INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 5, May 2026 | ISSN: 2456-4184 | IJNRD.ORG

An AI-Enabled Hybrid Deep Learning Framework for Cardiovascular Disease Diagnosis and Personalized Healthcare Recommendations

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Abstract : Cardiovascular Disease (CVD) remains one of the leading causes of mortality worldwide, making early diagnosis and effective healthcare recommendations essential for improving patient outcomes. Traditional machine learning approaches often struggle to capture complex patterns present in medical datasets, leading to reduced prediction accuracy. This paper proposes an AI-enabled Hybrid Deep Learning Framework that combines Improved Bi-GRU and LSTM networks for accurate cardiovascular disease diagnosis and personalized healthcare recommendations.

The proposed framework incorporates enhanced preprocessing using Z-score normalization, feature extraction using entropy-based techniques, and hybrid deep learning classification. The model was evaluated using benchmark cardiovascular disease datasets under varying training percentages of 60%, 70%, 80%, and 90%.

Experimental results demonstrate that the proposed model achieves a maximum accuracy of 94.68%, sensitivity of 93.99%, specificity of 93.33%, precision of 93.98%, and F-measure of 93.21%, outperforming conventional classifiers such as Decision Tree, CNN, Bi-LSTM, SVM, DNN, Random Forest, and RNN. Furthermore, the developed system generates personalized healthcare recommendations based on disease severity levels.

The obtained results indicate that the proposed framework can serve as an effective clinical decision support system for early cardiovascular disease diagnosis and patient management.

Keywords

Cardiovascular Disease, Deep Learning, Bi-GRU, LSTM, Healthcare Recommendation System, Disease Prediction, Artificial Intelligence.

I. INTRODUCTION

Cardiovascular Disease (CVD) is one of the leading causes of death worldwide and poses a significant challenge to healthcare systems. Heart-related disorders such as coronary artery disease, heart failure, arrhythmia, and myocardial infarction affect millions of people every year. Early detection and timely treatment of cardiovascular diseases can significantly reduce mortality rates and improve the quality of life of patients. However, traditional diagnostic methods often rely on manual assessment of clinical data, laboratory reports, and physician expertise, which can be time-consuming and may not always provide accurate predictions.
Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have revolutionized the healthcare sector by enabling intelligent disease prediction systems. These technologies can analyze large volumes of medical data, identify hidden patterns, and assist healthcare professionals in making informed decisions. Several machine learning algorithms such as Decision Trees, Random Forests, Support Vector Machines, and Artificial Neural Networks have been widely used for cardiovascular disease prediction. Although these methods have shown promising results, their performance is often limited when handling complex and sequential healthcare data.
Deep learning models, particularly Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Units (GRUs), have demonstrated superior capability in learning complex relationships from medical datasets. However, individual deep learning architectures may still face challenges such as information loss, limited contextual understanding, and reduced prediction accuracy. To overcome these limitations, hybrid deep learning approaches have gained significant attention due to their ability to combine the strengths of multiple models.
This research proposes an AI-Enabled Hybrid Deep Learning Framework for Cardiovascular Disease Diagnosis and Healthcare Recommendations. The framework integrates enhanced preprocessing techniques, entropy-based feature extraction, and a Hybrid Bi-GRU + LSTM classifier to improve disease prediction accuracy. In addition to disease diagnosis, the proposed system generates personalized healthcare recommendations based on the predicted disease severity, thereby assisting both patients and healthcare professionals in effective disease management.
Experimental evaluation demonstrates that the proposed model achieves superior performance compared to traditional machine learning and deep learning approaches, making it a reliable and efficient solution for intelligent cardiovascular disease prediction and healthcare support systems.

II. RELATED WORK

Cardiovascular Disease (CVD) prediction has become an important research area due to the increasing number of heart-related illnesses worldwide. Various machine learning and deep learning techniques have been developed to assist healthcare professionals in early diagnosis and treatment planning.

Traditional machine learning algorithms such as Decision Tree, Random Forest, Naïve Bayes, and Support Vector Machine (SVM) have been widely used for heart disease prediction. These methods provide acceptable prediction accuracy and require relatively low computational resources. However, their performance is often limited when dealing with complex and high-dimensional healthcare datasets.

Recent advancements in deep learning have significantly improved disease prediction capabilities. Convolutional Neural Networks (CNNs) have been employed for automatic feature extraction, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks have demonstrated effectiveness in handling sequential medical data. Although these models improve prediction performance, they may suffer from issues such as information loss, overfitting, and limited ability to capture bidirectional dependencies when used individually.

Several researchers have proposed hybrid deep learning approaches to overcome these limitations. By combining multiple neural network architectures, hybrid models can exploit the advantages of each network and improve classification accuracy. Existing studies have reported improved performance using combinations of CNN, LSTM, and GRU architectures for healthcare applications. However, many existing systems still face challenges related to feature selection, preprocessing efficiency, and prediction reliability.

To address these challenges, the proposed work introduces an AI-enabled Hybrid Deep Learning Framework that integrates enhanced preprocessing, entropy-based feature extraction, and a Hybrid Bi-GRU + LSTM classifier. The objective is to improve cardiovascular disease diagnosis accuracy while providing personalized healthcare recommendations to support clinical decision-making.

III. SYSTEM ARCHITECTURE

The proposed AI-enabled Hybrid Deep Learning Framework is designed to provide accurate cardiovascular disease diagnosis and personalized healthcare recommendations. The framework consists of five major stages: Data Collection, Data Preprocessing, Feature Extraction, Hybrid Deep Learning Classification, and Healthcare Recommendation Generation.

Initially, patient healthcare data are collected from cardiovascular disease datasets containing various clinical parameters such as age, blood pressure, cholesterol level, heart rate, fasting blood sugar, chest pain type, and electrocardiographic measurements. Since medical datasets may contain inconsistencies and variations in feature scales, preprocessing is performed using enhanced Z-score normalization to improve data quality and ensure uniform feature representation.

After preprocessing, entropy-based feature extraction techniques are employed to identify significant attributes that contribute to disease prediction. The extracted features are then supplied to the Hybrid Bi-GRU + LSTM classifier. The Bidirectional Gated Recurrent Unit (Bi-GRU) captures forward and backward dependencies in healthcare data, while the Long Short-Term Memory (LSTM) network preserves long-term relationships among patient records. The combination of these networks improves prediction accuracy and classification reliability.

Based on the prediction outcome, the healthcare recommendation module generates personalized suggestions including dietary advice, physical activity recommendations, medication adherence guidance, and lifestyle modifications. This enables the proposed system to function as an intelligent clinical decision support tool.

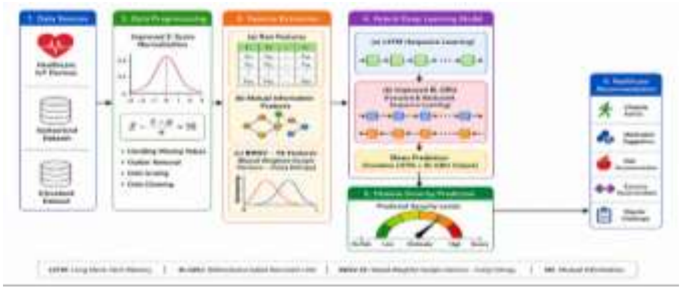

Figure1: Overall Architecture of Proposed Hybrid DL-based CVD Prediction System

IV. METHODOLOGY

The proposed methodology consists of a sequence of processes that transform raw healthcare data into meaningful disease predictions and personalized healthcare recommendations. The framework integrates data preprocessing, feature extraction, hybrid deep learning classification, and recommendation generation to achieve accurate cardiovascular disease diagnosis.

Initially, the cardiovascular disease dataset is collected and analyzed. The collected data undergo preprocessing to remove inconsistencies and normalize feature values. After preprocessing, entropy-based feature extraction is applied to identify the most relevant medical attributes. These extracted features are then supplied to the Hybrid Bi-GRU + LSTM classifier for disease prediction. Finally, healthcare recommendations are generated based on the predicted disease severity level.

The overall workflow of the proposed system is illustrated through the following stages.

4.1. Data Preprocessing

Data preprocessing is an important step in healthcare analytics because medical datasets often contain features with different scales and ranges. To improve learning performance, Z-score normalization is applied.

The normalization process is represented by:

$$Z = \frac{X - \mu}{\sigma}$$

Where:

- X = Original feature value
- μ = Mean of the feature
- σ = Standard deviation of the feature

This process transforms the dataset into a standardized form and improves the convergence speed of the deep learning model.

4.2. Feature Extraction

Feature extraction is performed to identify the most informative attributes contributing to cardiovascular disease prediction. Entropy-based feature extraction measures the amount of information contained in each feature and eliminates redundant attributes.

The entropy of a feature is calculated as:

$$E(X) = -\sum_{i=1}^{n} P(x_i) \log_2 P(x_i)$$

Where:

- $P(x_i)$ represents the probability of occurrence of feature value x_i
- $E(X)$ represents entropy

Features with higher information content are selected for further processing.

4.3. Hybrid Bi-GRU + LSTM Classification

The extracted features are provided as input to the Hybrid Bi-GRU + LSTM classifier.

The Bidirectional Gated Recurrent Unit (Bi-GRU) processes information in both forward and backward directions, enabling the model to learn contextual relationships within healthcare data.

The Long Short-Term Memory (LSTM) network preserves long-term dependencies and prevents the vanishing gradient problem commonly observed in conventional recurrent networks.

The integration of Bi-GRU and LSTM improves classification accuracy by combining bidirectional learning capability with long-term memory retention.

The classifier categorizes patients into different cardiovascular disease severity levels and generates prediction outcomes.

4.4. Healthcare Recommendation Generation

Based on the predicted disease severity level, personalized healthcare recommendations are generated automatically.

The recommendation module provides:

- Dietary suggestions
- Physical activity recommendations
- Lifestyle modification guidance
- Medication adherence reminders
- Periodic health monitoring recommendations

This module enhances the practical usefulness of the proposed system by supporting preventive healthcare and disease management.

V. RESULTS AND DISCUSSION

5.1 Outputs Obtained

The proposed Hybrid Deep Learning framework based on Improved Bi-GRU and LSTM was implemented using Python. The system accepts cardiovascular disease-related patient data as input and predicts the severity level of heart disease. The generated outputs include sensitivity, specificity, accuracy, precision, F-measure, MCC, NPV, FPR, and FNR values.

The model was evaluated at different learning percentages of 60%, 70%, 80%, and 90%. The obtained results demonstrate that the proposed Hybrid model consistently achieves better prediction performance when compared with existing techniques such as Decision Tree (DTree), Bi-LSTM, CNN, SVM, DNN, Random Forest (RF), and RNN.

The proposed model achieved a maximum accuracy of **94.68%**, sensitivity of **93.99%**, specificity of **93.33%**, precision of **93.99%**, F-measure of **93.21%**, MCC of **93.65%**, and NPV of **93.01%**. The false prediction measures such as FPR and FNR were significantly lower than those of the existing approaches, demonstrating the robustness of the proposed framework.

Figure 5.1: Output window showing prediction results generated by the proposed Hybrid Bi-GRU+LSTM model

5.2 Statistical Analysis of Results

The statistical analysis was carried out to evaluate the consistency and reliability of the proposed Hybrid model.

Table 5.1 presents the mean, median, standard deviation, minimum, and maximum values obtained for all compared classifiers.

Statistic	**Hybrid**	**DTree [1]**	**Bi_LSTM**	**CNN**	**SVM**	**DNN**	**RF**	**RNN**
Mean	0.938602	0.831065	0.878658	0.834162	0.892899	0.867822	0.867609	0.873706
Median	0.938673	0.812777	0.895283	0.822425	0.892954	0.877021	0.876816	0.885645
Std-Dev	0.00622183	0.0398897	0.0319343	0.0333486	0.0185278	0.0309955	0.0301072	0.0312198
Min	0.930189	0.800437	0.823787	0.801879	0.866768	0.817869	0.817868	0.821766
Max	0.946875	0.898268	0.900279	0.889917	0.918919	0.899377	0.898937	0.901768

Table5.1: Statistical Feature Comparison of Hybrid Model and Existing Methods

Discussion

From the statistical analysis, it can be observed that the proposed Hybrid model achieved the highest mean value of **0.9386** among all classifiers. The standard deviation value of **0.0062** indicates stable and consistent performance across different experiments. The maximum performance value achieved by the Hybrid model was **0.9469**, which is higher than all conventional approaches. Therefore, the Hybrid Bi-GRU+LSTM model provides more reliable disease prediction compared to traditional machine learning and deep learning models.

5.3 Ablation Study

An ablation study was conducted to evaluate the contribution of individual components of the proposed framework.

Metric	**With ConvBi_GRU**	**With ConvFuzzy Entropy**	**With ConvPreprocessing**	**Hybrid**

Sensitivity	0.892758	0.763158	0.721053	0.930179
Specificity	0.827669	0.898256	0.813548	0.926898
Accuracy	0.867668	0.817073	0.856767	0.935880
Precision	0.891787	0.873667	0.836547	0.926798
F-Measure	0.792766	0.816759	0.894335	0.923768
MCC	0.892658	0.807876	0.845669	0.926779
NPV	0.835782	0.899329	0.872483	0.923878
FPR	0.118769	0.132877	0.142656	0.099289
FNR	0.102787	0.117766	0.123566	0.089265

Table5.2: Ablation Study Results of the Proposed Hybrid Model

Discussion

The ablation study demonstrates that each module contributes significantly to the overall performance. The complete Hybrid framework achieved an accuracy of **93.59%**, which is higher than models using only preprocessing, fuzzy entropy, or ConvBi-GRU individually. The reduction in FPR and FNR values further confirms the effectiveness of combining preprocessing, feature extraction, and Hybrid classification within a unified framework.

5.4 Performance Evaluation

The performance of the proposed model was evaluated using multiple performance metrics.
The evaluation metrics considered are:

- Sensitivity
- Specificity
- Accuracy
- Precision
- F-measure
- MCC
- NPV
- FPR
- FNR

The performance was analyzed at learning percentages of 60%, 70%, 80%, and 90%.

5.4.1 Sensitivity Analysis

Sensitivity measures the ability of the model to correctly identify disease-positive cases.
The proposed Hybrid model achieved sensitivity values of 92.88%, 93.02%, 93.77%, and 93.99% at learning percentages of 60%, 70%, 80%, and 90%, respectively. These values are consistently higher than the existing classifiers.

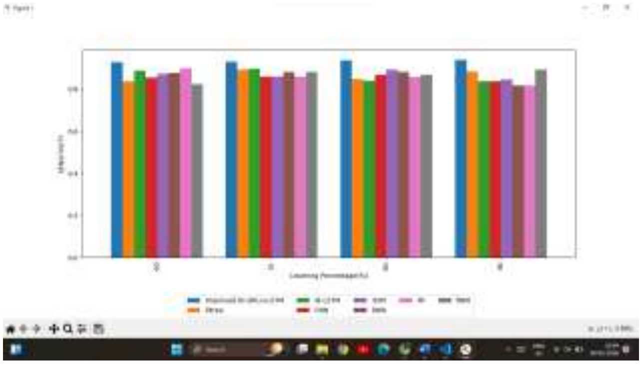

Figure 5.2: Sensitivity comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.2 Specificity Analysis

Specificity represents the capability of the model to correctly identify disease-negative cases.
The proposed framework obtained specificity values of 91.90%, 92.69%, 93.14%, and 93.33%, outperforming the benchmark methods.

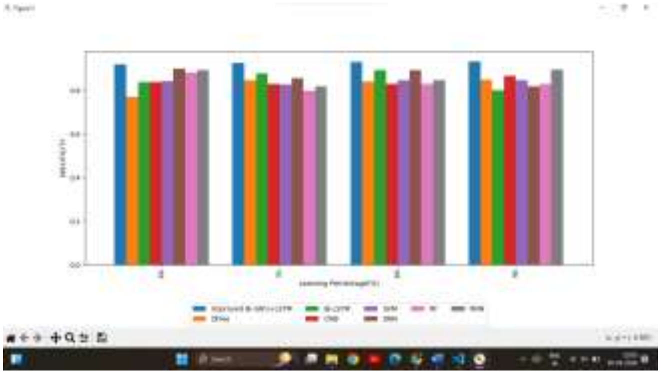

Figure 5.3: Specificity comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.3 Accuracy Analysis

Accuracy indicates the overall prediction capability of the model.
The proposed model achieved the highest accuracy of 94.68% at 90% learning percentage, which is considerably better than existing classifiers.

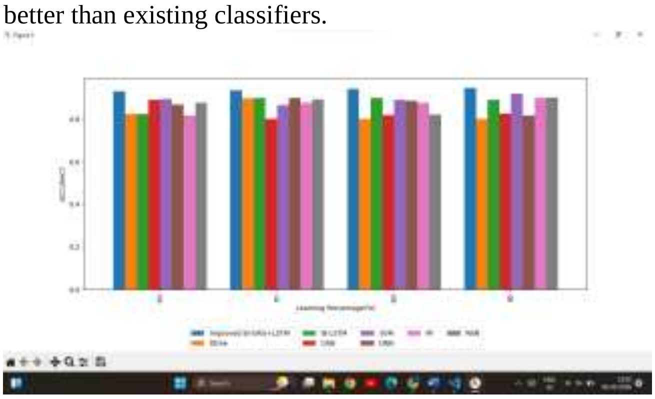

Figure 5.4: Accuracy comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.4 Precision Analysis

Precision evaluates the correctness of positive predictions generated by the model.
The proposed framework obtained precision values exceeding 92% across all learning percentages, demonstrating reliable prediction performance.

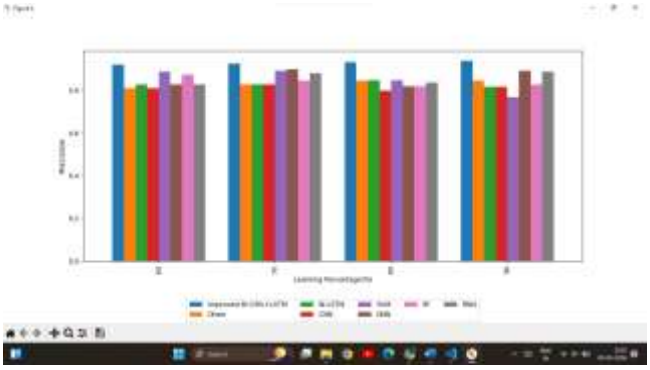

Figure 5.5: Precision comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.5 F-Measure Analysis

F-measure combines precision and recall into a single performance metric.

The Hybrid model achieved the highest F-measure values compared to all benchmark approaches.

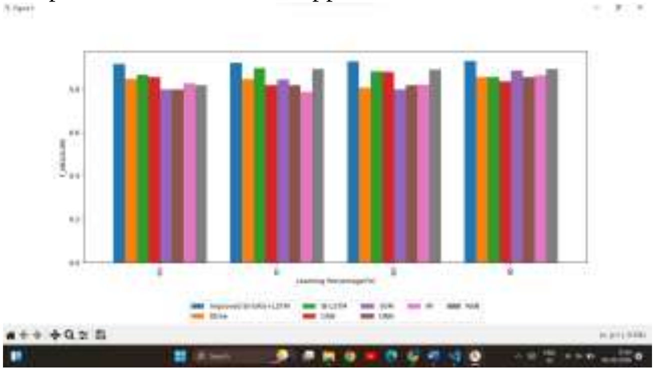

Figure 5.6: F-Measure comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.6 MCC Analysis

Matthews Correlation Coefficient (MCC) evaluates the quality of classification by considering all confusion matrix components.

The proposed framework consistently achieved MCC values above 92%, indicating strong classification capability.

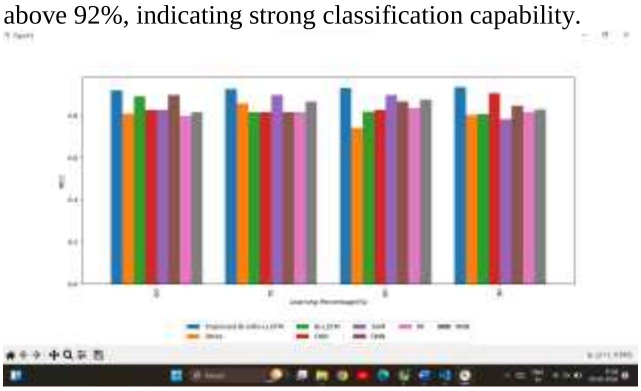

Figure 5.7: MCC comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.7 NPV Analysis

Negative Predictive Value (NPV) measures the probability that a negative prediction is truly negative.

The Hybrid model produced the highest NPV values among all classifiers.

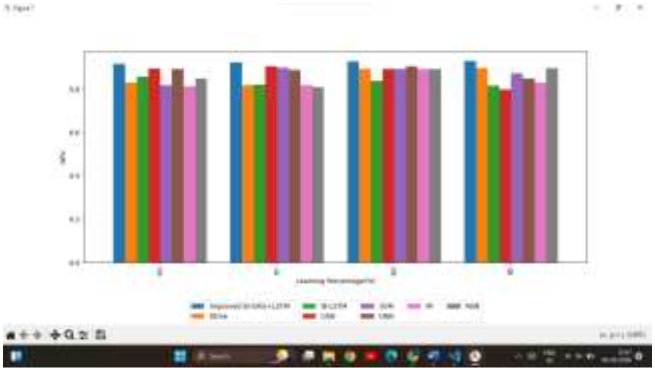

Figure 5.8: NPV comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.8 FPR Analysis

False Positive Rate (FPR) indicates how often healthy individuals are incorrectly classified as diseased.

The proposed framework achieved the lowest FPR values, reaching approximately **8.19%** at 90% learning percentage.

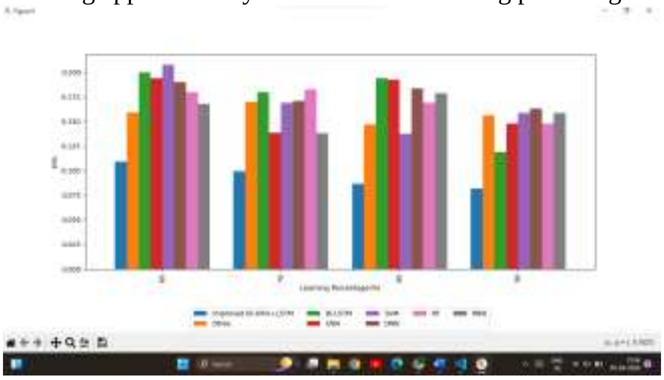

Figure 5.9: FPR comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

5.4.9 FNR Analysis

False Negative Rate (FNR) represents the percentage of actual disease cases missed by the model.

The Hybrid model achieved the lowest FNR values among all classifiers, indicating its effectiveness in detecting cardiovascular disease cases.

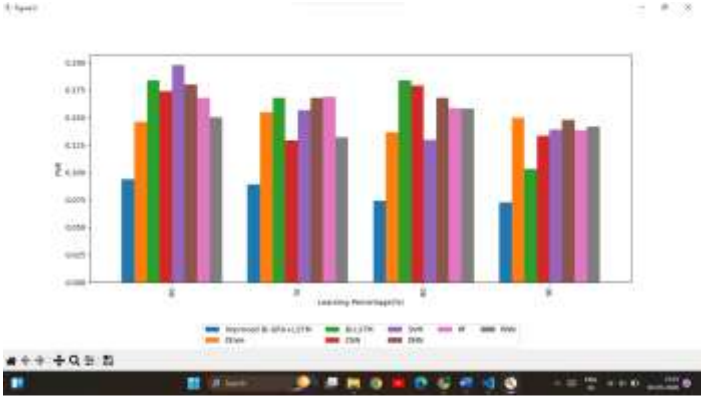

Figure 5.10: FNR comparison of Hybrid Bi-GRU+LSTM and existing classifiers.

VI. CONCLUSION AND FUTURE SCOPE

This paper presented an AI-enabled Hybrid Deep Learning Framework for Cardiovascular Disease Diagnosis and Personalized Healthcare Recommendations. The proposed framework integrates enhanced preprocessing, entropy-based feature extraction, and a Hybrid Bi-GRU + LSTM classifier to improve cardiovascular disease prediction accuracy and reliability. Experimental evaluation demonstrated that the proposed model consistently outperformed conventional machine learning and deep learning approaches, achieving a maximum accuracy of 94.68%, high sensitivity, and high specificity. The results confirm the effectiveness of the proposed framework in accurately identifying cardiovascular disease conditions while minimizing prediction errors.

In addition to disease prediction, the developed system provides personalized healthcare recommendations based on the predicted disease severity level. This functionality enhances clinical decision support and assists patients in adopting preventive measures and healthier lifestyle practices. The integration of prediction and recommendation modules makes the proposed framework suitable for real-world healthcare applications.

Future work will focus on incorporating real-time patient monitoring through wearable healthcare devices and IoT sensors. The framework can also be enhanced using Explainable Artificial Intelligence (XAI) techniques to improve model transparency and interpretability. Furthermore, cloud-based deployment, larger healthcare datasets, and integration with electronic health record systems can be explored to improve scalability, accessibility, and overall healthcare support.

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