely on small or single-center datasets, limiting generalizability to diverse populations.
- Real-time prediction from wearable devices is underexplored, restricting continuous monitoring applications.
- Few studies leverage transfer learning for tabular or ECG datasets, leaving potential for performance improvement unexploited.
- Many deep learning models lack explainability, making clinical adoption challenging due to low interpretability.
- Integration of feature optimization with temporal modeling is limited, reducing the efficiency and accuracy of predictions.
- There is a need for robust, hybrid models validated across multi-center datasets to enhance reliability.

IV. METHODOLOGY

The prediction of cardiac conditions using a Convolutional Neural Network (CNN) with the Adam optimizer is based on deep learning principles for automatic feature learning and efficient parameter optimization. In this approach, physiological signals such as ECG are used as input to the CNN model. The CNN extracts meaningful local patterns from the signal through convolution and pooling operations, while the Adam optimizer updates the network weights during training in order to minimize prediction error. This method is highly suitable for cardiac disease prediction because ECG and related biomedical signals contain hidden temporal and morphological patterns that can be learned effectively by CNN. The complete method can be explained in mathematical form as well as in documentation form. The mathematical form presents the equations used in the training and prediction stages, while the documentation explains each step of the algorithm in a structured and understandable manner.

Algorithm: CNN-Adam for Cardiac Condition Prediction

Step 1: Input Representation

Let the input cardiac signal dataset be represented by:

$$X = \{x_1, x_2, x_3, \ldots, x_n\}$$

where each x_i is an input sample such as an ECG segment, and n is the total number of samples. The corresponding target labels are:

$$Y = \{y_1, y_2, y_3, \ldots, y_n\}$$

where: $y_i \in \{0,1\}$

for binary classification:

- 0 = Normal cardiac condition
- 1 = Abnormal cardiac condition

For multiclass classification:

$$y_i \in \{1,2,3,\ldots,k\}$$

where k is the number of cardiac categories.

Step 2: Preprocessing and Normalization

The raw signal is normalized before being given to the CNN. A common min-max normalization is:

$$x_i' = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}$$

where: x_i = original signal value, x_i' = normalized signal value, $x_{\min}$ = minimum value in the signal, $x_{\max}$ = maximum value in the signal

This ensures that the input values lie in a uniform range.

Step 3: Convolution Operation (Iterate from step 3 to step 11 for each epoch)

The convolution layer applies a filter w over the input signal to extract local features.

For a 1D ECG signal, the convolution output at position t is: $z_t = \sum_{j=0}^{m-1} w_j \, x_{t+j} + b$

where: z_t = output of convolution at position t, w_j = filter weights, x_{t+j} = input signal values, b = bias term, m = size of the filter

This operation helps detect important waveform characteristics such as peaks, slopes, and local abnormalities.

Step 4: Activation Function

After convolution, a nonlinear activation function is applied. The most common one is ReLU:

$$a_t = \max(0, z_t)$$

where: a_t= activated output, z_t= convolution result

ReLU removes negative values and introduces nonlinearity into the model.

Step 5: Pooling Operation

Pooling reduces the dimensionality of the feature map and keeps the most important information.

For max pooling: $p_t = \max(a_t, a_{t+1}, \dots, a_{t+k-1})$

where: p_t= pooled output, k= pooling window size

This reduces computation and improves generalization.

Step 6: Flattening

The pooled feature maps are converted into a one-dimensional vector before entering the dense layer:

$$f = \text{Flatten}(P)$$

where: P= pooled feature map, f= flattened feature vector

Step 7: Fully Connected Layer

The dense layer computes: $h = Wf + b$

where: h= hidden layer output, W= weight matrix, f= flattened vector, b= bias vector

After this, another activation function may be applied.

Step 8: Output Layer

For binary classification, the sigmoid function is used:

$$\hat{y} = \sigma(h) = \frac{1}{1 + e^{-h}}$$

where: $\hat{y}$= predicted probability of abnormal cardiac condition

Decision rule: $\hat{y} = \begin{cases} 1, & \text{if } \hat{y} \geq 0.5 \\ 0, & \text{if } \hat{y} < 0.5 \end{cases}$

For multiclass classification, Softmax is used:

$$\hat{y}_i = \frac{e^{h_i}}{\sum_{j=1}^{k} e^{h_j}}$$

where: $\hat{y}_i$= probability of class i, k= total number of classes

Step 9: Loss Function

For binary classification, binary cross-entropy loss is:

$$L = -\frac{1}{n}\sum_{i=1}^{n}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

For multiclass classification, categorical cross-entropy loss is: $L = -\sum_{i=1}^{k} y_i \log(\hat{y}_i)$

The goal of training is to minimize this loss.

Step 10: Backpropagation

The gradients of the loss with respect to model parameters are computed: $g_t = \nabla_\theta L(\theta_t)$

where: g_t= gradient at iteration t, θ_t= parameters of the CNN at iteration t

These gradients are used by Adam to update the weights.

Step 11: Adam Optimizer Equations

Adam combines momentum and adaptive learning rate.

Step 11.1: First moment estimate

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

Step 11.2: Second moment estimate

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

Step 11.3: Bias-corrected first moment

$$\widehat{m}_t = \frac{m_t}{1 - \beta_1^t}$$

Step 11.4: Bias-corrected second moment

$$\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

Step 11.5: Parameter update

$$\theta_{t+1} = \theta_t - \alpha \frac{\widehat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

where: θ_t= current model parameters, θ_{t+1}= updated model parameters, α= learning rate, β_1= exponential decay rate for first moment, β_2= exponential decay rate for second moment, ϵ= small constant to avoid division by zero

Typical values are:

$$\alpha = 0.001, \beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$$

Step 12: Prediction Rule

After training, for a new cardiac signal x_{new}, the CNN computes: $\hat{y}_{new} = f(x_{new}; \theta^*)$

where: f = trained CNN model, θ^* = optimized parameters

Final class label: $C = \begin{cases} \text{Normal}, & \text{if } \hat{y}_{new} < 0.5 \\ \text{Abnormal}, & \text{if } \hat{y}_{new} \geq 0.5 \end{cases}$

V. RESULTS AND DISCUSSION

The table 1 presents a comparative performance analysis of five prediction techniques used for cardiac disease prediction, namely Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), Long Short-Term Memory (LSTM), and CNN-Adam (Proposed). The comparison is based on important evaluation metrics such as Sensitivity, Specificity, Accuracy, False Positive Rate, False Negative Rate, Precision, and F1-Score. These metrics collectively help in understanding how effectively each model identifies patients with and without cardiac disease.

Table 1: Comparison study of different metrics for cardiac disease prediction

Prediction Techniques	Sensitivity (%)	Specificity (%)	Accuracy (%)	False Positive Rate (%)	False Negative Rate (%)	Precision (%)	F1-Score (%)
LR	90.63	86.21	88.52	13.79	9.38	87.88	89.23
SVM	84.38	89.66	86.89	10.34	16.63	90.00	87.10
RF	84.38	82.76	83.61	17.24	15.63	84.38	84.38
LSTM	87.88	71.43	80.33	28.57	12.12	78.38	82.86
CNN-Adam (Proposed)	93.75	93.10	93.44	6.90	6.25	93.75	93.75

Among all the techniques, CNN-Adam (Proposed) shows the best overall performance. It achieved the highest Sensitivity of 93.75%, which means it is highly effective in correctly identifying patients who actually have cardiac disease. This is a very important measure in medical diagnosis because higher sensitivity reduces the chance of missing diseased patients. The proposed model also recorded the highest Specificity of 93.10%, indicating that it can accurately classify healthy individuals as non-diseased. In addition, it achieved the highest Accuracy of 93.44%, showing that the model gives the most correct predictions overall. Its False Positive Rate (6.90%) and False Negative Rate (6.25%) are the lowest among all methods, which proves that the model minimizes both types of prediction errors. The Precision and F1-Score of 93.75% further confirm that CNN-Adam provides a highly balanced and reliable classification performance.

The Logistic Regression (LR) model also performs well, with Sensitivity of 90.63%, Specificity of 86.21%, and Accuracy of 88.52%. This indicates that LR is effective in detecting positive cardiac cases and has a relatively strong overall prediction ability. Its False Positive Rate of 13.79% and False Negative Rate of 9.38% are moderate, meaning some misclassifications still occur. However, LR remains a good traditional baseline model.

The SVM model demonstrates strong results as well. Its Specificity of 89.66% is better than LR, which means it is more effective in correctly identifying healthy patients. It also has a good Precision of 90.00%, showing fewer false alarms. However, its Sensitivity of 84.38% is lower than LR and CNN-Adam, indicating that it misses more actual disease cases.

The Random Forest (RF) model shows moderate performance with 83.61% accuracy. Its Sensitivity and Precision are both 84.38%, but its False Positive Rate of 17.24% is relatively high. This suggests that RF makes more incorrect positive predictions compared to LR and SVM.

The LSTM model gives mixed results. Although it has good Sensitivity of 87.88%, its Specificity of 71.43% is the lowest among all methods, which means it struggles more in identifying healthy individuals correctly. It also has the highest False Positive Rate of 28.57%, indicating more false alarms.

Overall, the table clearly shows that CNN-Adam outperforms all other techniques across nearly all evaluation metrics. Therefore, the proposed model can be considered the most effective and dependable method for cardiac disease prediction in this comparative study.

Sensitivity

The bar chart compares the sensitivity (%) of different prediction models for cardiac disease detection. Sensitivity measures the ability of a model to correctly identify patients who actually have the disease.

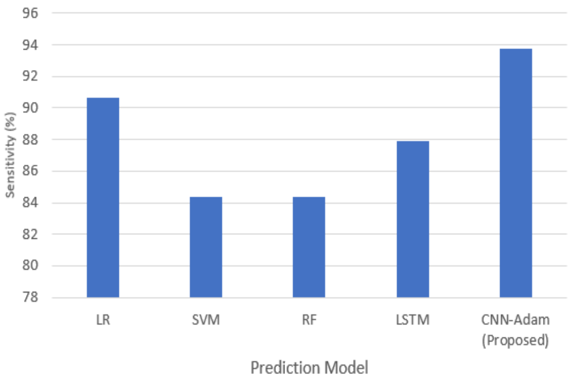

Figure 1: Comparison of Sensitivity

Among all models, CNN-Adam (Proposed) shows the highest sensitivity at about 93.75%, indicating the best performance in detecting positive cardiac cases. Logistic Regression (LR) follows with about 90.63%, while LSTM achieves around 87.88%. Both SVM and Random Forest (RF) have the lowest sensitivity, each at about 84.38%. Overall, the chart clearly shows that the proposed CNN-Adam model is the most effective in identifying diseased patients accurately.

Specificity

The bar chart compares the specificity of different prediction models used for cardiac disease detection. Specificity indicates the ability of a model to correctly identify patients who do not have the disease

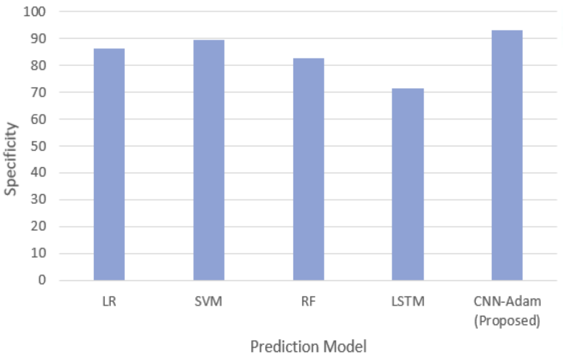

Figure 2: Comparison of Specificity

Among all models, CNN-Adam (Proposed) shows the highest specificity at about 93.10%, which means it is the most effective in correctly classifying healthy individuals. SVM follows with about 89.66%, while Logistic Regression (LR) achieves around 86.21%.

Random Forest (RF) has a specificity of about 82.76%. LSTM shows the lowest specificity at nearly 71.43%, indicating weaker performance in identifying negative cases accurately.

Accuracy

The bar chart presents the accuracy comparison of different prediction models for cardiac disease detection. Accuracy represents the overall proportion of correct predictions made by each model.

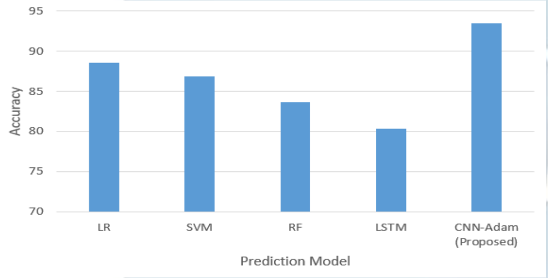

Figure 3: Comparison of Accuracy

Among all the models, CNN-Adam (Proposed) achieves the highest accuracy at about 93.44%, indicating the best overall classification performance. Logistic Regression (LR) follows with approximately 88.52%, while SVM shows around 86.89% accuracy. Random Forest (RF) performs moderately with nearly 83.61%, and LSTM records the lowest accuracy at about 80.33%. Overall, the figure clearly demonstrates that the proposed CNN-Adam model outperforms the other models in predicting cardiac disease more accurately.

False Positive Rate

The bar chart compares the false positive rate of different cardiac disease prediction models. False positive rate indicates how often a model incorrectly classifies a healthy person as having heart disease. A lower value is better because it reduces unnecessary concern, extra testing, and possible treatment.

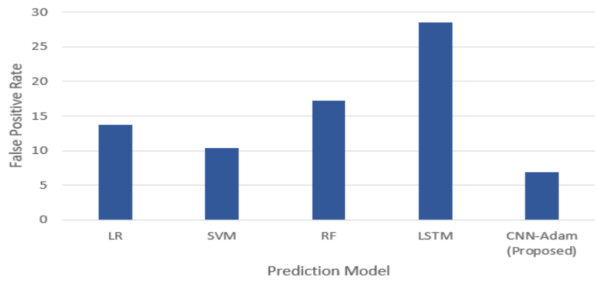

Figure 4: Comparison of FPR

Among all models, CNN-Adam (Proposed) has the lowest false positive rate at about 6.90%, showing the best performance. SVM follows with about 10.34%, while LR records nearly 13.79%. RF has a higher value of about 17.24%. LSTM performs the worst with around 28.57%, indicating the highest number of incorrect positive predictions.

False Negative Rate

The bar chart compares the false negative rate of different cardiac disease prediction models. False negative rate indicates how often a model fails to identify a patient who actually has heart disease.

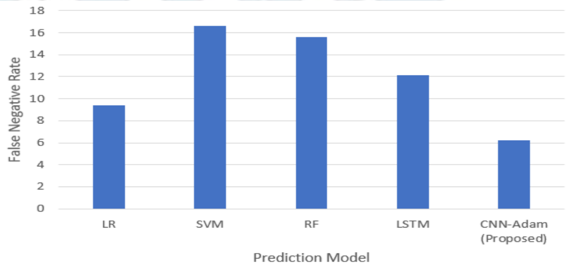

Figure 5: Comparison of FNR

In medical diagnosis, a lower false negative rate is very important because missed disease cases can delay treatment and increase risk. Among all models, CNN-Adam (Proposed) has the lowest false negative rate at about 6.25%, showing the best ability to detect diseased patients. LR follows with about 9.38%, while LSTM records nearly 12.12%. RF and SVM have higher values, around 15.63% and 16.63%, making them less effective.

Precision

The bar chart compares the precision of different cardiac disease prediction models. Precision shows how many patients predicted as having heart disease are actually diseased. A higher precision value means fewer false positive predictions and more reliable positive classification.

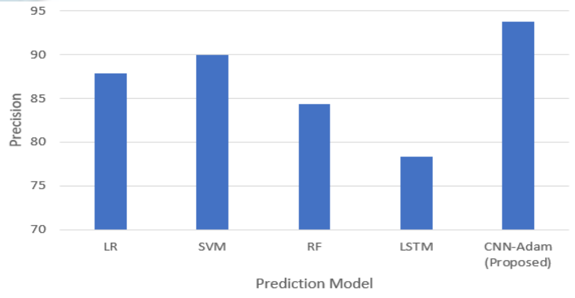

Figure 6: Comparison of Precision

Among all the models, CNN-Adam (Proposed) achieves the highest precision at about 93.75%, indicating the most trustworthy positive predictions. SVM follows with 90.00%, while LR records about 87.88%. RF shows moderate precision at nearly 84.38%. LSTM has the lowest precision at around 78.38%, meaning it produces more incorrect positive predictions compared to the other models.

F1-Score

The bar chart compares the F1-score of different cardiac disease prediction models. F1-score is an important evaluation metric because it balances precision and recall, giving a combined measure of classification performance

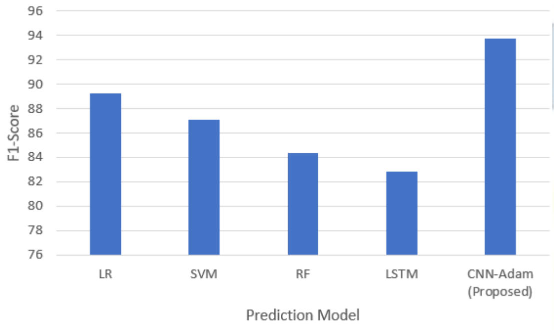

Figure 7: Comparison of F1-Score

A higher F1-score indicates that the model is better at correctly identifying diseased patients while also reducing incorrect predictions. Among all models, CNN-Adam (Proposed) achieves the highest F1-score at about 93.75%, showing the best-balanced performance. LR follows with around 89.23%, while SVM records about 87.10%. RF and LSTM have lower scores, approximately 84.38% and 82.86%, indicating comparatively weaker prediction performance.

VI. CONCLUSION

The study successfully demonstrated that the proposed CNN-Adam model outperforms traditional machine learning approaches, including Logistic Regression, SVM, Random Forest, and LSTM, in predicting cardiac disease. The model achieved high sensitivity (93.75%), specificity (93.10%), accuracy (93.44%), precision (93.75%), and F1-score (93.75%), while minimizing false positive (6.90%) and false negative rates (6.25%). These results indicate the system's reliability for early detection and its potential as a clinical decision-support tool. The study validates that intelligent, sensor-based, deep learning models can enhance proactive cardiac care, though real-time deployment and practical clinical integration remain future objectives.

Future work focuses on expanding dataset size and diversity to improve generalizability across populations. Integration with wearable devices and IoT monitoring is suggested for real-time cardiac risk assessment. Advanced architectures, such as CNN-LSTM, GRU, or Transformer-based models, may further improve predictive performance. Emphasis is also placed on model interpretability, explainable AI techniques (SHAP, LIME), integration with EHRs, real-time alert generation, and privacy-preserving mechanisms. Prospective clinical validation and the development of a personalized smart healthcare assistant are recommended to transform the system from a predictive model into a comprehensive patient-centered cardiac monitoring framework.

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