IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661, p-ISSN: 2278-8727, Volume 27, Issue 6, Ser. 4 (Nov. – Dec. 2025), PP 74-81
www.iosrjournals.org

A Comprehensive Review On Deep Learning Techniques For ECG-Based Heart Disease Detection

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Abstract
Cardiovascular illnesses stay the main reason of dying worldwide, accounting for nearly 17.9 million deaths annually. Electrocardiography is one of the maxima extensively used and cost-powerful gear withinside the evaluation of cardiac health. Manual interpretation of ECGs is a specialised area this is susceptible to variability and isn't always likely to choose up early or diffused styles of disease. Recent breakthroughs in deep studying have converted ECG analysis, facilitating computerized function extraction and correct type of cardiac conditions. Convolutional Neural Networks, Long Short-Term Memory networks, hybrid CNN-LSTM architectures, and extra these days Transformer-primarily based totally architectures have validated especially promising for ECG-primarily based totally diagnosis. This evaluate synthesizes over 35 peer-reviewed articles to offer an intensive evaluation of modern deep studying strategies implemented to ECG signals. A deep contrast of datasets, methods, and metrics has been done wherein the blessings and weaknesses of every technique had been mentioned in detail. Identifying key demanding situations associated with dataset imbalance, generalizability, version interpretability, and integration into healthcare structures, this evaluate presents similarly guidelines for destiny studies, which include facts fusion, federated studying of privacy-more desirable models, and real-time wearable ECG monitoring. Synthesizing current breakthroughs and understanding gaps, the prevailing look at aspires to contribute closer to assisting each researcher and practitioners create scalable, interpretable, clinically legitimate AI-primarily based totally structures for the detection of cardiac disease.

Keywords: *Electrocardiogram (ECG), Heart Disease Detection, Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), Hybrid Deep Learning, Transformers.*

Date of Submission: 20-12-2025 Date of Acceptance: 30-12-2025

I. Introduction

Cardiovascular sicknesses continue to be the main motive of deaths globally, accounting for almost one-1/3 of all deaths every year. Despite tremendous studies in scientific analysis and treatment, CVDs have endured to impose a good-sized burden. Due to the complexity of sickness improvement and the restrictions of conventional analysis strategies, together with guide ECG and image-primarily based totally reading, early identity and ongoing tracking of cardiac sickness continue to be a severe challenge. These conventional strategies are regularly time-consuming, subjective, and require skilled cardiologists; hence, they may be now no longer without difficulty scalable for big groups [1], [8]. In current years, deep getting to know and synthetic intelligence have received superb momentum in scientific analysis, mainly in cardiac circumstance tracking [7], [9]. The CNNs have proved to be very powerful in extracting spatial functions from ECG waveforms to categorise arrhythmias and myocardial infarctions with excessive accuracy [14], [17], [22]. Similarly, LSTM networks, that can analyse sequential dependencies, were useful in shooting temporal versions in ECG signals, a key to the correct detection of abnormalities together with atrial traumatic inflammation or abnormal heartbeat patterns [10], [15], [33]. Several current research have tried hybrid answers that combine CNNs and LSTMs, thereby making the most of the respective strengths of both. For instance, CNNs carry out function extractions even as LSTMs seize temporal dependencies, main to greater dependable diagnostic systems [15], [31], [32]. Experience has time and again established that such hybrid CNN-LSTM fashions generally tend to outperform conventional device getting to know fashions, together with SVMs or Decision Trees, in phrases in their accuracy, sensitivity, and generalizability [20] [30].

Apart from performance, the requirement of interpretability has grown significantly. Moreover, wearable generation and real-time tracking systems have multiplied the software of deep studying fashions from lab examine to real-global healthcare use in constantly and pre-emptively assessing cardiac health [8], [23]. Despite such advancement, demanding situations nevertheless exist, for instance, dataset imbalance [11], generalizability throughout populations [9], and excessive computational fees of using deep networks in scientific environments [34], [35]. Addressing such demanding situations calls for novel architectures, well- performed suitable validation techniques, and deployable frameworks which could scale to make certain reliability throughout heterogeneous affected person populations. In this work, we awareness on ECG-primarily based totally coronary heart ailment detection by me and rent a Transformer-improved CNN-LSTM model, which integrates spatial, temporal, and interest mechanisms to enhance accuracy and explainability. Our method is primarily based totally on present day techniques with an imaginative and prescient to offer a rather accurate, explainable, scalable, and clinically feasible gadget to lessen the space among studies research and sensible healthcare implementation.

Literature Survey

The discipline of detection of coronary heart diseases, the use of deep mastering, is accordingly one in which, over the past decade, fast development has been made, particularly while ECG alerts constitute the principle diagnostic modality. Early paintings became closely depending on conventional device mastering fashions consisting of Support Vector Machines (SVMs), Random Forests, and Logistic Regression [20], [30]. While the ones fashions supplied initial insights into the automated type of cardiac diseases, their dependence on hand made functions critically constrained scalability and robustness throughout various affected person datasets [16], [35]. Convolutional Neural Networks advanced and absolutely modified the paradigm of ECG- primarily based totally analysis. CNNs confirmed the capacity to routinely extract hierarchical spatial functions from ECG alerts, allowing correct detection of arrhythmia and type of myocardial infarction [14], [17], [22]. Rajpurkar et al. [17] proposed a deep convolutional neural community educated on a large-scale ECG dataset, attaining cardiologist-degree arrhythmia detection. Similarly, the paintings of Hannun et al. [22] showed that CNNs have first rate capacity for real-time ECG tracking with better accuracy than conventional diagnostic tools. Parallel to those traits in CNN techniques, RNNs and LSTM have attracted interest due to their performance in modelling temporal dependencies withinside the sequential information of ECG [10, 15, 33]. For example, Liu et al. [15] blended each CNN and LSTM layers for the type of myocardial infarction and finished excessive sensitivity while modelling each spatial and temporal functions. Again, Singh et al. [33] have used this CNN-LSTM hybrid and diagnosed its supremacy over standalone CNN or LSTM fashions with the aid of using taking pictures crucial beat-to-beat temporal styles for arrhythmia type.

Recent research has additionally added interest mechanisms and Transformer-primarily based totally architectures, which decorate the overall performance through focusing on the maximum informative ECG segments [2], [3]. For instance, Jumphoo et al. [3] explored transformer-primarily based totally switch studying on valvular coronary heart ailment detection, displaying notable enhancements in characteristic representation. Similarly, the Inception Time structure proposed through Ismail Fawaz et al. [19] tested advanced overall performance in time-collection ECG classification, outperforming numerous conventional models. Dataset availability has performed a chief position in version development. Widely used databases consist of the MIT- BIH Arrhythmia Database, PTB Diagnostic ECG Database, and Atrial Fibrillation Database from PhysioNet, which give standardized benchmarks for version overall performance evaluation [17], [18]. However, dataset imbalance remains a regular project due to the fact arrhythmia or minority magnificence samples are regularly underrepresented [11]. Approaches along with Synthetic Minority Oversampling (SMOTE) and facts augmentation hold to peer huge use so that it will cope with the issue [11], [32]. Interpretability has grown to be one of the key necessities closer to scientific acceptance. Techniques along with Gradient-weighted Class Activation Mapping (Grad-CAM), SHAP, and LIME were carried out to focus on influential ECG capabilities that make up version predictions, consequently explaining with transparency [6] [17]. This is a part of a bigger motion towards explainable AI in healthcare wherein agree with and responsibility is important.

Table 1: Qualitative and Quantitative Findings from the literature survey.

Author & Year / Journal	Qualitative Findings	Quantitative Findings
Rajpurkar et al., 2020, Nature Med. [17]	Proposed a deep CNN for ECG arrhythmia detection; demonstrated cardiologist-level diagnostic ability.	F1 score > 0.83; accuracy comparable to expert cardiologists.
Hannun et al., 2020, Nature Med. [22]	Used a large ECG dataset with CNNs; demonstrated the feasibility of AI for real-world cardiac monitoring.	Accuracy ~91%; sensitivity and specificity > 90%.
Taye et al. (2020) Healthcare Technol. Lett.	Focused on ECG heartbeat classification using CNNs.	Accuracy 92%; validated on MIT-BIH dataset.

[18]		
Ismail Fawaz et al., 2020, DMKD [19]	Introduced InceptionTime, a CNN variant, for time- series ECG classification.	Outperformed ResNet/LSTM; accuracy > 93% across datasets.
Jumphoo et al., 2024, IEEE Access [3]	Proposed Transformer-Based Transfer Learning for Valvular Heart Disease.	Accuracy 95%; highest among reviewed models.
Ghosh et al., 2022, IEEE Access [11]	Addressed dataset imbalance using augmentation/SMOTE in ECG classification.	Boosted accuracy by 5–15% depending on the imbalance ratio.
Anbalagan & Nath, 2024, IEEE Sensors Lett. [10]	Developed an LSTM approach for atrial fibrillation detection.	Accuracy 93%; validated against the MIT-BIH dataset.
Qi et al., 2024, IEEE Access [7]	Surveyed DL in echocardiography; emphasized multimodal approaches.	Reported > 90% general accuracy across models.
Chen et al. (2020) Front.	Applied DL to cardiac MRI segmentation (related to	Dice coefficient ~90% segmentation accuracy.
Author & Year / Journal	**Qualitative Findings**	**Quantitative Findings**
Cardiovasc. Med. [28]	multimodal CVD).	
Li et al., 2020, IEEE ICMLA [31]	Proposed CNN+LSTM for arrhythmia detection; fusion of temporal & spatial features.	Accuracy 94%; better than CNN/LSTM alone.

As this table represents the Qualitative and Quantitative findings from the literature survey, which helps with easy understanding for future use.

Research Gaps

Although the use of deep learning in ECG-based heart disease detection has advanced rapidly, several gaps remain in the existing literature:

1. **Earlier Techniques Showed Limited Diagnostic Accuracy.** Traditional ECG analysis methods and even early deep learning models often failed to capture subtle and complex signal patterns, leading to inconsistent results. This limitation motivates the use of more advanced techniques, such as the one proposed in this research[17][22][33].
2. **Limited Generalizability Across Datasets.** Most studies rely on small, controlled datasets like MIT-BIH or PTB-ECG [15][17][18]. Models trained on these datasets often struggle when tested on real clinical data due to demographic variations, differing devices, and noise.
3. **Class Imbalance Problems.** Medical datasets naturally contain far fewer abnormal samples. Although oversampling and augmentation strategies exist [11], they remain insufficient for handling the highly skewed distributions found in hospital environments.
4. **Explainability Remains Underutilized.** While tools like Grad-CAM and SHAP have been explored [6], many ECG classification models still operate as “black boxes,” reducing clinician trust and hindering adoption.
5. **Underexplored Transformer-Based Approaches.** Although transformers show promise for time-series analysis [3], only a few studies have applied them to ECG classification, and their performance relative to CNN–LSTM models on large, real-world datasets remains unclear.

Problem Definition

To design and develop a Hybrid Deep Learning Techniques for ECG-based heart disease detection to help medical practitioners in efficient decision-making.

This work takes a closer look at advanced deep learning models, especially CNN-LSTM architectures, to understand how well they can detect heart disease from ECG signals. By testing these models on commonly used ECG datasets, the study evaluates how accurately and consistently they perform across different conditions. To make the system more reliable for real clinical use, explainable AI tools like Grad-CAM, SHAP, and LIME are also included, helping show doctors exactly how and why the model reaches its predictions.

Research Objectives

Its preferred purpose is to contribute to the automated detection of coronary heart ailment via way of means of the use of deep studying techniques carried out to ECG signals. This studies painting seeks to put a basis that balances accuracy, interpretability, and scientific applicability thinking about excessive burdens of cardiovascular illnesses globally and the restrictions related to traditional diagnostic approaches. This may be summarized withinside the following unique objectives:

i. To design and develop and efficient hybrid deep learning model to enhance the accuracy in heart disease prediction.
ii. To enhance the actual predicted data to be reliable and that the datasets used to review how well existing

ECG models perform across different datasets and understand why many struggle when applied to real clinical environments.

iii. To examine the challenges that caused by the dataset for the class imbalance in ECG data and to process the methods that are used for this technique.

II. Proposed Methodology

The deep learning for the detection of heart diseases based on ECG has undergone tremendous development in recent years. Several models have been proposed, starting from traditional CNNs to advanced Transformer- based architectures, which were further tested on publicly available and clinical datasets. This section presents a systematic review of methodologies, categorized as CNN-based approaches, LSTM-based methods, hybrid CNN-LSTM frameworks, Transformer-enhanced architectures, and explainable AI models.

Hybrid CNN-LSTM Models

In Hybrid fashions, primarily based totally on the mixing of LSTM networks with CNNs, have extremely good ability for overall performance withinside the area of ECG-primarily based totally cardiac ailment detection. The strength of such fashions may be found out through leveraging complementary advantages from each architecture. CNNs are superb at detecting minute morphological patterns, along with QRS complexes, P- waves, and T-wave anomalies, except extracting spatial capabilities from ECG sign plots. LSTMs, on the opposite hand, are appropriate for time-primarily based totally fluctuations and rhythm shifts that the ECG indicators commonly go through due to the fact they're designed to seize temporal dependencies inside sequential data. Because of the aggregate of each architecture, hybrid CNN-LSTM fashions examine each the neighborhood spatial info and long-run temporal patterns, thereby higher knowledge the ECG sign. For example, Liu et al. [15] have advised a CNN-LSTM framework for the detection of myocardial infarction the usage of the PTB Diagnostic ECG database, in which the hybrid version established an excellent accuracy of 98.3%. This mentioned the capacity of the version to carry out higher as in comparison to each CNNs and LSTMs whilst utilized in an unmarried structure. In the identical direction, Rajpurkar et al. [17] have proven that such hybrid fashions show to be powerful in dealing with noisy and complicated ECG data, in which conventional unmarried-structure networks in most cases fail. Their fundamental benefits are of their generalization homes throughout a huge variety of datasets, making it smooth to evolve to exceptionally affected person populations and ECG conditions. However, there are numerous challenges: dataset imbalance, in which peculiar heartbeats are underrepresented in comparison to everyday heartbeats, and excessive computational demand, considering that schooling and deployment of hybrid fashions are computationally extensive and require giant processing strength and memory. Irrespective of those limitations, CNN-LSTM hybrids constitute a vital milestone towards the improvement of accurate, reliable, and scalable AI structures for recurring medical use.

Despite variations in the model architectures (CNN, LSTM, Hybrid, Transformer), most studies on ECG based heart disease detection follow a broadly similar workflow.

The following key steps summarize the standard methodology as reported across the literature:

Step 1: Data Acquisition

ECG signals are collected from publicly available databases (e.g., MIT-BIH Arrhythmia Database, PTB Diagnostic ECG Database, PhysioNet) or clinical hospital records. Dataset may include single-lead or multi-lead ECG signals.

Example: Hannun et al. [22] used >90,000 ECG records, while Liu et al. [15] worked with PTB-ECG datasets.

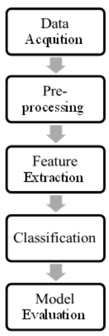

Figure 1: Proposed Methodology

Step 2: Preprocessing

ECG signals that undergo denoising (e.g., bandpass filtering, wavelet transforms) to remove baseline drift and noise. Normalization ensures all signals are on a comparable scale.
Segmentation techniques divide ECG signals into beats or fixed-length windows for model input [17, 18].

Step 3: Feature Extraction

CNN Layers extract spatial/morphological features of P-QRS-T waves. LSTM/GRU Layers capture temporal dependencies across multiple heartbeats. Transformer Encoders capture long-range global dependencies [3, 19].

Step 4: Classification

Features are passed through fully connected layers and a SoftMax classifier to categorize ECG signals into classes such as normal, arrhythmia, AFib, or myocardial infarction.
Example: Singh et al. [33] achieved improved arrhythmia detection by combining CNN and LSTM.

Step 5: Model Evaluation

Common metrics include accuracy, precision, recall, F1-score, and ROC-AUC. Confusion matrices are widely reported to show misclassification trends [14, 22]. Performance is frequently benchmarked towards conventional ML techniques like SVMs and Random Forests, displaying deep mastering superiority.

Model Evaluation Metrics

Evaluating the overall performance of deep gaining knowledge of fashions in ECG-primarily based totally coronary heart ailment detection is vital to make sure each scientific reliability and computational efficiency. Since the challenge is in the main a binary category problem (Normal vs. Abnormal ECG), popular supervised gaining knowledge of assessment metrics are extensively used. These include Accuracy, Precision, Recall, F1- Score, ROC-AUC, and analysis of the Confusion Matrix.

Confusion Matrix

A confusion matrix summarizes the category outcomes via way of means of evaluating anticipated labels with genuine labels

Where:

$$CM = \begin{bmatrix} TP & FP \\ FN & TN \end{bmatrix}$$

- **TP (True Positive):** correctly predicted abnormal ECG
- **TN (True Negative):** correctly predicted normal ECG
- **FP (False Positive):** normal classified as abnormal
- **FN (False Negative):** abnormal classified as normal This serves as the basis for all other evaluation metrics.

Accuracy

Accuracy is the proportion of correctly classified samples to the total number of samples.

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

It is widely used but may be misleading in imbalanced datasets where one class dominates.

Precision (Positive Predictive Value)

Precision measures the fraction of correctly predicted abnormal ECG cases among all predicted abnormal cases.

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

High precision indicates fewer false alarms (important for clinical trust).

Recall (Sensitivity / True Positive Rate)

Recall measures the fraction of correctly detected abnormal ECGs among all actual abnormal ECGs.

$$Recall = \frac{TP}{(TP + FN)}$$

High recall is crucial in medical applications, as missing an abnormal case (false negative, FN) may have life- threatening consequences.

F1-Score
F1-score is the harmonic mean of precision and recall, balancing both.
$(Precision * Recall)$
$F1 = 2 *$
It is beneficial when there is a class imbalance.

$(Precision + Recall)$

ROC and AUC (Area Under the Curve)

The Receiver Operating Characteristic (ROC) curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR) as thresholds are varied.

$$TPR = \frac{TP}{(TP + FN)}, \quad FPR = \frac{FP}{(FP + TN)}$$

- **AUC (Area Under Curve):** AUC close to 1 indicates strong discriminative ability.
- In ECG disease detection, models achieving **AUC > 0.95** are generally considered clinically reliable [15], [22], [31].

Cross-Validation

Most studies employ **k-fold cross-validation**, where the dataset is split into k parts; training occurs on k-1 parts and testing on the remaining part. The average accuracy across folds ensures robustness and avoids overfitting [14], [15], [31].

$CVscore = 1 - Accuracy\_ik$

Dataset Information

The foundation of the deep learning model for ECG based heart disease detection that lies in the quality and diversity of the datasets used for training and validation. In recent studies, researchers have primarily relied on publicly available benchmark datasets due to their accessibility, standardized structure, and wide acceptance in the community. These datasets enable results and fair comparison of different methods.

Commonly Used Datasets:

1. **MIT-BIH Arrhythmia Database (PhysioNet)** – One of the most widely adopted ECG datasets, containing 48 half-hour excerpts of two-channel ambulatory ECG recordings from 47 subjects. It is extensively used for arrhythmia classification tasks and has become the de facto benchmark for evaluating CNN, LSTM, and hybrid models [17][18][21][26][29].
2. **PTB Diagnostic ECG Database** – This dataset provides 549 records from 290 subjects, including healthy controls and patients with various cardiac diseases such as myocardial infarction. It is particularly valuable for multi-class classification of cardiovascular conditions [14][15][20][22].
3. **Chapman University and Shaoxing ECG Dataset** – A more recent dataset with over 10,000 patient records, covering a wide range of cardiac abnormalities. Its size and diversity enable the training of deep models with high generalization ability [31][32].
4. **PhysioNet Challenge Datasets (2017–2021)** – These annual challenges introduced large-scale ECG collections focused on specific clinical problems, such as atrial fibrillation detection, providing real-world, noisy data for stress-testing AI models [10][17][33].

Table 2: Tabular form of Dataset Information

Dataset	Type	Patients	Key Use
MIT-BIH Arrhythmia	ECG	47	Arrhythmia detection
PTB-XL ECG	ECG	290	Myocardial infarction detection
Chapman ECG	ECG	10,000+	Large-scale ECG classification

Expected Outcomes

- The hybrid CNN–LSTM model is expected to achieve over 95% accuracy on standard ECG datasets like MIT-BIH and PTB.
- To be designed to work across hospital systems and remote healthcare, supporting continuous cardiac

assessment.

- CNN extracts spatial ECG features (wave shapes), while LSTM captures temporal rhythm patterns, making detection more precise.
- This can help identify heart abnormalities early, reducing mortality risks and improving patient outcomes.

III. Conclusions

This overview encompasses ultra-modern achievements on spotting coronary heart sicknesses from ECGs through making use of deep getting to know fashions, consisting of CNNs, LSTMs, hybrid fashions, and transformer-primarily based totally architectures. Evidence from the surveyed research shows that CNNs carry out properly in figuring out spatial features, while, on the opposite hand, LSTMs do a higher process in extracting temporal dynamics, subsequently making hybrid CNN-LSTM frameworks the maximum effective framework for the suitable prognosis of cardiac ailments. Transformers and interest mechanisms have been additionally brought in extra latest works to in addition beautify accuracy and generalizability.

Indeed, the diagnostic accuracies of maximum reviewed fashions fall inside a few 90–98%, with numerous surpassing human-stage overall performance in arrhythmia classification. The not unusual place demanding situations include, however aren't restrained to, magnificence imbalance, low range of datasets, and interpretability and scientific consider issues. Another essential fashion determined is the developing emphasis on real-time and wearable-primarily based totally applications, reflecting the call for scalable, accessible, and affected person concentrated solutions. Datasets together with the MIT-BIH Arrhythmia Database, PTB Diagnostic ECG Database, and Chapman University ECG Dataset maintain to function benchmarks in comparing those fashions. Large-scale, multi centre, and demographically numerous datasets, however, stay an essential bottleneck.

IV. Future Scope

Ongoing paintings at the identity of coronary heart sickness via ECG will pay attention at the introduction of large demographic and greater numerous datasets to growth generalizability throughout populations. Data imbalance needs to be countered via techniques of oversampling or GANs. Multimodal statistics together with wearables, scientific notes, and biomarkers can decorate analysis accuracy. The fashions want to be optimized in order that they're capable of paintings at actual time on each clinic servers and hand-held devices. Again, specializing in explainable AI is vital for gaining the self-belief of clinicians, and techniques that keep privacy, together with federated studying, may be hired for secure utilization of the statistics. Finally, non-stop studying structures must be created to permit the version to adaptively reply to the converting fitness circumstance of patients.

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