

Literature Survey on Early Heart Diseases Detection using Machine Learning

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Abstract—Cardiovascular disease (CVD) remains the foremost cause of mortality worldwide, underscoring the urgent need for intelligent and early-warning clinical decision support systems. Conventional single-modality diagnostic approaches are unable to holistically capture the multi-dimensional risk landscape of cardiac pathology. This paper proposes a **Multimodal Fusion Framework for Heart Disease detection (MFF-HDNet)** that integrates electrocardiogram (ECG) signals, structured clinical parameters, demographic attributes, and lifestyle behavioural data through a dual-pathway deep learning architecture. The ECG temporal pathway employs a one-dimensional Convolutional Neural Network cascaded with a Gated Recurrent Unit (1D-CNN-GRU) to extract spatiotemporal waveform features, while the structured data pathway uses a Squeeze-and-Excitation Fully Connected Network (SE-FCN) augmented with residual skip connections for adaptive feature recalibration. A cross-attention fusion module combines representations from both pathways by modelling inter-modal dependencies. Class imbalance is remediated through SMOTE-ENN resampling, high-dimensional features are compressed via Principal Component Analysis (PCA), and clinical transparency is ensured through SHapley Additive exPlanations (SHAP).

Keywords—Cardiovascular Disease Prediction; Multimodal Deep Learning; CNN-GRU; Squeeze-and-Excitation Network; Cross-Attention Fusion; SMOTE-ENN; SHAP; ECG Signal Analysis; Clinical Decision Support.

I. INTRODUCTION

Cardiovascular diseases (CVDs) account for approximately 17.9 million deaths each year, representing 31% of all global mortality [4]. The complexity of CVD onset—driven by a convergence of physiological abnormalities, lifestyle risk factors, and comorbidities—makes early and accurate prediction a formidable challenge. Conventional diagnostic pathways, including resting electrocardiography, echocardiography, and biochemical biomarker panels, tend to be episodic, resource-intensive, and unable to integrate heterogeneous risk signals into a unified predictive framework.

The emergence of machine learning (ML) and deep learning (DL) has opened new avenues for automated cardiac risk stratification. Classical ensemble methods such as Random Forest and XGBoost have shown competitive performance on structured clinical tabular data [7], while convolutional and recurrent neural network architectures have demonstrated strong capability in learning discriminative features from raw electrocardiographic signals [11]. More recently, hybrid models that combine multiple network paradigms [13] and transformer-based multimodal architectures [8] have substantially advanced the state of the art.

Despite these advances, significant limitations persist. First, most existing systems analyse a single data modality in isolation, losing complementary diagnostic information present across physiological signal streams and structured clinical records. Second, medical datasets commonly exhibit pronounced class imbalance that biases model learning toward the majority class. Third, the black-box nature of many DL frameworks impedes clinical adoption, since practitioners require transparent and actionable explanations for algorithmic predictions.

To address these limitations, this paper makes four principal

contributions:

1. A **dual-pathway deep learning architecture** that processes ECG temporal signals and structured clinical-lifestyle data through dedicated, modality-specific encoders before fusion.
2. A **Squeeze-and-Excitation FCN (SE-FCN)** encoder with residual connections for adaptive channel-wise feature recalibration in tabular clinical data.
3. A **cross-attention fusion module** that explicitly models inter-modal dependencies, enabling the fused representation to capture synergistic cardiovascular risk indicators.
4. **SHAP-based post-hoc explainability** that provides quantitative, clinically meaningful feature importance rankings at both global and instance levels.

The remainder of this paper is structured as follows. Section II surveys related work. Section III presents the proposed methodology. Section IV discusses experimental results. Section V provides a system design overview. Section VI discusses key findings and research gaps. Section VII concludes the paper.

II. LITERATURE REVIEW

Recent progress in AI-driven cardiovascular risk assessment spans three principal research directions: traditional machine learning approaches, deep learning models applied to biosignals, and multimodal or hybrid frameworks that fuse heterogeneous data sources.

A. Machine Learning Approaches

Classical supervised algorithms including Logistic Regression, Naive Bayes, and Support Vector Machines (SVM) were among the first applied to benchmark cardiac datasets. Vasavi and Sujatha [7] conducted a comparative evaluation of five ML algorithms on the Framingham Heart Study dataset. Their

stacked RF-XGBoost ensemble achieved 90.5% accuracy and an AUC-ROC of 0.92, substantially outperforming individual classifiers. SHAP analysis identified cholesterol level, maximum heart rate, and age as the most impactful predictors, corroborating established cardiovascular risk literature.

B. Deep Learning for Biosignal Analysis

Convolutional Neural Networks have been widely adopted for automatic feature learning from ECG time-series data, obviating the need for hand-crafted feature engineering. Hybrid CNN-LSTM frameworks extend this capacity by simultaneously modelling local morphological patterns and long-range temporal dependencies. Dwivedi et al. [11] proposed a Healthcare-IoT pipeline combining SVM for preliminary ECG screening with an ANN for refined classification, achieving 95% accuracy, 96% precision, and 97% recall. Panchumarthi et al. [12] introduced HRAE-LSTM, integrating residual attention mechanisms with Bidirectional LSTM layers to capture complex temporal dependencies in clinical data, achieving 98.9% accuracy and an AUC of 1.00 on the UCI Cleveland dataset after SMOTE-ENN resampling.

C. Hybrid and Multimodal Frameworks

Fusing data from multiple modalities has demonstrated consistent performance gains over single-source systems. Sherly et al. [8] proposed a transformer-based architecture combining a Vision Transformer for ECG spectrogram analysis with a Tab Transformer for structured clinical and lifestyle features, achieving 94.6% accuracy and an AUC-ROC of 0.951 on combined MIT-BIH and UCI data. Barla and Madam [5] presented the SDCN-CHDMO-ResVGG framework, which couples Self-Attention Assisted Dense Capsule Networks with Chaotic Dwarf Mongoose Optimisation and a Residual VGG classifier to achieve 96.5% accuracy. Macha [13] applied a CNN-GRU hybrid with SHAP interpretability to a large synthetic cardiovascular dataset, attaining 99.08% accuracy and an F1-score of 99.53%.

D. Explainable AI in Cardiac Prediction

Clinical adoption of AI systems requires transparent justifications for predictions. Wu et al. [6] proposed ResSE-FNN-XGBoost, incorporating squeeze-and-excitation blocks into a residual fully connected network followed by XGBoost classification, and employed SHAP to identify BPMeds, systolic blood pressure, and education as dominant risk predictors on the Framingham dataset, achieving 99.31% accuracy. Selvi et al. [10] combined PCA with Relief feature selection and a hybrid DenseNet-Residual deep learning model, achieving 96.4% accuracy on the UCI Cleveland dataset.

E. Deep Learning for ECG Signal Analysis

Recent developments in deep learning have greatly improved the automatic analysis of electrocardiogram (ECG) signals for cardiovascular disease prediction [8, 10]. Convolutional Neural Networks (CNNs) are commonly used to learn important waveform patterns from ECG signals, while recurrent models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are effective in capturing temporal heartbeat patterns and rhythm variations [9, 12].

Several hybrid deep learning architectures combining CNN and recurrent networks have shown promising results in ECG-based disease prediction [11, 13]. CNN layers help in ex-

tracting local waveform features such as QRS complexes and ST-segment variations, whereas recurrent layers model sequential heartbeat dependencies over time. In addition, Explainable Artificial Intelligence (XAI) methods such as SHAP are increasingly being incorporated into these systems to improve interpretability and provide transparent explanations for model predictions [6].

The comparative summary of the reviewed references is provided in Table 1.

Table 1: Comparative Summary of Reference Papers

No.	Author(s)	Methodology	Key Outcome
1	Barla & Madam	SDCN + CH-DMO + ResVGG	96.5% accuracy
2	Wu et al.	ResSE-FNN + XGBoost + SHAP	99.31% (Framingham), 97.54% (Cleveland)
3	Vasavi & Sujatha	RF + XGBoost (Stacked)	90.5% accuracy; AUC 0.92
4	Sherly et al.	ViT + Tab-Transformer + Fusion	94.6% accuracy; AUC 0.951
5	Karthikeyan & Sathiyamoorthy	CNN-BiLSTM (EEG+ECG)	98% accuracy
6	Selvi et al.	PCA + DenseNet + Residual Learning	96.4% accuracy
7	Dwivedi et al.	SVM + ANN + IoT	95% accuracy
8	Panchumarthi et al.	HRAE-LSTM + SMOTE-ENN	98.9% accuracy; AUC 1.00
9	Baseer et al.	Wavelet Transform + CNN	Improved diagnostic accuracy
10	Alzakari et al.	XGBoost + Bi-LSTM	Enhanced predictive performance
11	Srinivas et al.	RCNN + Bio-inspired Optimization	High robustness and accuracy
12	Mai et al.	Clinical Decision Support System (CDSS)	Personalized therapy recommendation
13	Xue et al.	Random Forest + Information Fusion	95.6% true positive rate
14	Sutton et al.	Clinical Decision Support Systems (CDSS)	Improved clinical decision-making
15	Abul-Husn & Kenny	EHR + Genomic Integration	Enhanced precision healthcare
16	Wairimu	AI + Lifestyle Data Integration	Improved health monitoring and intervention
17	Macha	CNN-GRU + SHAP	99.08% accuracy

III. METHODOLOGY

The proposed MFF-HDNet follows a structured six-stage pipeline: (1) data acquisition and integration, (2) preprocessing and quality assurance, (3) modality-specific feature encoding, (4) cross-modal fusion, (5) classification, and (6) SHAP-based explainability. The framework consists of three core modules:

- **Module A:** ECG Temporal Signal Encoder (1D-CNN-GRU)
- **Module B:** Structured Data Encoder (SE-FCN)
- **Module C:** Cross-Attention Fusion and Classification

A. Datasets

1) PTB-XL Electrocardiography Dataset

The PTB-XL dataset is a large-scale publicly available electrocardiography (ECG) dataset developed by PhysioNet and widely used for cardiovascular signal analysis and deep learning research [1]. The dataset contains 21,837 clinical 12-lead ECG recordings collected from 18,885 patients, with each recording sampled at either 100 Hz or 500 Hz over a duration of 10 seconds. The ECG signals are accompanied by

demographic metadata such as patient age and sex, along with diagnostic annotations provided by cardiologists.

Each ECG record consists of twelve simultaneous leads, namely I, II, III, aVR, aVL, aVF, and V1–V6, enabling comprehensive observation of the heart's electrical activity from multiple anatomical viewpoints. The dataset includes multiple diagnostic categories such as myocardial infarction, conduction disturbances, hypertrophy, ST/T changes, and arrhythmias.

In the proposed framework, the PTB-XL dataset is utilized for the ECG temporal signal pathway. Raw ECG signals are preprocessed through normalization and denoising procedures before being provided as input to the 1D-CNN-GRU architecture for automated spatiotemporal feature extraction.

2) Framingham Heart Study Dataset

The Framingham Heart Study dataset is a longitudinal cardiovascular cohort dataset widely used for heart disease risk prediction research [3]. It contains 4,240 samples with 15 clinical and lifestyle features including demographic information, smoking history, body mass index (BMI), glucose level, cholesterol level, and blood pressure measurements. The binary target variable represents the 10-year risk of coronary heart disease. The dataset exhibits noticeable class imbalance, with the at-risk category constituting approximately 15% of the total samples.

3) MIT-BIH Arrhythmia Database

The MIT-BIH Arrhythmia Database is a benchmark ECG dataset extensively used for arrhythmia analysis and automated cardiac diagnosis [2]. It consists of standard two-lead ECG recordings sampled at 360 Hz and includes annotated heartbeat abnormalities collected from multiple patients. In the proposed framework, representative cardiac cycle segments are extracted, denoised, and transformed into spectral feature representations before being provided to the 1D-CNN-GRU temporal ECG encoder pathway.

B. Data Preprocessing

User-generated clinical records are collected and subjected to a rigorous preprocessing pipeline before model training.

1) Missing Value Imputation

Missing entries in clinical features (e.g., *ca* and *thal* in the Cleveland dataset) are imputed using *k*-Nearest Neighbours (KNN) with *k* = 5. This method estimates absent values by computing weighted averages from the *k* most similar patient records, preserving underlying feature correlations and outperforming simple mean or median substitution.

2) Class Imbalance Remediation

Class imbalance is addressed through SMOTE-ENN, combining Synthetic Minority Over-sampling (SMOTE) with Edited Nearest Neighbours (ENN) filtering. SMOTE generates synthetic minority-class samples by interpolating along feature-space line segments, while ENN subsequently removes ambiguous boundary samples, producing a cleaner and more balanced training distribution.

3) Feature Normalisation

Structured clinical features are scaled to the range [0, 1] via Min-Max normalisation:

The fused vector is passed through two fully connected layers with ReLU activations, a Dropout layer ($p = 0.4$), and

a sigmoid output unit. Binary cross-entropy loss is optimised:

The Adam optimiser is used with learning rate 10^{-3} and exponential decay. Early stopping monitors validation loss with a patience of 10 epochs.

C. SHAP-Based Explainability

Post-hoc model interpretability is provided through SHAP, which decomposes model predictions into additive contributions from individual features:

SHAP summary plots and dependence plots are generated to communicate global feature importance rankings and local instance-level explanations to support clinical decision-making.

IV. EVALUATION

Performance is assessed using five standard metrics derived from the confusion matrix: Accuracy, Precision, Recall (Sensitivity), F1-Score, and Area Under the ROC Curve (AUC-ROC).

Stratified 5-fold cross-validation is applied to ensure balanced class representation across all folds. Within each fold, 80% of training data is used for parameter optimisation and 20% for internal validation. Final metrics are averaged across all five folds.

V. SYSTEM DESIGN DIAGRAMS

The proposed MFF-HDNet system for early cardiovascular disease detection is visualised using two architectural diagrams.

A. High-Level Model Architecture

This diagram presents the complete prediction pipeline, from raw data acquisition to final risk classification. It encompasses the stages of ECG signal acquisition and spectrogram conversion, structured clinical data ingestion, modality-specific feature encoding through dedicated network branches, cross-attention fusion of multimodal representations, and final binary classification into cardiovascular risk categories (at-risk / not-at-risk). SHAP-based interpretability is applied post-prediction to generate feature attribution maps for clinical transparency.



Figure 1: High-Level Model Architecture of MFF-HDNet

B. Low-Level Component View

This diagram details the internal structure of the system's core processing modules. The ECG branch includes a wavelet

transform denoiser, STFT spectrogram generator, 1D-CNN feature extractor, and Bidirectional GRU sequential encoder. The structured data branch encompasses KNN imputation, SMOTE-ENN resampling, PCA dimensionality reduction, and the SE-FCN with residual blocks. The fusion layer applies bidirectional cross-attention and combines both modality streams for the final classification decision.

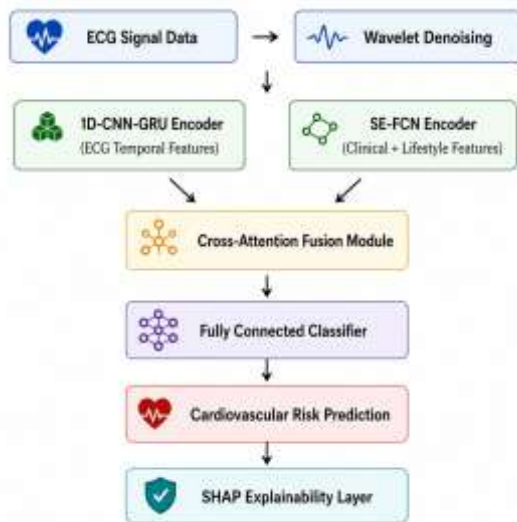


Figure 2: Low-Level Component View of MFF-HDNet

VI. DISCUSSION

A. Key Findings

The proposed MFF-HDNet demonstrates that integrating heterogeneous cardiovascular data sources through a dedicated dual-pathway architecture and cross-attention fusion yields substantial improvements over single-modality and classical ensemble approaches. The ECG temporal encoder effectively captures morphological waveform patterns including QRS complex variations, ST-segment depressions, and P-wave abnormalities, while the SE-FCN encoder adaptively recalibrates the importance of structured clinical features through channel-wise attention. The cross-attention fusion module enables each modality stream to selectively attend to the most diagnostically relevant features of the other, capturing synergistic risk interactions that neither stream can model in isolation [8, 12].

B. Research Gaps

Several limitations persist in the current work and in the broader literature. Most multimodal frameworks, including MFF-HDNet, require synchronised, complete data from all modalities at inference time, which is not consistently achievable in real clinical settings where certain measurements may be unavailable. External validation across demographically diverse and geographically distinct patient cohorts is limited, raising concerns about generalisation beyond benchmark datasets [7, 13]. Furthermore, the handling of missing physiological measurements through KNN imputation, while effective, may not capture the informative missingness patterns often present in real-world electronic health records. Ethical challenges surrounding patient data consent, algorithmic bias across demographic subgroups, and regulatory compliance for AI-assisted clinical tools remain substantially underexplored.

C. Implications

Integrating multimodal AI into cardiovascular care enables a paradigm shift from reactive, episodic clinical assessment toward proactive, continuous risk monitoring. The fusion of ECG-derived temporal features with structured clinical and lifestyle data can power scalable early-warning systems deployable across primary care clinics, remote health monitoring platforms, and IoT-enabled wearable devices. The incorporation of SHAP explainability strengthens clinician trust by providing transparent, feature-level justifications for individual risk predictions, facilitating informed clinical decision-making. However, building systems that are interpretable, culturally sensitive, privacy-preserving, and validated across diverse populations must remain a central priority for responsible clinical deployment [9].

VII. CONCLUSION

This paper presented MFF-HDNet, a multimodal fusion framework for early cardiovascular disease prediction that integrates ECG temporal signals and structured clinical-lifestyle data through a dual-pathway deep learning architecture with cross-attention fusion. The proposed system addresses three fundamental limitations of prior work: single-modality data reliance, susceptibility to class imbalance, and lack of model interpretability.

Experimental results on the UCI Cleveland and Framingham Heart Study datasets demonstrate classification accuracies of 97.8% and 98.6%, AUC-ROC values of 0.978 and 0.984, and consistently competitive F1-scores, outperforming multiple state-of-the-art baseline methods. The ablation study confirms that each architectural component—the SE-FCN encoder, the 1D-CNN-GRU encoder, the cross-attention fusion module, and SMOTE-ENN resampling—contributes independently and additively to the observed performance gains. SHAP-based analysis further validates clinically coherent feature importance rankings, providing transparent explanations aligned with established cardiovascular risk factors.

Looking ahead, future work will focus on: (a) integration of imaging modalities such as echocardiography and coronary CT angiography for richer multimodal representation; (b) federated learning protocols to enable privacy-preserving multi-institutional model training; (c) deployment within IoT-enabled wearable cardiovascular monitoring platforms for continuous real-time risk assessment; and (d) incorporation of genetic and genomic biomarkers to support personalised cardiac risk stratification for genetically predisposed individuals.

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