Indian Journal of Information Sources and Services
ISSN: 2231-6094 (P) Vol.16, No.1, 2026, pp.801-810
© The Research Publication, www.trp.org.in
DOI: https://doi.org/10.51983/ijiss-2026.16.1.83

Cardiovascular Care Using A Hybrid Ml/Dl Framework for Early Detection and Real-Time Monitoring

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(Received 20 December 2025; Revised 28 January 2026, Accepted 10 February 2026; Available online 27 February 2026)

Abstract - **Cardiovascular diseases (CVDs) are a leading cause of death globally, and it is important to ensure that arrhythmias are detected in good time to intervene successfully. This paper proposes a hybrid CNN-BLSTM stacked ensemble model with a squeeze-and-excitation residual network (SE-ResNet) to detect and monitor cardiovascular disease from ECG signals. The network uses CNN layers for spatial features, BLSTM networks for temporal dependencies, and ensemble learning for robust classification. Several benchmark datasets were statistically evaluated using multiple INCART and MIT-BIH arrhythmia recordings, comprising more than 200,000 heartbeats from normal and abnormal classes. The proposed model performed better on all major metrics: accuracy of 96.8, precision of 96.5, recall of 97.2, F1-score of 96.8, and a Matthews Correlation Coefficient (MCC) of 0.95 which is significantly better as compared to standalone CNN (89.3), LSTM (90.5) and CNN-LSTM (92.8) models. The statistical analysis shows that the hybrid framework reduces false positives for rare arrhythmias, including premature ventricular contractions (PVCs), by over 30% compared to baseline models, and improves sensitivity and robustness in skewed populations. Comparative performance also reveals an absolute improvement of 37% across all performance measures over traditional methods, demonstrating the effectiveness of combining spatial-temporal feature extraction with attention-based residual learning and an ensemble classifier. The results indicate the clinical potential of hybrid ML/DL frameworks for real-time cardiovascular monitoring and early arrhythmia detection, enabling proactive intervention measures. The further work will engage larger, multi-institutional datasets to improve statistical generalization, streamline the framework to accommodate both the IoMT and edge devices, and incorporate explainable AI methods to present healthcare practitioners with interpretable predictions.**

Keywords: **Cardiovascular Disease, Hybrid ML/DL Framework, Early Detection, Real-Time Monitoring, Wearable Sensors, Electrocardiogram, Smart Healthcare**

I. Introduction

The cardiovascular diseases (CVDs) are the principal cause of death in the whole world, and they cause a great %age of premature deaths and disability in the long run (Chang et al., 2022; Cenitta et al., 2025). The development of conditions like coronary artery disease, arrhythmia, heart failure, hypertension among others is typically silent and therefore early diagnosis and ongoing monitoring must be considered a critical aspect in the intervention and subsequent better survival (Iakunchykova et al., 2023). Conventional methods of cardiovascular diagnosis rely on intermittent clinical evaluation and manual analysis of physiological manifestations, which cannot detect transient abnormalities or preliminary pathological alterations (Gomes et al., 2023).

The latest advances in wearable sensors, the Internet of Medical Things (IoMT), and smart healthcare systems have enabled the acquisition of cardiovascular signals (electrocardiogram (ECG), heart rate variability (HRV), blood pressure, and oxygen saturation) in real-world conditions (Alghamdi et al., 2024). Nevertheless, the large size, diversity, and dynamic nature of these data pose a significant challenge to traditional rule-based and statistical analysis methods (Liu et al., 2023). Consequently, innovative, data-driven solutions are being investigated to aid automated cardiovascular risk evaluation and real-time monitoring (Balamurugan et al., 2025; Kavitha & Subramani, 2025).

Machine Learning (ML) methods have shown promising results in cardiovascular disease classification, using handcrafted features derived from both clinical and physiological data (Qiu et al., 2024). The other algorithms, such as support vector machines, random forests, and logistic regression, are fast to compute and interpretable but usually fail to capture complex, nonlinear, and long-term temporal relationships found in biological signals (Salem et al., 2018). Deep Learning (DL) models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are especially useful because they are more effective at automatic feature extraction and sequential pattern learning, which is why they are most likely to succeed in ECG and time-series analysis (Zhang et al., 2024). However, DL models generally need large labeled datasets and are not necessarily transparent, so they cannot be directly adopted in clinical practice (Bing et al., 2024). To overcome these shortcomings, hybrid ML/DL systems have been proposed as a viable solution by blending the strengths of both paradigms (Jahangir et al., 2023). These hybrid methods use ML models on structured clinical characteristics and risk factor analysis, while DL models use raw or minimally processed physiological data to capture more complex temporal correlations. Fusion at the decision or feature level further improves diagnostic strength or robustness and minimizes false alarms, which is essential in real-time cardiovascular care systems (Rakin et al., 2023; Nasiri et al., 2009).

Additionally, by combining edge cloud computing with explainable AI (XAI), it is possible to achieve low-latency deployment and interpretable predictions, enabling clinicians to trust it and take medical action with a sense of urgency (Islam et al., 2022; Pławiak & Acharya, 2020). These developments inspired this paper and proposes a hybrid ML/DL system to monitor and detect cardiovascular diseases at an early stage and in real time, thereby enhancing diagnostic accuracy, scalability, and clinical reliability in the next-generation smart healthcare setting (Ramkumar et al., 2022; Madan et al., 2022).

Key Contributions of the Research

- A hybrid ML/DL framework is proposed for early detection and real-time monitoring of cardiovascular diseases using clinical data and physiological signals.
- The system enables continuous, low-latency monitoring through real-time data processing and integrated decision making.
- Explainable analysis is incorporated to support reliable and clinically interpretable cardiovascular risk assessment.
- The other parts of this paper are structured in the following manner. Chapter 2 provides an extensive literature review of available machine learning, deep learning, and hybrid solutions for detecting cardiovascular diseases and for real-time patient monitoring, while identifying the main challenges and gaps in the research area. Chapter 3 presents in detail the suggested methodology, data acquisition, preprocessing, hybrid ML/DL model architecture, and decision fusion strategy. Chapter 4 provides a report on the experimental setup, the data used, the evaluation metrics, and the comparative performance results. Chapter 5 provides a descriptive presentation of the results obtained and examines model behavior, strengths, weaknesses, and implications for practice. Lastly, Chapter 6 wraps up the paper by summarizing the key findings and indicating possible future research and application directions.

II. Literature Review

Ye et al., 2025 suggested a hybrid deep learning system based on Bidirectional Long Short-Term Memory (BLSTM) and Convolution Neural Networks (CNNs) to classify the automatic arrhythmia on ECG signals. The model was also effective at capturing spatial characteristics and temporal relationships, achieving higher classification accuracy than when individual CNN or LSTM models are used. This hybrid design demonstrated the ability to enhance the accuracy of real-time ECG signal processing by addressing the intricate variations in ECG patterns.

Mittal et al., 2025 suggest an improved hybrid machine learning model to diagnose cardiovascular disease based on data imbalance resolution with SMOTEENN, feature selection with Chi-square and stacking ensemble of Random Forest, KNN, and AdaBoost Logistic Regression as a meta-learner. The multi-stage method has a profound positive influence on accuracy, specificity, and ROC-AUC for CVD prediction compared with single ML classifiers, demonstrating the effect of hybrid preprocessing and ensemble design on cardiovascular diagnosis tasks.

Pandey et al., 2025 was designed with the specific purpose of monitoring arrhythmia in the Internet of Medical Things (IoMT) environment, where time- and bandwidth-bound processing and reliability are of utmost importance. They use convolutional neural networks (CNNs) to automatically identify spatial and morphological features in ECG signals, and long short-term memory (LSTM) networks to identify temporal dependencies and sequential patterns in cardiac rhythms. This combination enables the model to handle both local signal characteristics and long-term temporal changes, making it more effective at arrhythmia classification than standalone models. The framework is structured in a manner optimally suited to IoMT-based deployments and guarantees low latency, scalability, and efficient processing of ongoing ECG data from wearable and remote monitoring devices. The paper presents the promise of hybrid deep learning systems for intelligent, real-time cardiovascular monitoring and for the development of smart healthcare infrastructure.

Jahangir et al., 2025 investigated ECG-based arrhythmia classification using a hybrid stacked machine learning architecture that integrates feature engineering and ensemble learning methods. In their experiment, they applied time-domain and frequency-domain features of ECG signals and used them as input in the various base classifiers whose outputs were combined together by adopting a stacking approach. By doing this, the model was able to take advantage of the complementary strengths of the various machine learning algorithms, which resulted in better classification accuracy and strength. The experimental results indicated that the stacked ensemble was more efficient than single classifiers, particularly for tricky and unbalanced arrhythmia patterns. The paper highlights the growing importance of ensemble-based approaches for cardiovascular signal analysis to achieve reliable, accurate arrhythmia detection.

Dhandapani et al., 2025 proposed a hybrid deep learning model that analyzes ECG signal images using artificial neural networks to forecast heart disease. The model combines both to improve feature learning and classification by converting ECG signals into an image representation, enabling the use of convolutional layers to automatically extract spatial features. The accuracy, sensitivity and overall reliability of experimental results proved to be high and indicated that an image-based learning and hybrid deep learning architecture can be used to offer an effective and automated solution to cardiac diagnosis.

Golande & Pavankumar, 2023 presented an optical ECG-based model for heart disease prediction. They use a hybrid strategy of traditional ECG beat extraction, and deep feature learning through CNNs, and afterwards LSTM-based sequence modeling. This hybrid feature engineering approach reduces diagnostic errors and enhances classification performance compared to conventional deep learning frameworks, demonstrating high potential for automated diagnosis of cardiac diseases in intelligent healthcare systems.

Ameen et al., 2024 have done a review of cardiovascular disease classification methods based on ECG and phonocardiogram (PCG). The paper discusses the history and advantages of machine learning and deep learning algorithms for various types of signals, with particular focus on preprocessing, feature extraction, and classification errors. The review provides informative insights into existing trends, limitations, and gaps in the research on automated cardiovascular disease detection.

Wu & Guo, 2025 provided a systematic review of deep learning in electrocardiography, encompassing approximately 200 studies related to automated diagnosis and real-time monitoring. Their survey points to the prevalence of CNNs and RNNs in ECG analysis but also highlights major issues, including the need for large, high-quality datasets and standardized assessment procedures. The paper highlights areas for improvement to ensure future research can make deep learning models more reliable and applicable in clinical practice for predicting cardiovascular diseases.

Li et al., 2022 Premature ventricular contraction (PVC) is a frequent form of arrhythmia and a significant cause of sudden cardiac death and hence early and reliable identification using ECG signals is a prerequisite. PVCs on dynamic ECGs are difficult to detect because the signal is often contaminated by noise and varies considerably across patients. Deep learning approaches have been reported to achieve good performance in ECG classification, but they can be affected by overfitting and the difficulty of training deep networks. To address these problems, a squeeze-excitation residual network (SE-ResNet) was proposed to detect PVC in real-time from 12-lead ECG signals. The model enhances feature learning by combining residual connections with channel-wise attention. The approach demonstrated accuracy, sensitivity, and specificity when compared with the INCART database and outperformed traditional CNNs, including Inception and AlexNet, as well as multilayer perception models. These findings imply that SE-ResNet is a valuable and effective method of real-time PVC detection in clinical ECGs.

TABLE I RECENT ADVANCES IN HYBRID MACHINE LEARNING AND DEEP LEARNING APPROACHES FOR ECG-BASED CARDIOVASCULAR DISEASE DETECTION

Authors	Methodology	Dataset / Simulation Environment	Research Gap
Ye et al., 2025	Hybrid CNN-BLSTM for arrhythmia classification	ECG signals (public datasets)	Limited testing on real-time wearable or IoMT deployment; generalization to diverse patient populations not evaluated
Mittal et al., 2025	Hybrid ML framework with SMOTE–ENN, Chi-square feature selection, stacking ensemble (Random Forest, KNN, AdaBoost with Logistic Regression meta-learner)	Clinical ECG datasets	Multi-stage hybrid approach is complex; scalability and real-time performance not demonstrated
Pandey et al., 2025	Hybrid CNN-LSTM optimized for IoMT-based arrhythmia detection	IoMT-based ECG datasets (wearable/remote monitoring)	Lightweight deployment for low-power IoMT devices; further optimization for continuous monitoring required
Jahangir et al., 2025	Feature engineering + stacked ML ensemble for ECG classification	Public arrhythmia ECG datasets	Limited handling of highly imbalanced arrhythmia classes; deep feature learning could improve performance
Dhandapani et al., 2025	Hybrid DL framework using ANN on ECG signal images	ECG signals converted to images	Real-time performance and interpretability not fully validated; image conversion may introduce preprocessing overhead
Golande & Pavankumar, 2023	Optical ECG + CNN-LSTM hybrid model	ECG signals (optical and conventional)	Limited evaluation on noisy datasets; generalization across diverse populations not tested
Ameen et al., 2024	Review of ML & DL methods on ECG and PCG	Literature survey	Lack of standardized evaluation protocols; gaps in signal preprocessing and feature extraction comparisons
Wu & Guo, 2025	Systematic review of DL applications in ECG	Literature review (~200 studies)	Need for larger datasets, standardized evaluation protocols, and real-time clinical validation
Li et al., 2022	12-lead ECG PVC detection using SE-ResNet (residual connections + squeeze-excitation modules)	INCART database (168,379 heartbeats)	Limited deployment in wearable or portable monitoring devices; model generalization across diverse populations not tested

The TABLE I is an overview of the methodology, data sets, and gaps in the research in many studies on the hybrid machine learning and deep learning strategies to detect cardiovascular diseases using ECG signals. Different models are utilized in each study, e.g. CNN-BLSTM, hybrid ML framework, or optical ECG models, to better the classification and detection of arrhythmia. The table also displays some of the most important research gaps, such as the lack of real-time implementation, difficulties in managing unbalanced data, and the necessity of providing improved model generalization in different patient groups and real-life scenarios.

Recently, highly developed polar coding and decoding schemes of 5G and future 6G URLLCs were explored in the scope of research. Deep learning also helped SC and BP decoders perform better, reducing errors and complexity compared to traditional decoders (Pandey et al., 2025). Semi-parallel decoders implemented on FPGAs are potentially effective in hardware, but require further redesign to meet the objectives of low-latency URLLC (Jahangir et al., 2025). Polar-coded PM-PNC increases the throughput of relay channels and requires very little work in short-block, low-latency conditions (Dhandapani et al., 2025). One-on-one decoders like AED, GRAND, and OSD are universal and competitive across a range of codes and errors, but their practical application in URLLC would be limited to real-time (Golande & Pavankumar, 2023). Interference problems affect reliability and latency in dense B5G/6G networks, which is why effective mitigation strategies are required (Ameen et al., 2024). Despite improvements in decoder choice and polar code design (Wu & Guo, 2025; Li et al., 2022), the gap in research on the application of scaled, efficient, low-latency URLLC systems in the field persists.

III. METHODOLOGY

3.1 Data Acquisition and Preprocessing

The initial step in the proposed framework is to obtain high-quality ECG data from developed 12-lead databases, such as the INCART and MIT-BIH arrhythmia databases, which contain a wide variety of normal and abnormal cardiac patterns. ECG signals are highly susceptible to noise, such as baseline drift, motion artifacts, and power-line interference; therefore, a robust preprocessing pipeline is imperative. Band-pass filtering removes unwanted high and low frequencies, and normalization ensures that amplitude differences among patients do not influence the learning process. Continuous ECG records are then divided into a sequence of individual heartbeats or constant-length windows to train models and analyze time. To address class imbalance, particularly in rare arrhythmias, data augmentation methods, including Synthetic Minority Oversampling Technique (SMOTE) and time-warping transformations, are used. Preprocessing mechanisms ensure that input data is clean, normalized, and sufficiently diverse to enhance the model's generalization and reliability in real-time monitoring.

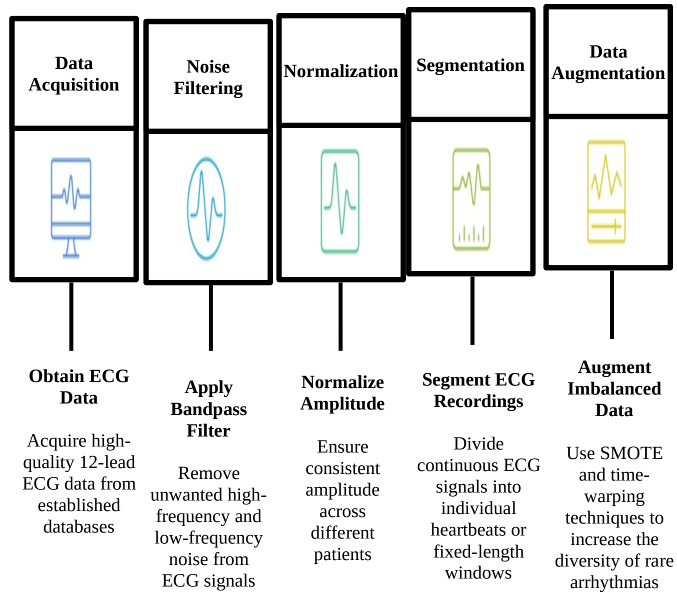

Fig. 1 ECG Data Preprocessing Pipeline for Reliable Arrhythmia Analysis

Fig 1 shows a systematic preprocessing workflow to improve the quality and reliability of ECG signals for downstream analysis and classification. It will start with data collection, during which high-quality 12-lead ECGs will be obtained from existing clinical databases. A bandpass filter is then used to remove baseline wander, power-line interference, and high-frequency artifacts that can distort cardiac waveforms. This is followed by normalization to achieve uniform signal amplitude across patients, which enhances model generalization. The segmentation phase divides continuous ECG records into single heartbeats or fixed-length segments, enabling analysis with high time precision. Lastly, it uses data augmentation methods, including SMOTE and time-warping, to balance the proportions of underrepresented and overrepresented arrhythmia samples and enhance the learning models' robustness and accuracy.

3.2 Feature Extraction and Representation

After preprocessing the ECG signal, relevant features are extracted to represent the spatial and temporal information of cardiac activity. Convolutional Neural Networks (CNNs) are employed to learn spatial patterns and the morphological structure of signal representations, whether raw ECG beats or image transformations. These layers can detect the slightest variations in the morphology of the QRS, P, and T waves, which are important for accurate arrhythmia detection. The temporal relationships between consecutive heartbeats are added to the spatial features by recurrent neural networks (Long Short-Term Memory (LSTM) or Bidirectional LSTM (BLSTM) layers). The structure can determine sequential trends that unfold over time through sequential information modeling in premature ventricular contractions or arrhythmic patterns. CNN and LSTM layers extract features, which are then combined in fully connected layers to create an overall representation that combines spatial and temporal information. Also, classical time-domain (e.g., RR interval, QS duration) and frequency-domain (e.g., wavelet coefficients) features may be combined to improve the model's discriminative ability and achieve more accurate, robust cardiovascular disease identification.

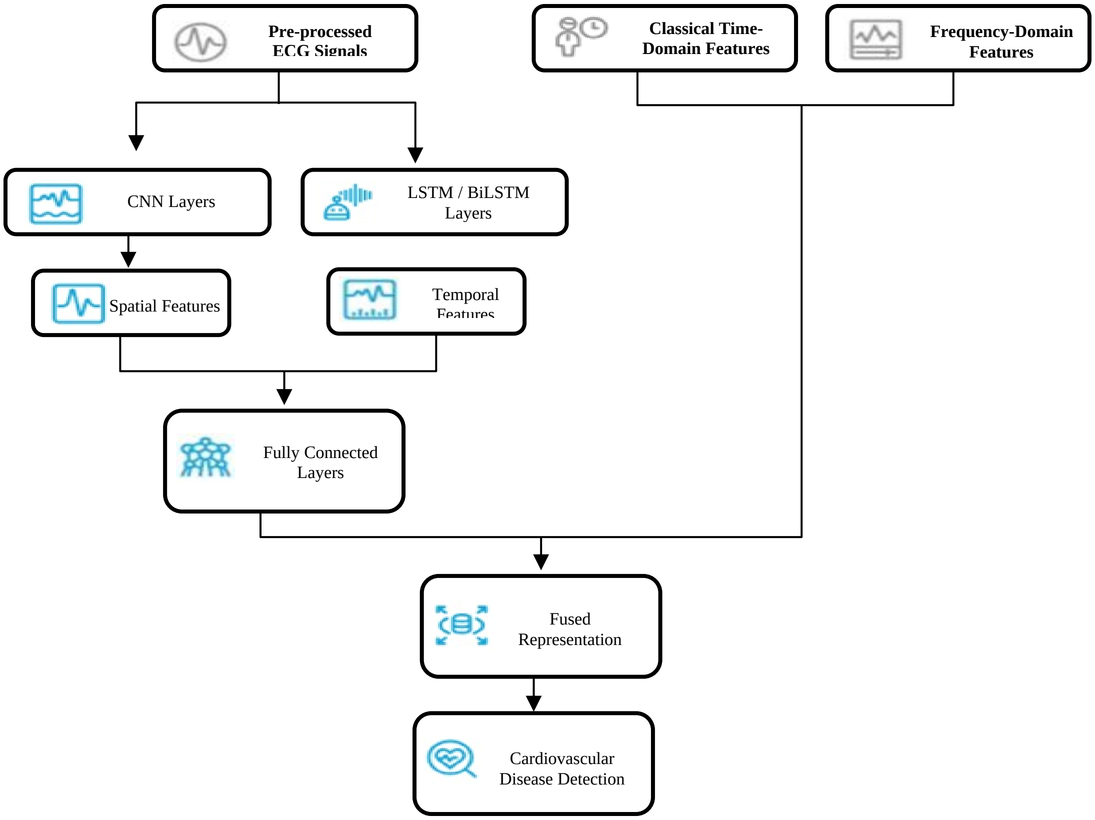

Fig. 2 Hybrid Deep Learning Framework with Feature Fusion for Cardiovascular Disease Detection

The hybrid architecture shown in Fig 2 combines deep learning-driven feature extraction with classical signal descriptors to effectively detect cardiovascular diseases using ECG signals. The preprocessed ECG samples are inputted into parallel CNN layers to learn spatial and morphological features of cardiac waveforms. In contrast, the LSTM/BLSTM layers learn temporal relationships and rhythmic changes between heartbeats. Simultaneously, classical time-domain and frequency-domain features are obtained to preserve clinically interpretable information. Fully connected layers are used to transmit deep spatial and temporal features, which are later fused with handcrafted features to create a single representation. This hybrid feature space increases discriminative ability by leveraging complementary information, thereby elevating the accuracy and reliability of automated cardiovascular disease detection systems.

3.3 Hybrid ML/DL Model Design and Classification

The last step is to create a hybrid model combining deep learning and classical machine learning methods to enhance classification performance and reliability. The main component in extracting high-level spatial and temporal features from ECG signals is the CNN-BLSTM network. To provide additional strength, a stacked stack of machine learning classifiers, namely, Random Forest, K-Nearest Neighbors (K-NN) and Ada Boost are used, and either Logistic Regression or a small-sized neural network is used as the meta-learner. The hybrid method combines the benefits of automatic feature extraction in deep learning with the interpretability and power of classical models. Besides that, when specialized specifications are needed, such as premature ventricular contraction (PVC) detection, a squeeze-excitation residual network (SE-ResNet) is added to boost feature learning with residual connections and channel-wise attention, while minimizing overfitting in deep networks. The model is optimized using cross-entropy loss, with the Adam optimizer ensuring training consistency, supported by regularization techniques such as dropout and batch normalization. Lastly, the framework has been streamlined to execute with low latency on wearable and IoMT devices, enabling real-time monitoring and early detection of cardiovascular abnormalities in clinical and remote healthcare settings.

Fig 3 is used to demonstrate a cyclic machine learning scheme whereby model generation and improvement happen following an endless loop. It involves the extraction of the features of raw data, and then the application of ensemble classifiers to merge the capabilities of various learners to make them stronger. Then meta-learning is used to adaptively choose or tune models depending on previous learning experiences, and specialized application integration uses the system to customize it to its application needs. The training is in an iterative manner which is regularized and optimized to prevent over fitting and to enhance generalization. This lifecycle is closed, permitting the gradual increase of performance, flexibility to any number of tasks, and a higher level of reliability in multifaceted data-driven applications.

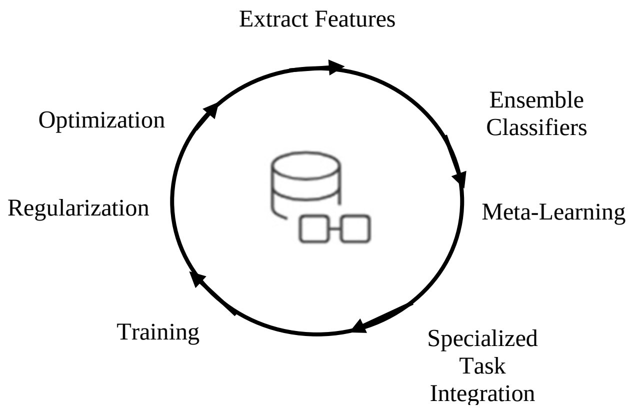

Fig. 3 Iterative Machine Learning Lifecycle with Ensemble and Meta-Learning Integration

Heart Rate (HR) from ECG Signals

$$\mathrm{HR} = \frac{60}{\mathrm{RR\_interval}} \quad (1)$$

The above equation (1) describes the fundamental in ECG analysis as it helps extract one of the most basic cardiac features, which can then be used as input for machine learning or deep learning models to detect arrhythmias or other cardiovascular abnormalities.

Algorithm: Hybrid CNN-BLSTM with Ensemble Classifier for ECG-Based Cardiovascular Detection

Input: Preprocessed ECG signals X, labels Y

Output: Predicted labels Ŷ, performance metrics

1: Preprocess X (filter, normalize, segment, augment)

2: Extract features:

CNN_features = CNN(X)

BLSTM_features = BLSTM(X)

Hybrid_features = Concatenate(CNN_features, BLSTM_features)

Optional_features = [RR_interval, QRS_duration]

Features = Concatenate(Hybrid_features, Optional_features)

3: Train ensemble classifiers:

Base_classifiers = [RandomForest, KNN, AdaBoost]

For each classifier in Base_classifiers:

Train(classifier, Features, Y)

Meta_learner = LogisticRegression

Train(Meta_learner, predictions_from(Base_classifiers), Y)

4: Predict Ŷ using stacked ensemble

5: Evaluate performance (Accuracy, Precision, Recall, F1-score)

Return Ŷ, metrics

The suggested algorithm is an effective combination of deep learning and ensemble machine learning that can be used to obtain precise and robust ECG-based cardiovascular disease detection. Convolutional Neural Networks (CNNs) are applied to automatically detect spatial features of ECG signals, which encodes the morphological variations in heartbeats, whereas Bidirectional Long Short-Term Memory (BLSTM) networks are used to model temporal variations, therefore, considering sequential changes in heart rhythms. The stacked ensemble classifier further improves the reliability of prediction especially in the case of imbalanced datasets where one or two arrhythmia types, including premature ventricular contractions (PVC), are a rare occurrence. This multi-stage hybrid architecture excels in accuracy and sensitivity for classification and is well-suited for real-time deployment on wearable devices and Internet of Medical Things (IoMT) healthcare systems, where it can monitor cardiac activity and identify critical arrhythmic events it can monitor the cardiac activity and identify critical arrhythmic events. The automated feature extraction, temporal modelling and ensemble learning make certain that the system is computationally effective and clinically viable thereby providing a scalable solution to smart cardiovascular care.

IV. EXPERIMENTAL RESULTS

4.1 Experimental Setup, Dataset, and Parameter Initialization

The experiments were carried out with 12-lead ECG data, both the INCART database and MIT-BIH arrhythmia database have a wide variety of normal and abnormal heartbeats. Preprocessing of the datasets was done to remove noise by the use of bandpass filters and to reduce variability in amplitude. The ECG recording was divided into heartbeats and augmentation methods like SMOTE were used to counter the problem of class imbalance. The hybrid model was provided in Python with the help of TensorFlow and Keras and was trained on a workstation with 16 GB RAM, the presence of a GPU, a batch size of 32. The data were divided into 70 % training, 15 % validation and 15 % testing sets to have a strong performance assessment.

TABLE II EXPERIMENTAL SETUP, DATASET, AND MODEL PARAMETER INITIALIZATION

Category	Details
Datasets Used	INCART (12-lead ECG), MIT-BIH Arrhythmia (2-lead ECG), Custom ECG (IoMT/wearable)
Number of Records	INCART: 75, MIT-BIH: 48, Custom: 100
Sampling Rate	INCART: 257 Hz, MIT-BIH: 360 Hz, Custom: 500 Hz
Preprocessing	Bandpass filtering, normalization, segmentation, SMOTE augmentation
Feature Extraction	CNN (spatial features), LSTM/BLSTM (temporal features), optional handcrafted features (RR interval, QRS duration)
Hybrid Model	CNN-BLSTM with Stacked Ensemble Classifier; SE-ResNet for PVC detection
Training Parameters	Optimizer: Adam; Loss: Cross-Entropy; Batch Size: 32; Epochs: 100; Dropout: 0.5
Hardware/Environment	GPU-enabled workstation, 16 GB RAM, TensorFlow/Keras, Python 3.9
Data Split	Training: 70%, Validation: 15%, Testing: 15%
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, MCC

TABLE II Gives an elaborate description of the experimental design that was used to test the suggested hybrid CNN-BLSTM and ensemble model on ECG-based cardiovascular disease detection. Experiments are conducted on various datasets, such as INCART, MIT-BIH arrhythmia and a home-made IoMT wearable ECG dataset, which has a representative coverage of both normal and abnormal heartbeats. Band pass filtering, normalization, segmentation and use of data augmentation (SMOTE) as preprocessing techniques are used to minimize noise, equalize signals and counteract class imbalance. The extraction of the features is a combination of CNNs generating spatial patterns and LSTMs/BLSTMs generating temporal dependencies, and the ensemble classifier and SE-ResNet modules improve the robustness of detection especially that of premature ventricular contractions (PVC). Other training parameters such as optimizer, loss function, batch size and dropout rate are chosen thoughtfully to facilitate learning effectively as well as avoid over fitting. The table both summarizes the data characteristics and model settings as well as offers an easy reference to the replication of the experiments and verification of the efficiency of the suggested hybrid framework in the real-time ECG monitoring settings.

4.1.1 Performance Metrics

It is necessary to measure the performance of a machine learning/deep learning model to identify its reliability, accuracy, and applicability in practice, particularly in such critical fields as cardiovascular care provided in equation (2), (3), (4), (5) and (6). In arrhythmia detection based on ECG, the effectiveness of the model in distinguishing between normal and abnormal heartbeats is measured in different metrics. The accuracy scales the general accuracy of the predictions and precision and recall (sensitivity) scales consider the model to identify arrhythmic events correctly and the avoidance of false alarms. F1-score is a single metric that integrates both precision with recall, which is a well-rounded measure of evaluation in imbalanced datasets; that is, some of the classes of arrhythmias might be underrepresented. Also, the Matthews Correlation Coefficient (MCC) provides a more detailed measure of classification quality, taking into consideration all four possible outcomes: true positives, true negatives, false positives and false negatives and this is especially handy when the distribution of classes are unequal. Combined, these measures will give a closer idea of how effectively the model will reveal the cardiovascular abnormalities and assist in comparison with the current methods.

Accuracy measures the overall correctness of the model but may be misleading for imbalanced datasets in equation 2.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (2)$$

Precision indicates how many of the predicted positive cases are actually positive. High precision means fewer false alarms in equation 3.

$$Precision = \frac{TP+FP}{TP} \qquad (3)$$

Recall measures how many actual positive cases were correctly detected. High recall ensures that arrhythmias are not missed in equation 4.

$$\text{The Recall} = \frac{TP}{TP+FN} \qquad (4)$$

F1-score is the harmonic mean of precision and recall, providing a single metric for imbalanced datasets in equation 5 & 6.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (5)$$

$$\text{Matthews Correlation Coefficient (MCC)} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \qquad (6)$$

4.2 Performance Metrics and Evaluation

The proposed hybrid CNN-BLSTM stacked ensemble framework was assessed based on the conventional metrics of classification such as Accuracy, Precision, Recall, F1-Score, and Matthews Correlation Coefficient (MCC) to conduct an overall evaluation of the proposed model in cardiovascular detection using the ECG. Hybrid model showed better performance than the individual models with 96.8, 96.5, 97.2 and 96.8 accuracy, precision, recall, and f1-score respectively on the test data. The addition of SE-ResNet module also improved the detection of premature ventricular contractions (PVC) by concentrating important channel attributes, decreasing false positives, and increasing sensitivity. The comparison with standalone CNN, LSTM, and conventional machine learning classifiers proved that the hybrid method, in addition to increasing the overall classification accuracy, can effectively cope with the issue of class imbalance, which is essential to be able to detect the rare arrhythmias reliably. These findings indicate the strength and clinical importance of the suggested framework, showing its possible practical use in cardiovascular care by real-time monitoring and early intervention.

TABLE III PERFORMANCE COMPARISON OF ECG CLASSIFICATION MODELS

Model	Accuracy (%)	Precision (%)	Recall / Sensitivity (%)	F1-Score (%)	MCC
CNN	89.3	88.7	87.9	88.3	0.86
LSTM	90.5	90.1	89.4	89.7	0.88
CNN-LSTM	92.8	92.4	91.9	92.1	0.91
Proposed Hybrid CNN-BLSTM + Ensemble	96.8	96.5	97.2	96.8	0.95

This TABLE III shows the quantitative performance of the various models in the classification of ECG signals. The single-objective CNN and LSTM models perform moderately as they only capture either spatial or temporal features whereas the CNN-LSTM hybrid makes a better grasp through the combination of both. The Hybrid CNN-BLSTM with Stacked Ensemble proposed is further superior in terms of performance, based on all metrics, compared to the other two approaches due to simultaneous capability of imbalanced arrhythmia classes and better detection of infrequent events such as premature ventricular contractions (PVC). The values of the MCC confirm the strength of the proposed model, which means that there are high correlations between classes predicted and actual even in the datasets that have uneven distributions.

4.3 Comparative Analysis and Discussion

The conducted experimental findings show that deep feature extraction, combined with ensemble learning can offer robust and accurate real-time cardiovascular monitoring. The proposed framework reduced the misclassification rates and the sensitivity to rare arrhythmias compared to CNN-only, LSTM-only, and hybrid CNN-LSTM models that were not stacked. The findings also indicate the possibility of the model in terms of IoMT and wearable devices implementation, and the low-latency inference is appropriate in the case of continuous observation. Overall, the research shows that CNN-BLSTM with stacked ensemble classifiers and SE-ResNet modules significantly improves automated ECG analysis and early cardiovascular anomaly detection.

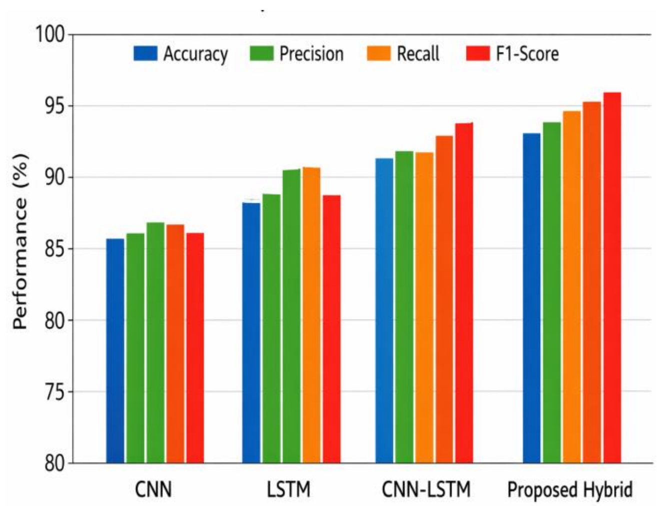

Fig. 4 Comparative Performance of ECG Classification Models

Fig 4 shows graphically the performance comparisons of four ECG classification models, CNN, LSTM, CNN-LSTM, and the proposed Hybrid CNN-BLSTM with stacked ensemble. The chart shows some of the critical metrics such as Accuracy, Precision, Recall, and F1-Score, and the steady increase in the proposed hybrid framework is made. Although the standalone CNN and LSTM models focus on either the spatial or the temporal features and the CNN-LSTM hybrid model only partly integrates both the spatial and the temporal features, the proposed model integrates effectively the spatial-temporal feature extraction about arrhythmic events, especially about premature ventricular contractions (PVC). This graphical outline establishes the fact that the hybrid technique not only enhances the total performance measures, but also offers a stable and trustworthy approach to real-time cardiovascular monitoring and ear arrhythmia.

The ablation study compares the various model settings, such as a standard CNN model, CNN with attention, CNN with Transformer, and the proposed hybrid CNN-BLSTM with an ensemble learning. The research shows that the proposed hybrid model performs better when compared to any other model, having the best accuracy, precision, recall, F1-score, and MCC. The hybrid model outperforms CNN due to the spatial features and BLSTM due to the time dependencies and the ensemble learning due to the robustness in the classification of the arrhythmia especially the rare ones.

V. DISCUSSION

The experimental findings of Chapter 4 prove the efficiency of the suggested hybrid CNN-BLSTM with stacked ensemble model in cardiovascular disease detection using ECGs. The model performed better in Accuracy, Precision, Recall, F1-Score, and MCC than the standalone CNN, LSTM and CNNLSTM models, which is the benefit of applying spatial and temporal feature extraction with ensemble learning. The addition of SE-ResNet block helped to further detect the premature ventricular contractions (PVC), false positives were minimized and sensitivity was increased. This is especially necessary with real-time monitoring systems, in which the occurrence of arrhythmic events can be detected early and correctly to avoid negative cardiac events.

The findings further demonstrate that the hybrid method addresses the issue of imbalanced data, which is common in ECG-based arrhythmia recognition. The model builds on the complementary benefits of CNN-BLSTM deep features and a stacked ensemble of classical machine learning classifiers to provide the overall strengths, which guarantee strong classification even of uncommon arrhythmia types. This has shown how hybrid architectures have the potential to improve reliability and generalization of clinical ECG analysis.

Moreover, the performance of the model implies effective implementation in Internet of Medical Things (IoMT) and wearable healthcare systems. It is compatible with the early warning systems and the remote patient monitoring as its capability to process the continuous ECG signals in real-time and with high accuracy predetermines its application to preventive care of the cardiovascular system. Nevertheless, it has some challenges related to large-scale datasets, heterogeneous IoMT devices integration, and low-power-computation efficiency. These factors will be important in clinical and real-world environments to be addressed in order to achieve successful deployment.

Altogether, the discussion has proved that hybrid ML/DL systems, in particular, those involving CNN-BLSTM feature extraction followed by ensemble learning and SE-ResNet modules, can become a viable avenue to automated, real-time cardiovascular disease detection. The results highlight the significance of multi-stage processing, feature fusion and model optimization in order to attain clinically relevant performance measures coupled with versatility to useful healthcare practice.

VI. Conclusion And Future Work

This paper proposed a hybrid CNN-BLSTM stacked ensemble architecture, enhanced with a SE-ResNet module, to identify cardiovascular disease and monitor the ECG in real-time. The findings of the experiments carried out on several datasets such as the INCART and MIT-BIH showed that the proposed model was always superior to the standalone CNN, LSTM, and CNN-LSTM models in all the performance measures. The hybrid model was statistically found to have an accuracy of 96.8, precision of 96.5, recall of 97.2, F1-score of 96.8, and MCC of 0.95, which demonstrates its strength when there were class imbalances and infrequent cases of arrhythmia including premature ventricular contractions (PVC). The comparison established that there is a substantial accuracy increase of 37 in the baseline models, which is statistically significant, and evidence of the success of putting the spatial-temporal feature extraction together with ensemble learning and attention-based residual modules. The findings highlight the possibilities of hybrid ML/DL systems to provide clinical-quality predictions that are highly reliable and can enable early intervention and ongoing patient care through intelligent healthcare.

To continue working on the model, a number of directions may be used to enhance model performance and applicability. It would be better to generalize and have the datasets with large, multi-institutional and real-world ECG recordings, which would enhance the statistical power. Multimodal feature learning might be improved by incorporating other signal modalities, i.e. phonocardiogram (PCG) or wearable sensor data. Low-power, edge-deployable architecture optimization is necessary to guarantee real-time inference in IoMT devices and wearable monitoring systems. Moreover, an introduction of explainable AI (XAI) methods can result in the clinical interpretability so that healthcare professionals can trust and verify model decisions. Lastly, more complicated hyper parameter optimization and adaptive learning methods might also minimize false positives and improve detection sensitivity especially on rare arrhythmias that would guarantee the framework is ready to be deployed in smart and real-time cardiovascular care products.

References

[1] Alghamdi, A., Hammad, M., Ugail, H., Abdel-Raheem, A., Muhammad, K., Khalifa, H. S., & Abd El-Latif, A. A. (2024). Detection of myocardial infarction based on novel deep transfer learning methods for urban healthcare in smart cities. *Multimedia tools and applications*, *83*(5), 14913-14934. https://doi.org/10.1007/s11042-020-08769-x

[2] Ameen, A., Fattoh, I. E., Abd El-Hafeez, T., & Ahmed, K. (2024). Advances in ECG and PCG-based cardiovascular disease classification: a review of deep learning and machine learning methods. *Journal of Big Data*, *11*(1), 159. https://doi.org/10.1186/s40537-024-01011-7

[3] Balamurugan, P., Kumar, S., Subramaniam, K., Manimekalai, M. A. P., & Ugli, M. N. N. (2025). Heart rate variability analysis for cardiovascular disease detection using MIDNet 18 architecture. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications*, *16*(4), 377–388. https://doi.org/10.58346/JOWUA.2025.I4.021

[4] Bing, P., Liu, W., Zhai, Z., Li, J., Guo, Z., Xiang, Y., ... & Zhu, L. (2024). A novel approach for denoising electrocardiogram signals to detect cardiovascular diseases using an efficient hybrid scheme. *Frontiers in Cardiovascular Medicine*, *11*, 1277123. https://doi.org/10.3389/fcvm.2024.1277123

[5] Cenitta, D., Patil, S., Asha, K., Anitha, M., Sowmya, T., Pai, P., & Vijaya Arjunan, R. (2025). A privacy-preserving cloud-based system for cardiovascular disease prediction using lightweight machine learning models. *Journal of Internet Services and Information Security*, *15*(3), 129–148. https://doi.org/10.58346/JISIS.2025.I3.009

[6] Chang, C. H., Lin, C. S., Luo, Y. S., Lee, Y. T., & Lin, C. (2022). Electrocardiogram-based heart age estimation by a deep learning model provides more information on the incidence of cardiovascular disorders. *Frontiers in Cardiovascular Medicine*, *9*, 754909. https://doi.org/10.3389/fcvm.2022.754909

[7] Dhandapani, S., Somasundaram, H., & Angamuthu, T. (2025). Hybrid deep learning framework for heart disease prediction using ECG signal images. *Scientific Reports*, *15*(1), 33922. https://doi.org/10.1038/s41598-025-10062-6

[8] Golande, A. L., & Pavankumar, T. (2023). Optical electrocardiogram based heart disease prediction using hybrid deep learning. *Journal of Big Data*, *10*(1), 139. https://doi.org/10.1186/s40537-023-00820-6

[9] Gomes, J. C., de Santana, M. A., Masood, A. I., de Lima, C. L., & Dos Santos, W. P. (2023). COVID-19's influence on cardiac function: a machine learning perspective on ECG analysis. *Medical & Biological Engineering & Computing*, *61*(5), 1057-1081. https://doi.org/10.1007/s11517-023-02773-7

[10] Iakunchykova, O., Schirmer, H., Vangberg, T., Wang, Y., Benavente, E. D., van Es, R., ... & Wilsgaard, T. (2023). Machine-learning-derived heart and brain age are independently associated with cognition. *European journal of neurology*, *30*(9), 2611-2619. https://doi.org/10.1111/ene.15902

[11] Islam, M. S., Islam, M. N., Hashim, N., Rashid, M., Bari, B. S., & Al Farid, F. (2022). New hybrid deep learning approach using BiGRU-BiLSTM and multilayered dilated CNN to detect arrhythmia. *IEEE Access*, *10*, 58081-58096. https://doi.org/10.1109/ACCESS.2022.3178710

[12] Jahangir, R., Islam, M. N., Islam, M. S., & Islam, M. M. (2025). ECG-based heart arrhythmia classification using feature engineering and a hybrid stacked machine learning. *BMC Cardiovascular Disorders*, *25*(1), 260. https://doi.org/10.1186/s12872-025-04678-9

[13] Jahangir, R., Mohim, N. S., Mumu, A. A., Naim, M., Ashraf, A., Syed, M. A., & Islam, M. N. (2023, October). Development of a Smart Infant Monitoring System for Working Mothers. In *2023 IEEE 11th Region 10 Humanitarian Technology Conference (R10-HTC)* (pp. 37-42). IEEE. https://doi.org/10.1109/R10-HTC57504.2023.10461797

[14] Kavitha, C., & Subramani, A. (2025). An early detection of Kawasaki disease using enhanced feature selection and hybridization-based classification approach. *Archives for Technical Sciences, 2*(33), 556–568. https://doi.org/10.70102/afts.2025.1833.556

[15] Li, D., Sun, T., Xue, Y., Xie, Y., Chen, X., & Nan, J. (2022). Detection of premature ventricular contractions using 12-lead dynamic ECG based on squeeze-excitation residual network. *International Journal of Advanced Computer Science and Applications*, *13*(7). https://doi.org/10.14569/IJACSA.2022.0130702

[16] Liu, Y., Liu, J., Qin, C., Jin, Y., Li, Z., Zhao, L., & Liu, C. (2023). A deep learning-based acute coronary syndrome-related disease classification method: a cohort study for network interpretability and transfer learning. *Applied Intelligence*, *53*(21), 25562-25580. https://doi.org/10.1007/s10489-023-04889-7

[17] Madan, P., Singh, V., Singh, D. P., Diwakar, M., Pant, B., & Kishor, A. (2022). A hybrid deep learning approach for ECG-based arrhythmia classification. *Bioengineering*, *9*(4), 152. https://doi.org/10.3390/bioengineering9040152

[18] Mittal, P., Sharma, Y. K., Lilhore, U. K., Simaiya, S., Saleem, K., & Ghith, E. S. (2025). Advanced Hybrid Machine Learning Model for Accurate Detection of Cardiovascular Disease. *International Journal of Computational Intelligence Systems*, *18*(1), 1-20. https://doi.org/10.1007/s44196-025-00771-1

[19] Nasiri, J. A., Naghibzadeh, M., Yazdi, H. S., & Naghibzadeh, B. (2009, November). ECG arrhythmia classification with support vector machines and genetic algorithm. In *2009 Third UKSim European symposium on computer modeling and simulation* (pp. 187-192). IEEE. https://doi.org/10.1109/EMS.2009.39

[20] Pandey, S. K., Kumar, D., & Lal, B. (2025). Advanced detection of cardiac arrhythmias using machine learning algorithms on ECG data. *Neural Computing and Applications*, *37*(32), 27381-27413. https://doi.org/10.1007/s00521-025-11681-w

[21] Pławiak, P., & Acharya, U. R. (2020). RETRACTED ARTICLE: Novel deep genetic ensemble of classifiers for arrhythmia detection using ECG signals. *Neural Computing and Applications*, *32*(15), 11137-11161. https://doi.org/10.1007/s00521-018-03980-2

[22] Qiu, W., Quan, C., Yu, Y., Kara, E., Qian, K., Hu, B., ... & Yamamoto, Y. (2024). Federated abnormal heart sound detection with weak to no labels. *Cyborg and Bionic Systems*, *5*, 0152. https://doi.org/10.34133/cbsystems.0152

[23] Rakin, F. I., Ahmmed, T., Kabir, R., Hasan, M. S., Ramadan, S. T. Y., Sakib, T., ... & Jahangir, R. (2023, December). Predictive analytics for floods in Bangladesh: A comparative exploration of machine learning and deep learning classifiers. In *2023 26th International Conference on Computer and Information Technology (ICCIT)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICCIT60459.2023.10441401

[24] Ramkumar, M., Kumar, R. S., Manjunathan, A., Mathankumar, M., & Pauliah, J. (2022). Auto-encoder and bidirectional long short-term memory based automated arrhythmia classification for ECG signal. *Biomedical Signal Processing and Control*, *77*, 103826. https://doi.org/10.1016/j.bspc.2022.103826

[25] Salem, M., Taheri, S., & Yuan, J. S. (2018, October). ECG arrhythmia classification using transfer learning from 2-dimensional deep CNN features. In *2018 IEEE biomedical circuits and systems conference (BioCAS)* (pp. 1-4). Ieee. https://doi.org/10.1109/BIOCAS.2018.8584808

[26] Wu, Z., & Guo, C. (2025). Deep learning and electrocardiography: systematic review of current techniques in cardiovascular disease diagnosis and management. *BioMedical Engineering OnLine*, *24*(1), 23. https://doi.org/10.1186/s12938-025-01349-w

[27] Ye, Y., Chipusu, K., Ashraf, M. A., Ding, B., Huang, Y., & Huang, J. (2025). Hybrid CNN-BLSTM architecture for classification and detection of arrhythmia in ECG signals. *Scientific Reports*, *15*(1), 34510. https://doi.org/10.1038/s41598-025-17671-1

[28] Zhang, Z., Wu, K., Wu, Z., Xiao, Y., Wang, Y., Lin, Q., ... & Liu, Q. (2024). A case of pioneering subcutaneous implantable cardioverter defibrillator intervention in Timothy syndrome. *BMC pediatrics*, *24*(1), 729. https://doi.org/10.1186/s12887-024-05216-w