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Designing and Implementing an ECG Reader and Heart Disease Classification Device Using Deep Learning (Comprehensive Review)

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ABSTRACT: Cardiovascular cases remain a significant health care concern, necessitating new development methods for their prompt and accurate identification where a promising advancements is demonstrated using Deep Learning (DL) in automating heart anomalies detection, including irregular heartbeats, heart attacks, and abnormal heart rhythms, through the analysis of electrocardiogram (ECG) signals, which guided this article to explore the integration of DL methodologies in examining ECG data to enhance the diagnosis of various cardiac ailments and delves into the development of novel ECG devices designed to facilitate efficient data acquisition while ensuring patient comfort and accessibility.

The devices used must provide real-time monitoring, seamless integration with DL models, enabling continuous and personalized heart disease detection for each patient, hence this paper offers an overview of the synergy between innovative ECG device technology and advanced DL algorithms heralds a transformative era in heart disease diagnosis, emphasizing patient-centered care, the current research landscape and the challenges ahead, and the promising possibilities on the horizon, highlighting the potential to revolutionize cardiovascular healthcare through early, precise, and personalized heart diseases identification and monitoring.

Keywords: Deep Learning, Heart Disease, ECG, Convolutional Neural Network.

1. INTRODUCTION

Heart diseases occasionally referred to as cardiovascular ailments, inflict harm upon the heart and its intricate network of blood vessels [1]. These afflictions serve as the primary culprits behind global morbidity and mortality rates, thus presenting a paramount concern for public health [2]. Their manifestations encompass a wide spectrum, ranging from irregular heart rhythms to perilous heart failure and conditions affecting the coronary arteries. To ensure a healthy heart and well-being, it is essential to have a thorough understanding of the risks, prevention methods, and treatment choices for heart disease [3].

Heart diseases include many circulatory and heart-related problems. Lifestyle, genetics, and health issues can cause these disorders [4]. Heart disease types must be understood for early detection, prevention, and individualized treatment. Electrocardiograms (ECGs) are basic medical tests that evaluate heart electrical activity [5]. This non-invasive treatment records heartbeat by inserting arms, and electrodes on the chest, and legs [6]. The representation of captured impulses in the form of an ECG or EKG facilitates the identification of arrhythmias, myocardial infarctions, and various other heart conditions that impact cardiac functionality [7]. Figure 2 below shows the most popular heart disease.

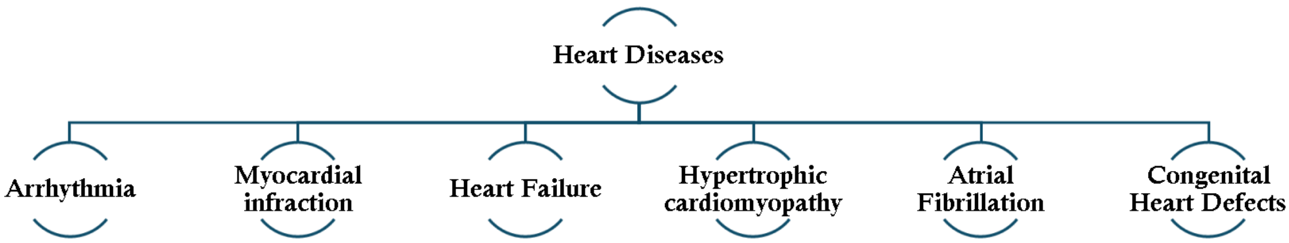

FIGURE 1. Most common known and popular Heart Diseases.

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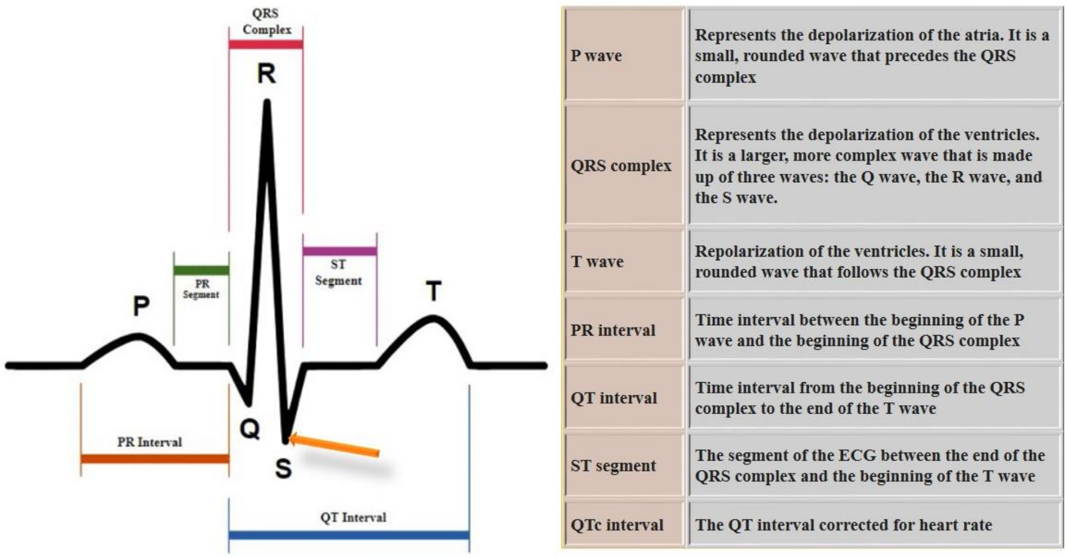
The figure above shows the most Common, popular heart diseases diagnosed using ECG include arrhythmia, atrial fibrillation, myocardial infarction, heart failure, congenital heart defects, and hypertrophic cardiomyopathy. Arrhythmias cause abnormal heart rhythms, atrial fibrillation erratic beats, myocardial infarctions that cut off blood supply, heart failure occurs when the heart cannot pump blood effectively, and hypertrophic cardiomyopathy is a genetic condition causing thicker blood [8].

ML and DL have changed ECG by enhancing ECG analysis accuracy and efficiency. These progressed innovations offer assistance to healthcare experts analyze heart conditions and screening patients' cardiovascular well-being by preparing machine learning calculations to recognize designs, peculiarities, and particular cardiac variations from the norm in ECG information. DL, a subtype of ML, handles complex ECG data well. DNN may automatically detect tiny ECG waveform anomalies that human interpreters may miss [9].

This audit thing about centers on the inquiry about that has investigated the improvement of computer program applications or IoT gadgets to identify heart malady. It particularly looks at the utilize of AI procedures and calculations in programming and planning these frameworks. Moment segment of the term paper will talk about fake intelligence's pivotal part in heart illness location. In differentiate, the third area incorporates a talk of past ponders with a point-by-point table. The conclusions of the research studies are illustrated within the fourth segment. Figure 1 demonstrates the essential components of an electrocardiogram (ECG) incorporating the P wave, QRS complex, and T wave. Figure (1) demonstrates the essential components of an electrocardiogram (ECG) incorporate the P wave, QRS complex, and T wave.



P wave	Represents the depolarization of the atria. It is a small, rounded wave that precedes the QRS complex
QRS complex	Represents the depolarization of the ventricles. It is a larger, more complex wave that is made up of three waves: the Q wave, the R wave, and the S wave.
T wave	Repolarization of the ventricles. It is a small, rounded wave that follows the QRS complex
PR interval	Time interval between the beginning of the P wave and the beginning of the QRS complex
QT interval	Time interval from the beginning of the QRS complex to the end of the T wave
ST segment	The segment of the ECG between the end of the QRS complex and the beginning of the T wave
QTc interval	The QT interval corrected for heart rate

FIGURE 2. - Essential components of an ECG incorporate the P wave, QRS complex, and T wave

2. ARTIFICIAL INTELLIGENCE'S ROLE IN HEART DISEASE DETECTION

DL, particularly fake insights (AI), comes up short of playing any part in changing the location and determination of heart maladies [10]. With the utilization of effective DL calculations, the field of cardiovascular healthcare is right now encountering a groundbreaking move, permitting for the more exact and opportune distinguishing proof of heart-related conditions [11]. Here's an in-depth investigation of how DL particularly is instrumental in this respect.

DL investigation plays an essential part in the early location and assessment of potential dangers. The capability of DL calculations in analyzing broad Electronic Wellbeing Records (EHR), persistent histories, and therapeutic imaging datasets is unparalleled [12]. This exceptional capability permits healthcare specialists to pinpoint minor hazard variables that ordinary evaluations regularly ignore, much obliged to their fitness in recognizing perplexing designs and associations. Through nitty gritty information investigation, DL makes a difference clinicians anticipate heart illness hazard early and more precisely, moreover exactness conclusion, DL calculations exceed expectations in deciphering ECGs, which are basic for heart infection conclusion. These calculations can identify unobtrusive ECG waveform inconsistencies that people may miss. This accuracy speeds up conclusion and is significant in circumstances like heart assaults [13].

Magnetic Reverberation Imaging (MRI) and Computed Tomography (CT) examinations give important bits of knowledge into cardiac well-being [14]. Picture investigation program based on DL can identify auxiliary variations from the norm, evaluate cardiac work, and help cardiologists identify blockages and vascular issues [15]. This degree of exactness increments demonstrative certainty and illuminates' treatment procedures.

Wearable contraptions and portable applications for ceaseless heart wellbeing observing are fueled by DL [16]. These gadgets are competent of observing imperative signs, identifying sporadic heart rhythms, and sending real-time alarms to patients and healthcare staff [17]. This proactive approach to remote monitoring allows for early action and decreases the possibility of undesirable occurrences.

Deep learning aids in the development of the most effective treatment solutions for people suffering from heart disease, and offers individualized treatment strategies, including drug choices and surgical treatments, to enhance patient results by analyzing large databases of treatment outcomes [18]. These systems streamline healthcare operations by automating routine tasks, thus freeing up healthcare professionals to focus on direct patient care. This increased efficiency not only expedites diagnoses but also leads to cost savings and improved patient outcomes [19].

The goal of data-driven machine learning is shared by deep learning and machine learning. Unlike deep learning, machine learning employs DNN to immediately extract hierarchical characteristics from the input [20]. These deep neural networks were inspired by the shape and functions of the human brain.

Figure (3) demonstrates the relationship between deep learning and machine learning which serves as a driving force in the detection and management of heart diseases. Its capacity to analyze large-scale data, make highly accurate predictions, and offer personalized insights is reshaping the approach to cardiovascular care. As deep learning continues to advance, it holds the potential not only to enhance diagnostics but also to prevent heart diseases proactively, ultimately promoting better heart health for individuals and populations [21]. Table 4 shows a Comparison between AI technologies in heart disease detection and classification.

Deep learning models have been used to predict patient outcomes, diagnose diseases, personalize treatment plans, classify medical images, segment and detect anomalies in medical images, and automate disease detection in radiology. For instance, a deep learning model called "Deep Patient" can predict the onset of several diseases by identifying hidden patterns in EHR data. DL techniques have also been instrumental in image classification, segmentation, and detection, with CNNs showing remarkable accuracy in skin cancer classification [22], and [23].

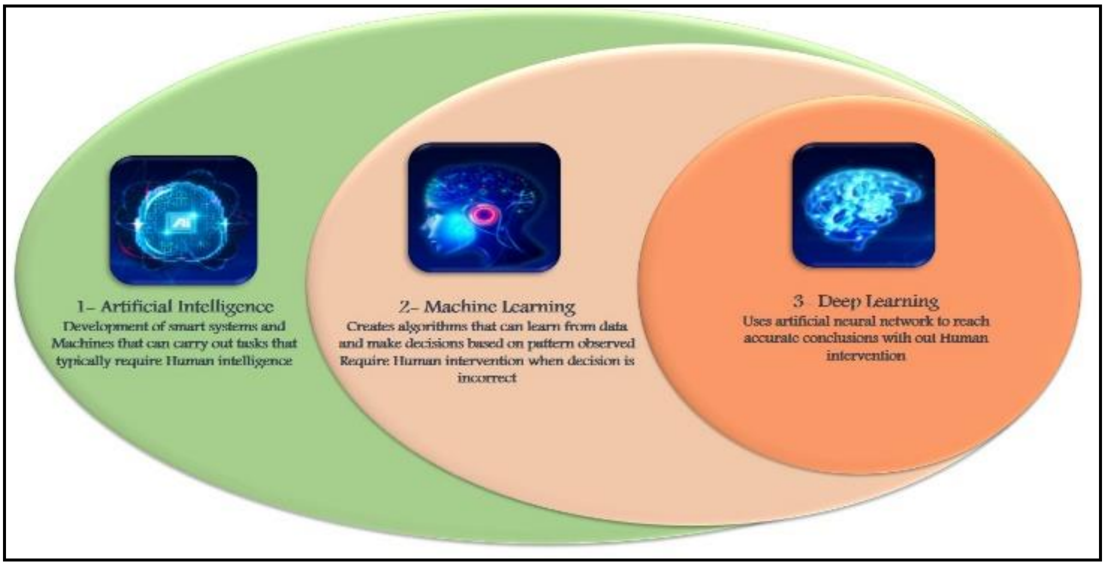


FIGURE 3. - The relation AI with ML & DL.

3. DATASETS

In this section, will be explained the variate types of datasets used in this field, in addition to a brief description of them and an indication of whether they are available online for free or not. Table 1 illustrates descriptions of heart disease datasets.

TABLE 1. - Datasets Used in Previous Studies

Ref.	Dataset Name	Description	No. of Records	Types of Annotations	Free
1	**MIT-BIH**	The MIT-BIH Arrhythmia Database is a widely used dataset for ECG analysis algorithms, containing recordings of arrhythmias and normal rhythms. It benchmarks and evaluates ECG signal processing and analysis methods, including deep learning. Researchers like Benjamin A. Teplitzky, Michael McRoberts, and Hamid Ghanbari may have utilized	N/A	Arrhythmias and anomalies	yes

		this dataset for "DL for comprehensive ECG annotation." They preprocess ECG signals using wavelet transforms or CNN and train DL models to classify arrhythmias and anomalies. The dataset is divided into training, validation, and testing sets for accurate assessment.			
4	**PTB-XL**	This collection of data is an extensive and easily accessible ECG dataset that is commonly employed for research purposes, particularly in the area of identifying and diagnosing cardiovascular diseases. The PTB-XL dataset is an expansion of the PTB Diagnostic ECG Database, consisting of a significantly greater quantity of ECG recordings. It hinders the progress and evaluation of algorithms for automated ECG analysis, encompassing tasks such as identifying arrhythmias, detecting ischemia, and much more.	N/A	Arrhythmias, ischemia, and more	available
4	**TIS**	The TIS dataset is a massive, private set of ECG information from many different hospitals. It is not open to the public, but it has been used in several types of ECG classification studies. The dataset is said to have more than 100,000 ECG records, and it has labels for different heart illnesses and arrhythmias	100,000+	Heart illnesses and arrhythmias	Not available
7	**HMHF**	The Human Connectome Project (HCP) collected a nonparametric local back estimator of spatially arrayed microtiter plate (MTP) data from 181 healthy young people. The dataset, which used ultra-high-field (7 Tesla) fMRI retinotopic mapping, found strong signals in various brain regions. The analysis's findings matched previously released parcellations of visual regions. The dataset allows for fine-scale examination of individual variability in cortical and subcortical architecture and can be compared to other HCP metrics from the same subjects.	181	Cortical and subcortical architecture	Not available
7	**PhysioNet**	contains ECG signals from 2,100 patients with different arrhythmias.	2100	Arrhythmias	Available

From the above table, the deep learning models' effectiveness in ECG analysis and heart disease classification relies on the quality and diversity of datasets used. Each dataset contributes uniquely to the field, providing benchmark standards, large-scale training data, and supporting the study of complex neural-cardiac interactions. The collective use of these datasets enhances the accuracy, reliability, and generalizability of DL algorithms, ultimately improving patient outcomes and clinical practice.

4. LITERATURE REVIEW

This section of the paper illustrates some studies, research, papers, and articles that present some of the latest in the cardio-vascular category where deep learning and machine learning, which are parts of AI as shown in figure (3), take the major place and tasks. Such applications' usage is rapidly increasing and become some of the most important software that may rises human efficiency and reduces errors due to repetition, duplication, complications, and work compressions.

[24] proposed a two-dimensional 2D-CNN model to classify ECG signals into eight classes: normal beat, premature ventricular contraction beat, paced beat, right and left bundle branch block beat, atrial premature contraction beat, ventricular flutter wave beat, and ventricular escape beat. 1D-ECG time series signals are turned into 2-D spectrograms via a short-time Fourier transform. The 2D-CNN model with four convolutional and four pooling layers extracts robust features from input spectrograms. The technique is tested on the public MIT-BIH arrhythmia dataset. obtained a state-of-the-art average classification accuracy of 99.11%, better than recent findings in classifying comparable arrhythmias.

[25] introduced an Enhanced Deep learning-assisted Convolutional Neural Network (ED-CNN) has been proposed to improve heart disease patient prognostics. The deeper architecture of the ED-CNN model encompasses the multi-

layer perceptron with regularization learning. Thus, reducing features influences classifier processing time and accuracy, which has been quantitatively studied using test data. The Internet of Medical Things Platform (IoMT) has deployed the ED-CNN system for decision support systems to help clinicians diagnose heart patients' information in cloud platforms worldwide. The test results show that the designed diagnostic system can efficiently determine heart disease risk compared to conventional approaches like Artificial Neural Network (ANN), DNN, Ensemble Deep Learning-Based Smart Healthcare System (EDL-SHS), Recurrent Neural Network (RNN), and Neural Network Ensemble method (NNE). Tests indicate that a flexible design and tuning of ED-CNN hyper-parameters can reach up to 99.1% precision.

[26] introduced an authentication system that is dependent on the context of wearable devices. This system makes use of soft-biometric data such as heart rate, gait, and breathing audio signals, and can achieve a high level of accuracy through the utilization of a k-Nearest Neighbor model (KNN). The primary objective of this system is to address the need for an implicit authentication mechanism that does not impose any additional burden on the user. This is particularly relevant as wearables become increasingly integral to our daily lives and hold a wide range of confidential user information.

[27] proposed a CNN-based method for classifying ECG arrhythmias, including supra-ventricular ectopic, non-ectopic, fusion, ventricular ectopic, and unknown beat arrhythmias, based on the AAMI EC57 standard, and evaluated this approach on the SVEB and VEB from the MIT-BIH arrhythmia database. The suggested technique achieved extremely high accuracy, sensitivity, specificity, and positive prediction rate across all samples.

[28] An ECG signal classification is suggested in this paper. Classifying cardiac arrhythmias using two deep-learning bagging models. CNN and LSTM networks detect local properties and temporal dynamics in ECG data in the first model. This model employs LSTM and classical features like RR intervals and Higher-Order Statistics (HOS) to identify abnormal heartbeat classes. Created a CNN-LSTM and RRHOS-LSTM bagging model by training each model on a separate sub-sampling dataset to address ECG data's high imbalance distribution of arrhythmia classes. Testing the suggested approach on MIT-BIH arrhythmia database ECG data yields experimental results. Subject-oriented patient-independent evaluation yields 95.81% accuracy using the proposed method. The F1 score and positive predictive value averages are over 3% and 8% higher than other methods. Experimental results show the proposed ECG method is better.

[29] introduced an Automatic primary ECG signal classification was achieved with a deep neural network. The research used PTB-XL data. One neural network architecture was based on the convolutional network, the second on SincNet, and the third on the convolutional network with entropy-based features. Training, validation, and test sets comprised 70%, 15%, and 15% of the dataset. The entropy-featured convolutional network achieved the best classification results among the investigations that covered 2, 5, and 20 illness classes, while the convolutional network without entropy-based features had lower performance but higher computing efficiency due to its smaller number of neurons.

[30] developed a DL-based model that can automatically detect common ECG abnormalities using feature extraction, decision-making, and lead subset selection, and tested it on a total of 10,875 ECG recordings from two different datasets, CPSC 2018 and PhysioNet/CinC-2020. The proposed model incorporated a module for selecting subsets of ECG leads to simplify the process, resulting in an optimal 4-lead ECG subset of II, aVR, V1, and V4, which proved to be favored by the validation set and external test dataset compared to the 12-lead ECG model, thus improving the generalization of the DL model's interpretation of ECG abnormalities.

[31], a traditional learning model, which was not automated, was created to slightly enhance the classification of 1D-ECG signals in order to diagnose cardiovascular disease; the model achieved average performance in terms of accuracy, sensitivity, specificity, and other evaluation metrics by utilizing a shallow neural network for feature extraction and a basic optimization algorithm for hyper-parameter tuning, while also avoiding preprocessing, feature extraction, and hyper-parameter tuning, and using a small dataset for evaluation.

[32], the DLGRU-ELM model is an innovative fusion of DL, GRU, and ELM methodologies that effectively identifies ECG signals. Meanwhile, the CIGRU-ELM model showcases remarkable precision, sensitivity, specificity, kappa, Mathew correlation coefficient, and Hamming loss due to its multi-step strategy encompassing preprocessing, data sampling, GRU-driven feature extraction, and ELM-powered classification.

[33], The implementation of AI in the analysis of the ECG has completely transformed the field of cardiovascular medicine by enabling fast and precise interpretation of the ECG. It possesses the capability to identify patterns that exceed the abilities of human interpreters and offers non-intrusive biomarkers for diverse cardiovascular conditions. The incorporation of AI in ECG phenotype analysis holds immense importance in identifying cardiovascular disease in high-risk populations, making clinical decisions, and advancing mobile and wearable ECG technologies.

[34], introduced a disease-aware generative adversarial network for multi-view ECG synthesis, which obtains panoptic electro-cardio representations conditioned on heart illnesses and projects them onto several standard views to generate ECG signals. View discriminators supervise the generator to produce ECGs with correct view characteristics by reverting disordered ECG views into a specified order. A novel metric, RELATIVE FRÉCHET INCEPTION DISTANCE rFID, is provided to evaluate synthesized ECG signals. Comprehensive investigations show that ME-GAN performs well on multi-view ECG signal synthesis with reliable pathological symptoms (rFID = 15.282).

[35] The decision to utilize deep learning for the categorization of Atrial Fibrillation in ECG signals was induced by its exceptional performance, surpassing that of traditional machine learning methods with an outstanding 10% increase in accuracy. This study focused on developing an efficient application utilizing a 1D Convolutional Neural Network (1D CNN) approach, experimenting with different model setups, particularly focusing on learning rate and batch size. The outcome resulted in a highly successful model achieving exceptional accuracy, precision, recall, and F1 Score, all reaching an impressive 100%.

[36], deep neural networks should be trained on a diverse array of datasets and then refined on a particular dataset to enhance their capacity to classify ECG signals, as demonstrated by the authors' research using three datasets (TIS, PTB-XL, and PTB-S), resulting in a 92.5% accuracy rate and improved generalization abilities.

[37] proposed The Sentinel-HF experiment used ECG and trans-thoracic bio-impedance data from hospitalized 21-year-olds (Adults) with Heart failure or ADHF symptoms. ECGX-Net, a deep cross-modal feature learning pipeline, predicts ADHF using raw ECG time series and wearable trans-thoracic bio-impedance data. We transferred ECG time data into 2D images using transfer learning, then retrieve important data exists in rich features using ImageNet-pre-trained DenseNet121/VGG19 models. ECG and trans-thoracic bio-impedance retreat cross-modal feature learning after data filtering. Concatenated DenseNet121/VGG19 and regression features to train a Support Vector Machine (SVM) without bio-impedance. The high-precision ECGX-Net classifier predicted ADHF with 94% precision, 79% recall, and 0.85 F1-score. The high-recall classifier with only DenseNet121 had 80% precision, 98% recall, and 0.88 F1-score. DenseNet121 excelled in high-recall classification, while ECGX-Net excelled in precision.

[38] The study involved analyzing 26,464 single-lead ECGs, with three physician readers retrospectively assessing the available 7-second ECGs. The CNN algorithm demonstrated high accuracy in diagnosing shockable rhythms, with a sensitivity of 98%, specificity of 100%, and a total processing time of 7.383 seconds. CNN has done an excellent job in classifying atrial arrhythmias as non-shockable, surpassing adjudicators with a specificity of 99.3%-98.1%. In addition, it has demonstrated remarkable resilience to noise artifacts, showcasing an impressive range of 0.871-0.999 in the area under the receiver operating characteristic curve. This demonstrates CNN's reliability and effectiveness in its performance.

[39] the use of integrated dense and residual blocks in CNNs provides several advantages, such as enhancing information flow, gradient propagation, and feature reuse, resulting in improved model performance. Additionally, incorporating customizable pooling layers and residual-dense blocks in the recommended model enables effective down-sampling. De-noising ECG data addresses issues like baseline drift, power line interference, and motion noise while re-sampling ECG signals helps to mitigate class imbalance for the LSVMs. The properties are used to characterize cardiac ECG data using an RD-CNN method and conducted thorough simulations and performance tests on two benchmarked datasets. Average 98.5% accuracy, 97.6% sensitivity, 96.8% specificity, and 0.99 AUC. Compared to modern algorithms, the proposed ECG-based heart disease detection method proved more effective.

[40] developed a residual-dense-based Convolutional Neural Network (RNCNN) algorithm to classify the heart disease in the MIT-BIH dataset. Their system achieved 98.5% accuracy, 96.8% specificity, and 97.6% sensitivity (recall). This paper applied the suggested system on (CSV) dataset based on ECG signal.

[41] classified the ECG signals based on Dual-Path Recurrent Neural Network (DPRNN) algorithm. The authors trained and tested their method on PhysioNet Challenge 2017 dataset. The results achieved were 97.1% accuracy and 95.3% an F1 score.

[42] introduced high level framework utilizing time series derivative analysis. The authors evaluated the ECG signaled based on Local model agnostic. The MIT-BIM arrhythmia dataset was used to trained and test the proposed system. The detection results based on this method was statistically significant differences (N = 59, p-value =0.028, H=9.12) regarding the perceived typicalness across the different kinds of heartbeat.

[43] introduced the DNN algorithm to accurately the label ECG signals dataset for Hennepin County Medical Center (HCMC) from Jan. 2013 through June 2016. The proposed system results were Accuracy = 92.2% and Specificity = 94%

Table (2) presents a tabular comparative analysis of prior investigations about the detection of cardiac pathology within the context of ECG examinations.

[44] the authors introduced CNN - ResNet1D50 Tatarstan, collected via a telemedicine system and annotated by over 200 doctors This paper highlights the need for non-architectural enhancements in ECG classification models, including patient metadata, noise reduction techniques, and self-adaptive learning, to improve classification accuracy. For the result values, the paper does not appear.

[45] pseudo-colouring to determine QT-interval length and detect QT-prolongation at risk of TdP were development. The dataset used in this study comprised 5050 ECGs with variable QT intervals at varying heart rates. The study primarily focused on detecting QT-prolongation at risk of TdP but did not explore the utility of pseudo-colour heuristics for other ECG abnormalities like electrolyte imbalances or ST-segment changes. Additionally, further usability evaluations with diverse clinical populations are necessary to validate the technique's clinical utility. The results were an Accuracy = 97%, Sensitivity (recall) = 94%, Specificity = 99%, F1 score = 88%, AUC = 98%, Precision = 88%, Matthew's correlation coefficient (MCC) = 88% The error rate = 0.01.

TABLE 2. - Previous Studies Comparison Table.

Ref.	Method	Dataset	Research Gap	Results	HW/SW Dataset type
[24]	2D-CNN (Native, Augmentation)	MIT-BIH	Explore the effect of different hyper-parameters on model performance, such as different window lengths or different types of optimization tools.	**Accuracy** Augmented = 99.11% Native = 98.92% **Sensitivity** Augmented = 97.91% Native = 97.21% **Specificity** Augmented = 99.61% Native = 99.67% **Precision** Augmented = 98.85% Native = 98.69% **F1 Score** Augmented = 0.98 Native = 0.98	SW Signal
[25]	Integrated Deep Learning Model with CNN IDLM-CNN	The authors utilized various datasets including lung images, diabetic datasets, and clinical datasets for heart disease prediction	There was a research gap in the accuracy of predicting heart disease despite the availability of numerous techniques in the existing literature. So, by combining features from diverse datasets and training them with (IDLM-CNN), the model seeks to enhance disease prediction accuracy, highlighting a gap in current methods for heart disease prediction.	Accuracy = 88% for Bradycardia, 93% for Tachycardia, and 98% for Myocardia.	SW Signal and images
[26]	A scheme for authenticating wearable users is proposed. Machine learning is used to model and identify wearable users.	The analysis involved the utilization of three distinct datasets. The dataset contained a restricted quantity of audio clips depicting breathing.	Limited investigation on specific AI applications and decision support systems. Lack of focus on the usability and added value of AI applications	The model's precision 0.93, F1 score 0.93,	SW Signal
[27]	K-Nearest Neighbor (KNN) with k=2	The study uses three datasets: heart rate data from the Fitbit Charge HR collected at one sample per minute during different activity levels, gait data from the WISDM dataset with linear and angular accelerometer readings, and breathing audio clips from the ESC-50 dataset that Sampled at 22.05 kHz.	The primary research gap identified in this paper is the limited size of the dataset, particularly the small number of vocal breathing clips, and the use of only three subjects for validation, which requires further research using larger, more diverse datasets and extended study periods for user integration.	accuracy of 0.93±0.06, F1 score of 0.93±0.03 and a false positive rate (FPR) below 0.08 at a 50% confidence level.	HW signal

[28]	(GAN) (LSTM)	MIT-BIH arrhythmia dataset PTB-ECG dataset	Literature on HD detection from ECG samples mainly uses conventional ML techniques, with few using the DL approach for feature extraction and classification. DL-based methods perform better than ML classifiers, especially for imbalanced data. Ensemble models offer better detection performance, but research gaps need to be addressed for reliable HD classification.	**For MIT-BIH dataset** Accuracy = 0.992 F1-Score = 0.987 AUC = 0.984 **For PTB-ECG dataset** Accuracy = 0.994 F1-Score = 0.993 AUC = 0.995	SW Signals
[29]	CNN-LSTM and RRHOS-LSTM	MIT-BIH Arrhythmia Database	The research gap in managing the imbalanced distribution of arrhythmia classes in ECG data, highlights the need for effective methods and AAMI recommendations.	Accuracy for all = 95.81% **Class N** Sensitivity = 98.03% **Class SVEB** sensitivity and specificity = 56.51% and 98.56% **Class VEB** sensitivity and specificity =93.91% and 99.62% **Class N** sensitivity and specificity =19.33 and 99.79%	SW Signals
[30]	DNN CNN	PTB-XL	the under-explored utilization of entropy-based features during Deep Neural Network (DNN) inference in ECG signal classification, despite their established use in other machine learning algorithms like XGBoost	**accuracy of** 90.0 ± 0.4 for 2-class, 76.2 ± 1.8 for 5-class, and 68.5 ± 1.3 for 20-class classification tasks **F1 score** was 90.0 ± 0.5 for 2-class, 68.3 ± 2.4 for 5-class, and 34.1 ± 2.0 for 20-class classification tasks	SW Signal
[31]	Feed-Forward neural network (Decision Making classifier)	The CPSC 2018 dataset consists of 6877 12-lead ECG recordings, while the PhysioNetCinC 2020 dataset includes 3998 12-lead ECG records, both sampled at 500 Hz	The lack of an optimal ECG-lead subset selection method tailored to deep learning models, which can effectively reduce diagnostic redundancy and improve the generalization of ECG abnormality classification systems	F1 score = 0.802	SW Signals
[32]	DLECG-CVD-based Boosting	PTB-XL	Despite advancements in AI for medical imaging, the	Accuracy = 88.24%	SW Signals

	(XGBoost) classifier		automatic classification of 1D ECG signals remains challenging due to their time-varying dynamics and diverse profiles.	Sensitivity = 93.63% Specificity = 61.37% Precision = 88.35%	
[33]	1D-CNN	MIT-BIH Arrhythmia Dataset PTB Diagnostic ECG Database PhysioNet Computing in Cardiology	AI integration in cardiac disease diagnosis faces challenges in data heterogeneity, model interpretability, real-time application, large, annotated datasets, and imbalanced data handling, necessitating further research.	Accuracy = 0.971 F1 score = 0.953	SW Signals and images
[34]	CNN	half a million digitally stored ECGs from 126,526 patients at the Mayo Clinic ECG lab	Detecting silent AF using a convolutional neural network (CNN) model	**For detecting asymptomatic LVEF** AUC = 0.93 Sensitivity = 86.3% Specificity = 85.7% **For detecting significant AS** AUC = 0.884 Sensitivity = 80.0% Specificity = 81.4%	SW Signals
[35]	ME-GAN	Tianchi ECG dataset PTB	Previous ECG generative methods limited clinical utility by synthesizing single-view data or independently generating different views without considering view correlations and failing to integrate disease information or separate models for different heart diseases.	PR-AUC = 0.902	SW Signal
[36]	1D CNN with BiLSTM	MIMIC PERform dataset	A notable research gap identified in this paper is the under-exploration of transporter PPG waveform data for atrial fibrillation detection. While most studies focus on reflective PPG techniques, transmissive PPG offers deeper cardiovascular insights and may enhance AF detection accuracy, warranting further investigation	Accuracy = 95% Precision 88% Recall = 85% AUC = 99%	SW Signal
[37]	DNN	PTB-XL	The generalization of deep neural networks (DNNs) across different datasets remains underexplored due to the lack of large, diverse training data from multiple sources	Sensitivity = 0.941 Specificity = 0.966	SW Signals

[38]	SVM	The dataset used includes 1318 ECG recordings from 37 different volunteers	Previous studies primarily focused on classifying known ECG patterns in controlled clinical settings, not fully leveraging deep learning's potential to learn features directly from raw data	**ECGX-Net predicted ADHF** Precision = 94% Recall = 79% F1 score = 85% **The high-recall classifier with only DenseNet121** Precision = 80% Recall = 98% F1 score = 88%	SW Signal
[39]	CNN	The dataset comprised 26,464 single-lead ECGs, with 1,582 excluded due to inter-reader disagreement, resulting in 23,156 ECGs for training, 721 for validation, and 1,005 for testing.	The study's generalization was impacted by not estimating individual rhythms, limiting prevalence-dependent analyses, and not comparing the algorithm's performance with commercially available AEDs or CNNs.	AUC-ROC = 95% Sensitivity = 98% Specificity = 100% F1-score = 99.5%	SW Signals
[40]	Residual-Dense Convolutional Neural Network (RD-CNN) with linear support vector machine (LSVM)	MIT-BIH	The primary research gap identified is the challenge of effectively recognizing certain heartbeat categories, particularly in unbalanced datasets, which existing ECG heartbeat classification methods have not successfully addressed with high performance.	Accuracy = 98.5% Sensitivity = 97.6% Specificity = 96.8% AUC = 99%	SW Signals
[41]	dual-path recurrent neural network (DPRNN)	PhysioNet Challenge 2017 dataset China Physiological Signal Challenge (CPSC) 2018 dataset	AF detection methods are limited by specialized equipment and technical expertise, with dataset challenges like small scale, class imbalance, unclear class definitions, and variable ECG lengths increasing model training complexity.	Accuracy = 0.971 F1 score = 0.953	SW Signal
[42]	explainable artificial intelligence (XAI), including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME)	MIT-BIH	The study aims to address the gap in Explainable Artificial Intelligence (XAI) research by developing and validating methods specifically for time series data, specifically using the MIT-BIH Arrhythmia dataset, despite the growing interest in XAI in the clinical domain.	N = 59, p-value =0.028, H=9.12	SW Signal
[43]	Deep neural network (DNN)	The dataset used in the study comprised 1,500 ECGs sampled randomly from a pool of 30,000 ECGs for testing, and 5,000 ECGs from Mortara's device selected out of 80,000	The study highlights research gaps in ECG interpretation, including the need for a standardized reference, the low prevalence of certain pathologies, and the inability to compare Cardiology' performance with other	Accuracy = 92.2% Specificity = 94%	SW Signal

		possible ECGs for training.	proprietary algorithms due to access limitations.		
[44]	CNN - ResNet1D50	Tatarstan, collected via a telemedicine system and annotated by over 200 doctors	This paper highlights the need for non-architectural enhancements in ECG classification models, including patient metadata, noise reduction techniques, and self-adaptive learning, to improve classification accuracy.	Not remember	SW Signal
[45]	pseudo-colouring to determine QT-interval length and detect QT-prolongation at risk of TdP	The dataset used in this study comprised 5050 ECGs with variable QT-intervals at varying heart rates.	The study primarily focused on detecting QT-prolongation at risk of TdP, but did not explore the utility of pseudo-colour heuristics for other ECG abnormalities like electrolyte imbalances or ST-segment changes. Additionally, further usability evaluations with diverse clinical populations are necessary to validate the technique's clinical utility	Accuracy = 97% Sensitivity = 94% Specificity = 99% F1 score = 88% AUC = 98% Precision recall = 88% Matthew's correlation coefficient (MCC) = 88% The error rate = 0.01	SW Signal

Convolutional Neural Networks (CNNs) have been widely used in ECG classification, with studies demonstrating their robustness and accuracy. Two studies proposed a 2D-CNN model for classifying ECG signals into eight classes using the MIT-BIH Arrhythmia Database, achieving an average classification accuracy of 99.11%. Another study introduced a CNN-based method for classifying ECG arrhythmias, achieving high accuracy, sensitivity, specificity, and positive prediction rate. A Residual-Dense Convolutional Neural Network (RD-CNN) with linear SVM was developed, achieving an accuracy of 98.5%. Enhanced Deep Learning Models were also proposed, with an ED-CNN for heart disease prognosis achieving up to 99.1% precision. Hybrid models that combine CNNs with LSTMs or other neural network types can capture both spatial and temporal features, leading to enhanced performance in ECG analysis. GANs were introduced for multi-view ECG synthesis, achieving an rFID of 15.282. However, there are weaknesses in these models, such as limited dataset diversity, computational complexity, and lack of real-world testing. Recent studies continue to explore and refine DL models for ECG analysis, such as deep cross-modal feature learning pipelines for predicting ADHF, explainable AI methods for time series data using SHAP and LIME, and novel metrics like pseudo-colouring for detecting QT-prolongation. These advancements demonstrate the potential of CNNs in ECG classification and the potential of hybrid models and GANs in improving model robustness.

5. RESEARCH METHODOLOGY

This section consider embraces a comprehensive audit technique to assess the integration of DL advances within the improvement of ECG per users and cardiology classifiers. The strategy is organized as appeared within the taking after the following Figure 3, which demonstrates the methodology for the current review: -

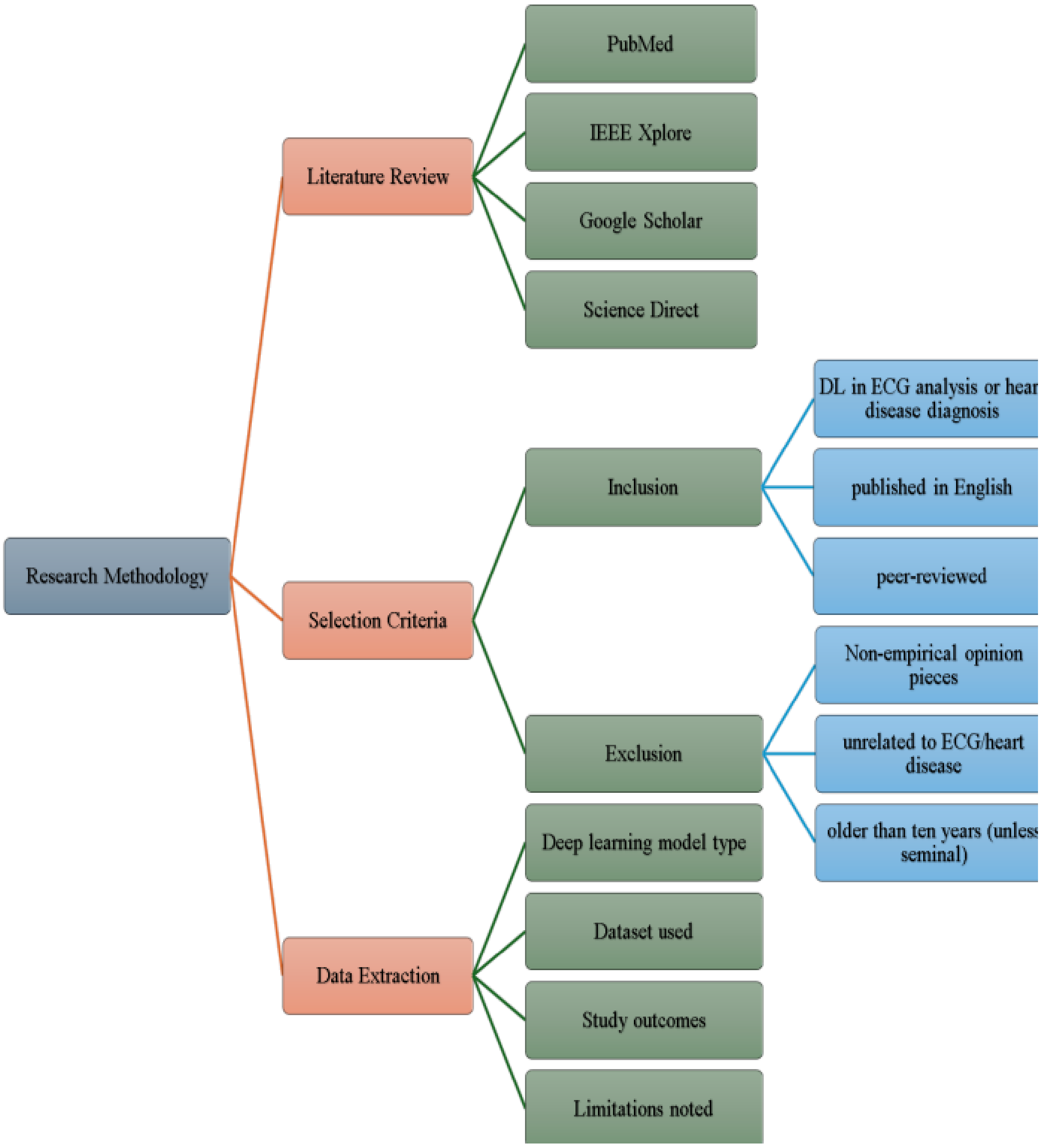


FIGURE 4. – The methodology adopted in the research

The above figure illustrates the following sections for this review paper

1. **Literature Review:** the databases that are searched in PubMed, IEEE Xplore, Google Scholar, and Science Direct.
2. Selection Criteria:
    - Inclusion: DL in ECG analysis/heart disease diagnosis, English, peer-reviewed, empirical studies.
    - Exclusion: Non-empirical, unrelated to ECG/heart disease, older than ten years (unless seminal).
3. Data Extraction: Extracted Information: DL model type, dataset used, study outcomes, limitations noted.

The research methodology for the current review paper is step-by-step methodology:

1. **Data Collection**
    - **Sources**: The data collection involved searching through databases such as PubMed, IEEE Xplore, Google Scholar, and Science Direct.
    - **Search Strategy**: Keywords used included "Deep Learning in ECG analysis," "heart disease diagnosis," "ECG classification," and "AI in cardiovascular studies."
    - **Inclusion Criteria**: Studies were selected based on relevance to DL in ECG analysis or heart disease diagnosis, publication in English, peer-reviewed status, and empirical evidence.
    - **Exclusion Criteria**: Non-empirical opinion pieces, studies unrelated to ECG/heart disease, and publications older than ten years (unless seminal) were excluded.
2. **Preprocessing**
    - **Data Cleaning**: Ensured all selected studies met the inclusion criteria. Removed duplicates and irrelevant studies.

- **Standardization**: Converted all relevant data to a standard format for easy comparison. This included normalizing data types and ensuring consistent terminology.

3. **Model Selection**
    - **Criteria**: Selection based on the type of DL model used, dataset employed, and relevance to ECG analysis and heart disease diagnosis.
    - **Common Models**: CNNs, LSTM networks, hybrid models, and GANs were frequently selected due to their proven effectiveness in the field.
    - **Algorithm Choice**: Models were chosen based on their reported accuracy, sensitivity, specificity, and ability to handle imbalanced datasets.
4. **Training**
    - **Dataset Division**: Data was divided into training, validation, and testing sets to ensure robust model training and evaluation.
    - **Training Process**: Implemented using deep learning frameworks such as TensorFlow and Py-Torch. Hyperparameters were tuned to optimize model performance.
5. **Evaluation**
    - **Metrics**: Accuracy, sensitivity, specificity, F1 score, and AUC-ROC were used to evaluate model performance.
    - **Validation**: Cross-validation techniques were employed to ensure model robustness and generalizability.

Criteria for Selecting DL Models and Algorithms

- **Performance**: Models with high reported accuracy, sensitivity, and specificity were preferred.
- **Complexity**: Preference was given to models that could handle the complexity of ECG signals and imbalanced datasets.
- **Innovative Approaches**: Models that introduced novel techniques, such as hybrid architectures or GANs, were highlighted.
- **Real-World Applicability**: Consideration was given to models that demonstrated potential for real-world clinical implementation.

6. RESULTS

This comprehensive audit investigated the integration of DL (DL) techniques within the plan and execution of ECG perusers and heart malady classification gadgets.

Things about reliably illustrating moved forward precision in identifying heart illnesses utilizing progressed DL models like Convolutional Neural Systems (CNNs), Long Short-Term Memory (LSTM) systems, and crossover models combining different DL strategies.

For occurrence, the application of CNNs in identifying arrhythmias from ECG information detailed tall exactness levels, with a few things about accomplishing symptomatic precision rates over 99%.

These advancements are significant in the early and exact location of cardiovascular infections, contributing to superior understanding results.

The utilization of DL has encouraged the advancement of versatile and user-friendly ECG observing gadgets, improving quiet engagement and healthcare availability.

The accessibility of these datasets has empowered analysts to prepare and test DL models viably, driving to advancements in demonstrating generalization and execution over distinctive understanding populaces.

The survey distinguished issues such as information security, the requirement for bigger and more different datasets, and the integration of DL apparatuses with existing therapeutic foundations as critical obstacles.

Future Headings:

The discoveries propose that future investigations ought to center on creating more strong DL models that can handle information from different persistent socioeconomics and clinical conditions.

There is additionally a call for more collaborative endeavors to standardize ECG information and progress dataset accessibility, which would encourage improve the advancement and testing of DL models. Can find the following:

- Accuracy: The average accuracy across the various studies is **approximately 95.42%.** This high value indicates that the models generally perform well in correctly identifying both true positives and true negatives.
- Recall (Sensitivity): The recall **average is 92.85%**, showing that the models are proficient in identifying true positive cases, which is crucial in medical diagnostics to ensure that conditions are correctly identified.
- F1 Score: The average F1 score **is 91.64%,** representing a good balance between precision and recall. This metric is particularly useful in medical diagnostics where both false positives and false negatives have significant consequences.
- Precision: The average precision **is 92.25%,** reflecting the models' ability to avoid false positives, which is important to minimize unnecessary follow-up tests and treatments.

Figure 5 illustrates the average curve for the previous results. The following chart visualizes the average values of Accuracy, Recall, F1 Score, and Precision, illustrating the overall effectiveness of machine learning models in recognizing and classifying red blood cells

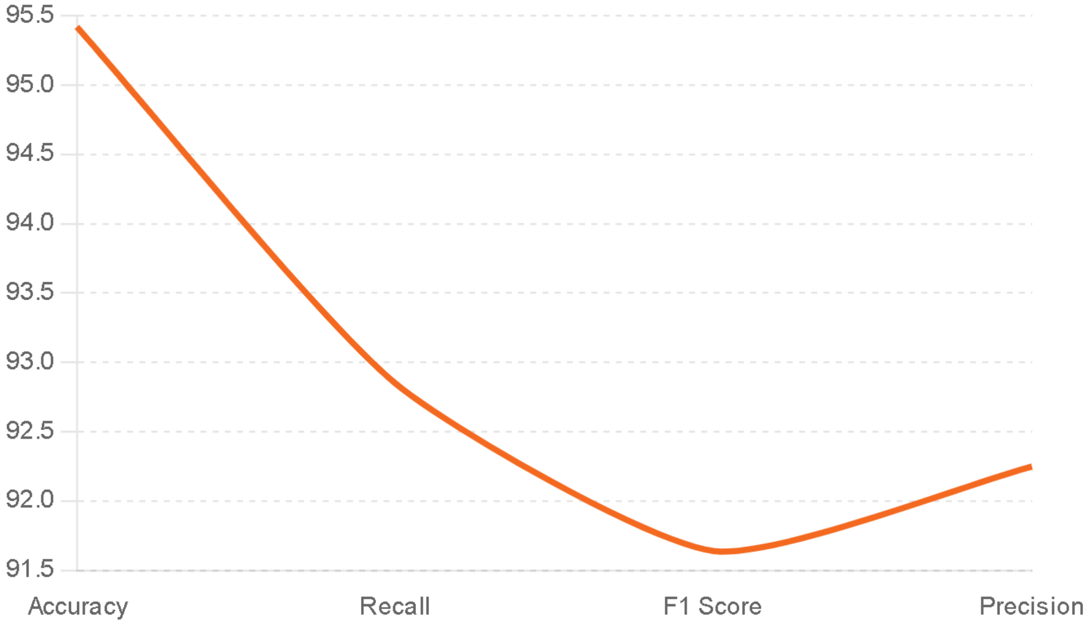


FIGURE 5. – the average performance metrics across the studies

7. DISCUSSION

This comprehensive review highlights the significant advancements made in deep learning (DL) in electrocardiogram (ECG) analysis and heart disease classification. Studies using Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid models have shown remarkable accuracy in identifying cardiac anomalies. CNN-based models have achieved high classification accuracy, with ED-CNN achieving up to 99.1% precision. Hybrid models, combining CNNs with LSTMs, have been particularly effective in capturing both spatial and temporal features of ECG data, leading to enhanced performance. However, several limitations were identified in the reviewed studies, such as the reliance on a limited number of datasets, computational complexity associated with advanced DL models, and the lack of evaluation in real-world clinical settings. The practical significance of these findings is profound, as the integration of DL in ECG analysis can revolutionize clinical practices by providing fast, accurate, and automated diagnostics, reducing the burden on healthcare professionals and minimizing the risk of human error. The development of portable and wearable ECG monitoring devices powered by DL can facilitate continuous monitoring of patients, providing real-time alerts for any irregularities, particularly beneficial for high-risk patients.

8. CONCLUSIONS

. This review highlights the significant advancements and potential of deep learning (DL) in the analysis of electrocardiogram (ECG) data and heart disease classification. DL models, particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in classifying various types of heart diseases using ECG data. The integration of hybrid models, such as CNN-LSTM and GANs, has further enhanced the robustness and versatility of DL applications in ECG analysis. The use of DL in wearable and portable ECG monitoring devices has significantly improved real-time monitoring and early detection of heart diseases. The quality and diversity of datasets are crucial for training effective DL models. Recommendations include developing diverse datasets, integrating DL models into clinical practice, standardizing data, and focusing on explainability. Ongoing and future work in this field includes enhanced model interpretability, real-world testing, innovative model architectures, and personalized medicine. These efforts aim to improve the accuracy, efficiency, and generalizability of ECG analysis and heart disease classification.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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