Ibn Al-Haitham Journal for Pure and Applied Sciences
Journal homepage: jih.uobaghdad.edu.iq
PISSN: 1609-4042, EISSN: 2521-3407
IHJPAS. 2024, 37(3)

An Exhaustive Survey of Deep Learning Techniques in ECG Signals

Tamara Hameed Yousif[1] **and Mohammed S. H. Al-Tamimi**[2*]

[1,2]Department of Computer Science, College of Science, University of Baghdad, Baghdad, Iraq.
*Corresponding Author.

Received:7 January 2024 Accepted:27 February 2024 Published:20 July 2024
doi.org/10.30526/37.3.3901

Abstract

The electrocardiogram (ECG) is a widely utilized signal in the prediction of Cardiovascular Diseases (CVDs). ECG signals have the ability to detect the heart's unusual rhythmic patterns, which are generally referred to as arrhythmias. A comprehensive examination of ECG signals is crucial for the precise identification of patients' chronic heart conditions. This literature survey investigates some of the most recent studies in cardiac research where researchers embarked on the arduous task of creating an ECG signal image model to identify possible signals signifying the presence of heart disease. This survey covers algorithms for fusing ECG signal features with deep learning methods to develop deep neural networks for predicting heart disease using images obtained from recordings of ECG signals. Respectively, every study provides an aspect of understanding how complicated Deep Learning (DL) models can find undiscovered elements from ECG data that lead to earlier and correct diagnoses of cardiovascular disorders in this objective of the discussed project. Through this journey through these research findings, we will look closely at the methods used and draw conclusions on how DL models can be improved in the context of cardiac health. This paper endeavors to introduce novelty into this developing field and thus forms part of this extensive review of what is currently available in this area.

Keywords: ECG Signal; Neural Network; Machine Learning; Deep Learning.

1. Introduction

Cardiomyopathy is a life-threatening medical disorder that impacts the heart and blood vessels. As per the World Health Organization (WHO), in 2020, about 18 million people died from heart disease. This constitutes 32% of the total number of deaths worldwide, surpassing all other non-infectious diseases in terms of fatality [1]. Furthermore, over 75% of these fatalities transpire in nations with little economic resources [2]. Clinicians use several diagnostic modalities to diagnose heart failure, including non-invasive tests such as ECG [3], echocardiography [4], Coronary Computed Tomography Angiogram (CCTA) [5], cardiac Magnetic Resonance Imaging (MRI) [6,7], and invasive techniques such as hematology [8] and coronary endoscopy [9]. In addition to the listed diagnostic methods, the ECG is a noninvasive and noninvasive medical test that can easily be used to diagnose cardiac diseases [10].

Diagnostic ECG is used for the detection and diagnosis of many cardiac disorders, including heart failure, pericardial dysfunction, cardiovascular disease, electrolyte imbalance, and pulmonary diseases [11,12]. However, general practitioners need help with ECG readings, which are two significant problems in their daily practice. The inaccuracies and time-consuming nature of manually analyzing Holter ECGs are evident [13].

J. Higueras et al. [14] study panel of 195 physicians consisting of 153 individuals and 42 staff found that physicians lack adequate ECG interpretation skills. The study found that resident physicians accounted for 13.4% of Acute Myocardial Infarction (AMI) and 44.1% of Ventricular Tachycardia (VT) and missed 64.6% of cases of second AV block. The presence of cardiac conditions makes it difficult to accurately diagnose a patient's condition based on ECG signal interpretation alone, even when a cardiologist is highly skilled and presents further difficulties in making the distinction. In addition to these problems, recording the ECG signal can reveal variations for the same medical condition depending on factors such as patient age, race, and overall physical health [15]. Computerized interpretation (CIE) of ECG records has been employed to address these difficulties and aid clinicians in the diagnosis of cardiomyopathy [16]. However, research has shown distinct shortcomings in the use of this technique and barriers to computerized ECG analysis. Thus, Although attempts have been made to establish uniform automated systems for interpreting ECGs [17], interpretation of the final ECG still requires physician rereading. Moreover, the need for universally accepted standards for computed ECG analysis poses difficulties in validating CIE [18].

2. ECG Signal

ECG equipment is utilized to capture the electrical signals produced by the heart. The sensors or electrodes, as shown in **Figure 1**, are put on the patient's arms, legs, and chest to detect these signals.

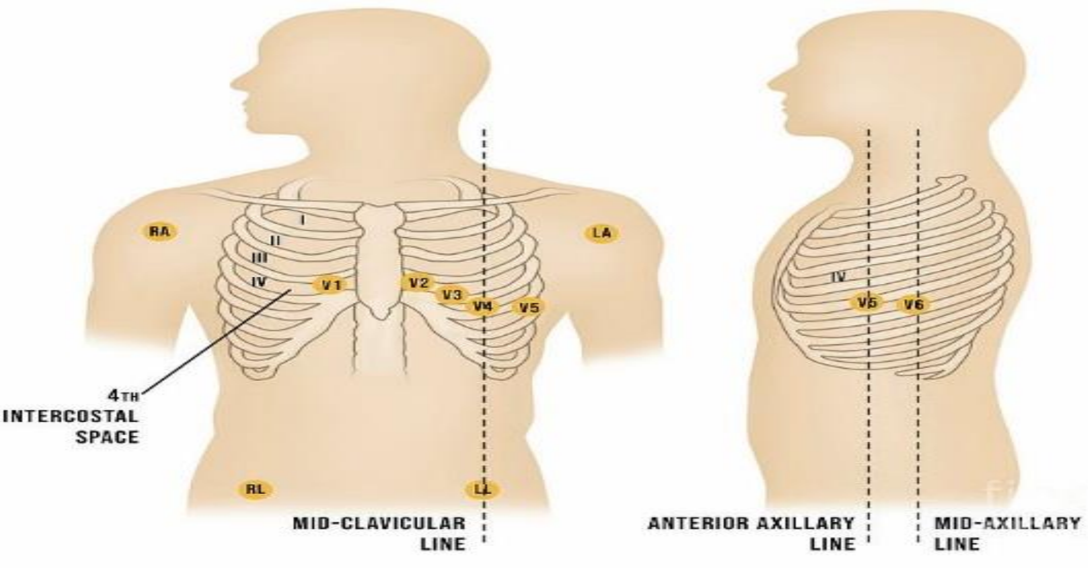

Figure 1. The positioning of ECG electrodes on the chest, upper extremities, and lower extremities [2].

The electrodes ascertain electrical impulses that are associated with a 12-lead ECG equipment. This device captures the comprehensive electrical activity of the heart from various angles for a specified period, typically lasting 12 seconds [19]. Among the 12 leads, the three bipolar leads particularly measure the differences in electrical potential between both arms and between one arm and the leg [20]. The remaining nine electrodes are unipolar and consist of six chest leads (V1 to V6), which offer a horizontal perspective of the heart, and six limb leads (I, II, III, aVR, aVL, and aVF), which assist in obtaining a vertical representation of the heart [2,21], as depicted in **Figure 1. Figure 2** illustrates an individual's standard ECG recording.

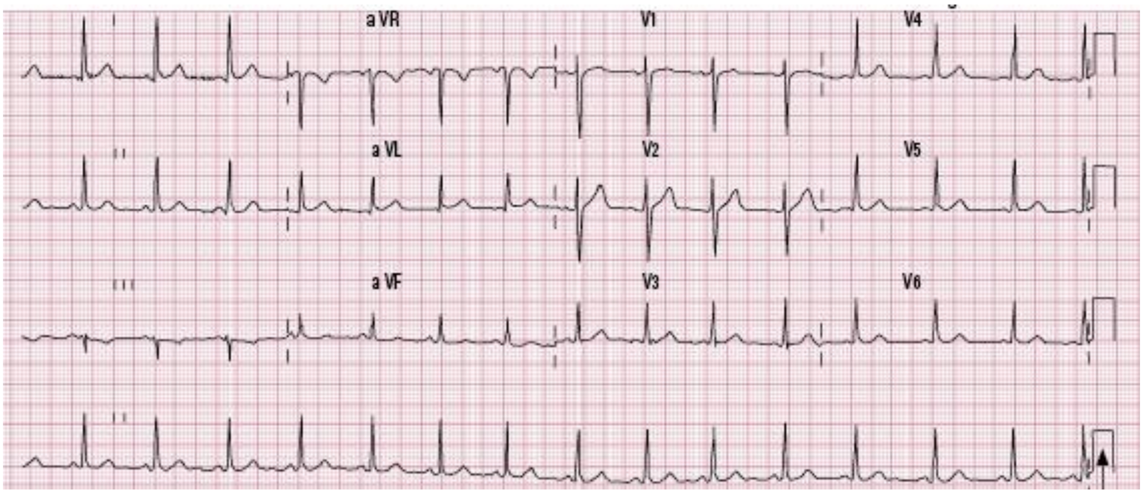

Figure 2. An ECG recording consisting of the conventional 12 leads for a single patient [2].

A single repetition of an ECG comprises a series of wave patterns, illustrated in **Figure 3**. Upon initiation of an electrical signal by the Sino Atrial (SA) node, the fibres in the atria experience depolarization, leading to the creation of a P wave, which subsequently leads the atria to contract. **Figure 3** depicts a standard ECG, with the P wave having an approximate duration of 0.08 seconds [22,23]. Leads II and V1 demonstrate the presence of a P wave. **Figure 2**. a single patient underwent the acquisition of a 12-lead ECG [24]. Moreover, it demonstrates an inverted orientation in lead aVR and a positive orientation in leads I and II, as illustrated in **Figure 2**.

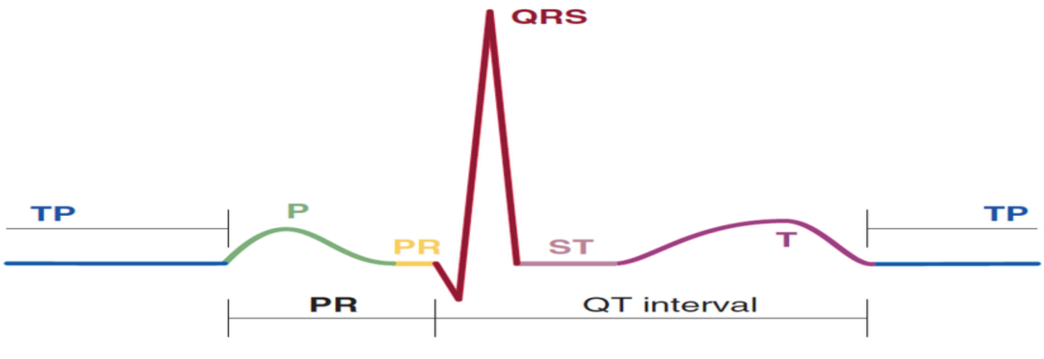

Figure 3. An individual cardiac cycle of the ECG waveform [2].

Figure 3 demonstrates that the PR interval corresponds to the time interval between the P wave and the QRS. The PR interval signifies the length of time it takes for electrical conduction to travel from the SA to the Atrio Ventricular (AV) nodes. The conduction mechanism enables the depolarization of the atria, leading to their contraction and subsequent propagation of depolarization waves. The ST segment represents the electrical depolarization of the ventricular myocardium and typically lasts for approximately 0.25 seconds. QT interval, which has a duration of about 0.38 seconds, signifies the period between the start of ventricular depolarization and repolarization [25,26]. The TP segment is a specific area in the ventricular myocardium where there is a lack of substantial variation in electrical potential, indicating electrical neutrality. The diastolic phase is the interval during which the ventricular myocardial cell finishes repolarization and before the initiation of the next depolarization [27,28]. Aberration from the typical cardiac cycle may indicate cardiac illness and irregularities in the conduction system. **Figure 4** illustrates that a QRS length of more than 0.13 s, The presence of wide monophasic R waves in leads I, V5, and V6, along with the absence of Q waves in leads V5 and V6, are distinctive features of Left Bundle Branch Block (LBBB) [29].

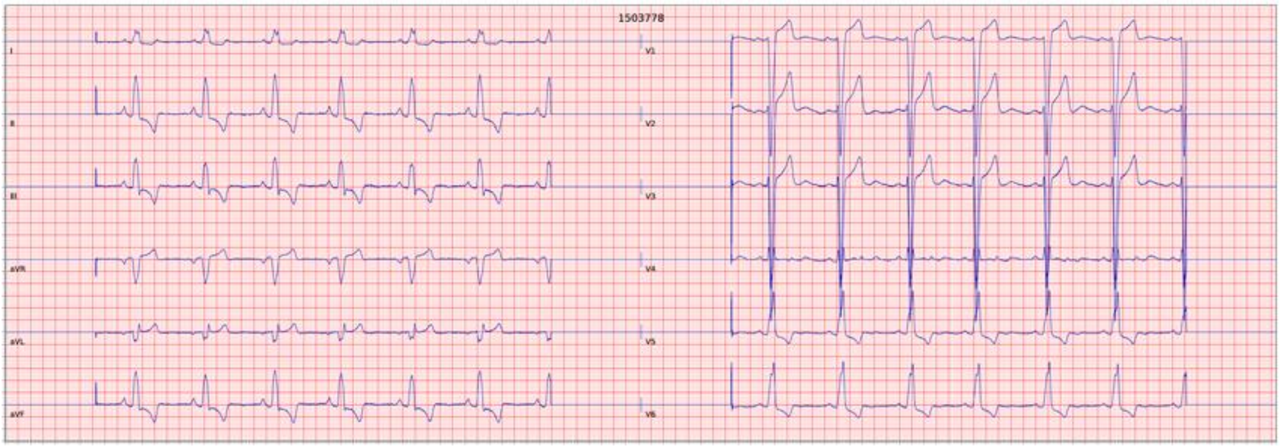

Figure 4. The 12-lead ECG was performed on a patient diagnosed with LBBB diagnosis [2].

3. Deep Learning in An ECG Signal

3.1. Artificial Neural Network (ANN)

Neural networks are essential in determining the structure of brains, which is why the term ANN originated in the field of biology. DL algorithms frequently employ it. An ANN Typically comprises three layers: the input, hidden, and output layers [30]. The hidden layers are located between the input and output layers. It carries out all calculations required to reveal hidden attributes. A shallow neural network is characterized by its single hidden layer, while a deep neural network is defined by having multiple hidden layers. Typically, each node within a given layer is connected to every other node in the subsequent layer. Augmenting the quantity of concealed layers in the network leads to an elevated degree of profundity. **Figure 5** illustrates the design [31].

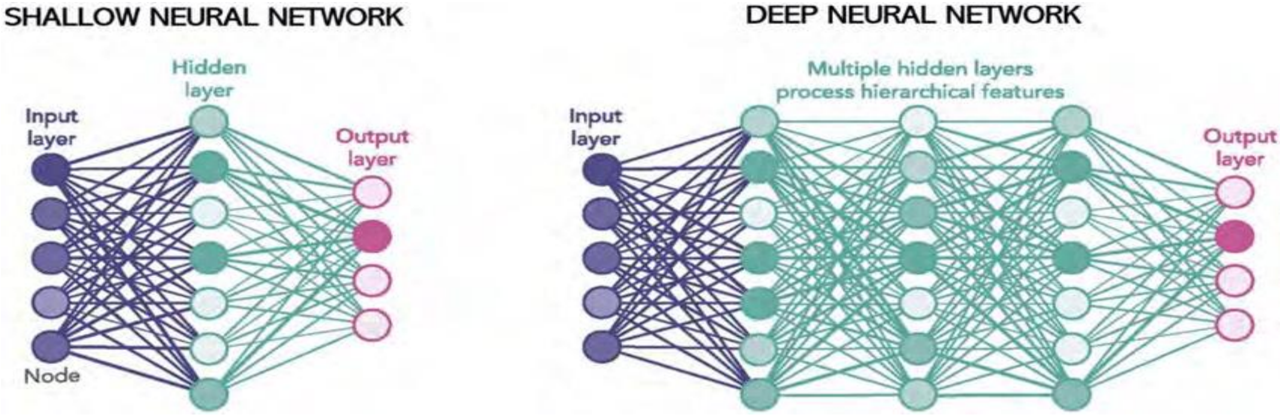

Figure 5. Architecture of a general ANN [31]

ANNs provide numerous advantageous features that render them highly suitable for addressing specific problems and circumstances [31]:

1. ANNs have the ability to acquire knowledge and represent intricate and non-linear relationships, which is crucial given that numerous connections between input and output variables in real-world scenarios are non-linear and intricate.

2. ANNs can generalise. This means that after being trained on the original inputs and their associations, the model may deduce unknown relationships from anonymous data and, consequently, make predictions about unknown data.

3. ANN does not enforce any limitations on the input variables, in contrast to conventional prediction methods that require specific distributions. Moreover, multiple research studies have shown that ANNs are capable of more accurately replicating hetero skedasticity, which refers to data with significant volatility and varying variance. This is due to the ANNs' ability to uncover hidden connections within the data without imposing any predetermined linkages. This is especially beneficial in the prediction of financial time series, such as stock prices, when there is substantial volatility in the data.

3.2. Convolutional Neural Network (CNN)

A CNN is a type of DL model that utilizes ANNs to extract significant characteristics from images. By employing a technique called extraction learning, CNNs efficiently process images and analyse them as input. The pseudo nerves are subjected to pressure from the brain. CNN employs the mathematical action of convolution, which is linear in nature, in several hidden layers situated between the input and output layers.

CNNs' main advantage is their capability to generate visual representations of two-dimensional images. This imparts the model with information regarding the spatial coordinates and dimensions across several datasets, which is crucial for image processing. The user's text is empty [34].

3.3. Recurrent Neural Network (RNN)

An RNN is an ANN specifically intended to analyze time series data. It has emerged as a significant algorithm in the DL field due to its ability to analyze the temporal aspects of data. RNNs can handle input data and generate output data that changes over a period of time. In the context of RNNs, the term "memory" pertains to the capacity to retain and utilize data from prior inputs to ascertain subsequent outcomes. It possesses the capacity to store or retrieve information from the past.

LSTM uses the concept of a gate. There are three gates in the system: an entry gate, a forget gate, and an exit gate. The input gateway controls the selection of additional information to be contained within the cellular state. The forget gateway is responsible for selecting the information from the cell state to be discarded. In contrast, the exit gateway is used to process the final output of the LSTM section. In LSTM, the outputs are processed using sigmoid functions, which compute a value ranging from 0 to 1. This value is often rounded to either 0 or 1 based on a predefined threshold. The value "0" represents gates that completely obstruct the passage of any object, whereas the value "1" signifies gates that allow unrestricted passage [37].

4. Manual Diagnosis Problem

Prior to the advent of CAD, diagnoses were conducted manually, which included time-consuming and less precise diagnostic methods. Potential inaccuracies may arise in the computation of computational and statistical characteristics during manual diagnostic methods. In order to address the shortcomings of manual diagnostic techniques, the use of DL has been presented for the purpose of diagnosis. The use of CAD technology has enhanced the accuracy of diagnosis by radiologists who are not experts in the field. Irrespective of the radiologist's level of experience, the advantage of CAD is it minimizes false-negative results and improves sensitivity. CAD technologies exhibit enhanced speed, reliability, and precision while also enabling improvements in computational and statistical calculations [38,39]. This research aims to speculate about useful technology and provide a traditional solution.

5. State-of-the-Art Techniques

In [40], numerous classification approaches have been extensively applied to the topic of heart diagnosis through ECG signals. The intricate patterns of ECG data have been used with different techniques such as Decision Tree (DT), Super Vector Machine (SVM), K-Nearest Neighbors (KNN), and ANN, among others, to classify heart diseases accurately. Importantly, the study uses different types of classifiers, including ANN, SVM, KNN, Left-to-Right (LR), Random Forest (RF), Ethereum Classic (ETC), Naïve Bayes (NB), DT, Gradient Boosting (GB) and Alpha Beta (AB). The quality of input features was enhanced in the pre-processing phase through the utilization of feature selection methods, such as FCBF, for future classification tasks. This advanced approach ensures that only useful features are incorporated into models that reduce dimensionality, resulting in a superior classifier. Additionally, computational processes of P- value and Chi-square have been reserved particularly for the Extra Tree (ET) classifier while improving the input quality of optimization models. After extensive assessment, it was found that the extra-tree classifier offered a precision of 92.09%. While very accurate, the classifier also had a sensitivity of 91.82% and a specificity of 92.38%. However, there is a significant warning concerning how transferable this classifier may be over multiple datasets. Due to the inherent variability among data sets, it is essential to consider contextual factors while using the extra tree classifier, as it affects the ability to generalize findings about the model’s performance.

In [41], the researchers focused on predicting heart disease using a dataset comprising records from 1988 with four databases. In addition, the data set consisted of seventy-six traits. However, this paper examined only fourteen of them, which included age, sex, kind of chest pain experienced, resting systolic blood pressure, and total cholesterol concentration in serum. This included pre-processing of the data set to deal with outliers and the distribution imbalance, e.g., normal distribution to counter overfitting and Isolation Forest for outlier detection. The plotting methods used helped determine the skewness of the data and also helped understand its structure. Feature selection was used, with the Lasso algorithm being a part of embedded methods that offer more reliable predictive performance than filter methods. The results showed that Random Forest (FR) reaches an accuracy of 80.3%, Logistic Regression – 83.31%, KNeighbours is more accurate with a percentage of 84.86%, SVM shows performance accuracy of 83.29%, Decision Tree gives a Surprisingly, the KNeighbors turns out to be the best model of 77.7% precision and 80% specificity. Noteworthy results are obtained after applying different Machine Learning (ML) algorithms to the pre-processed dataset.

In [42], the authors aim to present DL’s performance in scoring coronary calcification on typical CT images, including both cardiac gated and un-gated studies, as a tool for the estimation of cardiovascular risk. A retrospective secondary analysis with DL-based coronary calcium segmentation in the randomized clinical trials and the cohort study conducted as part of a methodological process will be used. Prior to this step, CT scans had been padded and cropped, with their resolution adjusted uniformly. A series of U-Net architecture CNN models are adopted for detection and heart localization, segmentation, and coronary arteries (calcium) segmented with an outcome calcium score. These were done using Tensor Flow-GPU and Keras, requiring four GPUs that had a minimum of 64GB of memory. The assessment revealed that coronary calcium scores from the automated system indicate a high risk of cardiovascular events correlating closely with manual quantification and good internal validity.

The researchers in [43] have presented a new hybrid model, which combines image processing and DL techniques for the detection of CVDs using paper-based complex ECGs. They applied image pre-processing technology, which included the removal of artifacts and enhancement, and then applied DL models such as InceptionV3 and ResNet50. In addition, they developed an integrated architecture that combined such models. Paper-based ECG images generally have problems such as different artifacts, background lines, and low contrast. Various DL algorithms were applied in this research in order to address these challenges by exploring two approaches. The first involved employing five distinct DL models such as InceptionV3, ResNet50, DenseNet201, VGG19, and MobileNetV2, while the second introduced and integrated model with InRes-106 designed as a deep convoluted neural network, which will focus on extracting any hidden and high-level features from EGC images. The InRes-106 model achieved the highest accuracy at 98.34%, while the other models also showed promising results: InceptionV3 (90.56%), ResNet50 (89.63%), DenseNet201 (88.94%), VGG19 (87.87%), and MobileNetV2 (80.5). However, the limitation of diverse datasets may affect external validity or applicability.

In [44], the authors propose building and assessing DL approaches that consider ECG signal image traces for automatic detection and forecasting of heart defects. This includes improving algorithms' performance with the possibility of inference being done on the fly on an embedded smart device for ECG Mobile (ECGM). This approach entails converting unprocessed one-channel ECG time series data into 2D pictures in order to utilize advanced computer vision algorithms. Fine-tuning of already trained deep CNN architectures, namely MobileNetV2 and VGG16, on extracted ECG images for classification of recordings into normal or abnormal heart condition categories is studied. Model optimization was done using a number of techniques, such as batch normalization, drop-out regularization, data augmentation, and hyper parameter tuning. This study used comprehensive testing based on large publicly accessible ECG datasets (thousands of recordings). In this study, it is demonstrated that two DL models yielded a validation accuracy above 95% for distinguishing between normal and abnormal ECG classes related to different forms of heart diseases. Accuracy of more than 90% was maintained even with a minor performance decrease when implementation was done on a Raspberry Pi device, a collection of single-board computers produced by the Raspberry Pi Foundation, a charitable organization based in the UK. The foundation's primary goals are to promote computer literacy and enhance accessibility to computer education.

Moreover, an investigation of the utilization of DL for ECG image diagnosis has been done in [45]. For up to ten epochs, they were training the classification head of the model using early stopping with other layers frozen. Then, all the layers were thawed out and trained until validation loss reached the minimum value. Most training instances were based on binary cross-entropy loss, while the study also attempted to use focal loss in highly skewed datasets. However, the models performed relatively well using unseen holdout test data from the training datasets rather than external datasets. Models with holdout test splits containing these mixed datasets performed better than others in performance evaluation. They used Gradient-weighted Class Activation Mapping (Grad-CAM) to create heat maps that highlighted regions pertinent to different classes. The models performed well on the ECGs from the same populations and datasets used for training, suggesting that they are internally valid.

However, problems with using them outside of this scope were acknowledged. To this end, the study also recognizes the limitation of current state-of-the-art DL tools for signals that may not be optimized for low-resource settings such as rural and remote areas where ECG traces are usually print-outs or scanned.

Golande, A.L. *et al.* in [46] proposed an adaptive and secure pre-processing of raw input ECG signal for ECG-based focused on heart disease diagnosis. Before the signal was further treated to improve its quality, baseline drift and external noise factors were reduced by elimination. This system utilized a mixed strategy of autonomous CNN features with CNN features extracted humanly for prediction purposes as well as an early warning about heart diseases using an LSTM classifier. The pre-processing procedures comprised the 1D median filters and the 2D notch filters that were used to delete the baseline wander artifacts and lower the impact of the power line interference. This included an adaptive transform-domain function for heartbeat segmentation as well as a 3-layer CNN model for automated feature extraction. In terms of results regarding the suggestion, the Short-Time Fourier Transform CNN (STFT-CNN) attained an accuracy of 91.45%, Grasshopper Optimization Algorithm Cnn (GOA-CNN) scored 94.78%, 5L- CNN achieved 98.58%, and 18C- Nonetheless, hybrid feature extraction and CNN-based methods are complicated and computationally expensive which could be a challenge for implementation in resource-limited scenarios.

The authors in [47] created a CNN for Atrial Fibrillation (AF) prediction. A model with a DL feature extracted from ECG data had better results than models that depended on other inputs. To be precise, the 'DL only' model based exclusively on DL characteristics showed negligible loss in the Area Under the Curve (AUC) compared to the 'all feature' model. The AUC score was 0.86 and .72, respectively, among people under 65 years and over. Another important finding is that wider monitoring windows for ECG signals enhanced the quality of the predictions through the calculation of AUC and mean average precision.

In [48], the authors offer a smart healthcare system that can help in the remote diagnosis of heart diseases through ECG. It uses both linear and temporal characteristics of ECG. Therefore, it combines CNN in order to extract discriminative linear features with the LSTM model that processes long-term dependencies in time series ECG. The key objective is to enhance existing ML techniques that automatically identify heart disease using ECG signals by merging the advantages of the CNN and LSTM models into a new architecture. Their proposed innovations include the use of the GeLU activation function, generalized ID-based gated pooling modules, and Synthetic Minority Over-sampling TEchnique (SMOTE) based data balancing. Processing of the raw single-lead ECG signals for developing beat segments and extracting RR- RR-interval derived time series features is their main methodology, along with 1D CNN layers, which are used to extract the linear features automatically to this dual-input model. At the same time, the LSTM units capture the long-term temporal context. Finally, the outputs were made using both the MIT Beth Israel Hospital (MIT-BIH) arrhythmia data and the Pulmonary TuBerculosis (PTB) diagnostic ECG, and a comprehensive assessment was made. This model provides state-of-the-art performance, attaining a mean accuracy of 99.14 % and 95% recall for classifying ECGs as normal versus one of seven abnormal heart disease categories.

In [49], the author intended to increase the classification of heart disease based on ECG, leading to the identification of healthy and unhealthy individuals with machine lean modelling. The methodology was based on pre-treatment ECG data. Firstly, all outliers were excluded and normalized. Pre-processing was essential in order to provide a good and uniform data set for classification. For the classification, the study employs several ML models: Gaussian NB, RF, Logistic Regression (LogReg), Latent Dirichlet Allocation (LDA), and a Dummy classifier. To address the issue of reliability and reduce potential biases, the study applies a 10-fold cross-validation process. The results indicated that the Gaussian NB classifier had an accuracy of 96% in classifying both healthy people and patients with heart diseases. Both RF and logistic regressions had 92 percent accuracy, respectively. Its accuracy was only 50%, which is compared with the use of the Dummy Classifier as a baseline. The findings indicate that ML-based methods can be used for heart disease diagnosis through ECG signal classification, and Gaussian NB was the best algorithm in the test.

In [50], the review on ML and DL-based classification of heart disease and its predictive powers is concerned with the growing importance of early diagnosis of coronary arteries in modern healthcare. The authors employ different ML and DL ensemble models for early-stage heart disease prediction. Data pre-processing methodology works with video datasets in which videos are turned into frames. These frames undergo the process of feature extraction to become input. It involves 3072 patient data from the three classes, including test, training, and validation. Eighty percent of the data is used for training, and twenty percent for testing in terms of model training as well as evaluation. CNN consists of an input layer, hidden layers, and an output layer, with the hidden layers activating using the ReLU function. Once the testing phase is complete, the data is utilized for classification. The results show that the CNN model had a high accuracy level of 97.50%, thus demonstrating how successful these methods are in early-stage heart disease diagnosis and classification.

An improved arrhythmia detection from ECG signal by exploiting the DL method has been done in [51]. The methodology involves the pre-processing of ECG signals, including filtering, resampling, and normalization. Scaling signals with range, the use of bandpass filters, and ultimately resampling on a constant frequency make this pre-processing crucial to reduce any noise or artifacts. After that, signals are separated into different beats or segments under the references of R-peaks in an annotation. The paper looks into DL Models such as CNNs and CNN with LSTM network. The models are evaluated using an input dataset that has been divided into 80% for training and 20% for testing to avoid overfitting. This article is focused on comparing the models, and it states that the CNN model first reported an accuracy of 70.2%. Still, upon the addition of more convolutional layers, this number grew to 79.3%. Combining CNN and LSTM led to the highest accuracy score of 96.3%, showing the improved performance of the model. Conversely, the other tested model, which is VGG-16 architecture, had an accuracy value of 72.2%, which was lower.

The most used technique was neural network with more than 90% accuracy, RF, Xgboost, KNN, and support vector machines. Ensemble predictors performed very well in terms of accuracies for the prediction of CVS in real-time utilizing IoT/IoMT technologies. The most disregarded disorders are listed, with mention of hypertension and arrhythmia being the two most discussed diseases. The paper considers the application of ML in identifying abnormal anomalies and arrhythmias. Various methods and instruments are analyzed. These may have included customized processors, biomedical sensors, ECG vests, or perhaps smartphones designed to monitor for arrhythmias. ML approaches such as the Naive Bayes, CNNs, k-NN, and DL-based neural network architectures are utilized in this approach. This is supported by other studies whose findings point to accuracy levels ranging between 0.93% and 0.99% [52].

6. Literature Survey Conclusion

After an extensive review of the presented papers on heart disease prediction and diagnosis using ECG signals, several common themes emerge. The majority of studies showcase the versatility of ML and DL techniques in achieving high accuracy in classifying heart diseases based on ECG data.

Notably, the use of diverse classifiers and pre-processing methods, including feature selection algorithms and outlier handling, is a prevalent trend. However, a critical perspective reveals certain limitations and areas for improvement across the studies.

The transferability of models, especially DL architectures, is often understated, and the potential impact of dataset variability on model generalization is not adequately addressed. Many studies lack robust external validation on diverse datasets, raising concerns about the true scalability and reliability of the proposed models. Moreover, the trade-offs between model complexity, computational expense, and real-world applicability are not consistently addressed.

The challenge of implementing these sophisticated models in resource-limited settings, particularly in rural or remote areas, is largely overlooked. Furthermore, the lack of standardized evaluation metrics and benchmark datasets in some studies hinders a fair comparison of model performances. While the findings collectively underscore the potential of advanced computational models in cardiac health, a critical perspective urges researchers to address these limitations to enhance the credibility and real-world impact of their contributions.

Table 1. Summarizes the Previous Studies

Year	Author(s)	Dataset(s)	Methods	Results
2020	Yar Muhammad *et al.* [40]	Cleveland heart disease dataset and Hungarian heart disease dataset	Logistic Regression, Decision Tree, Naïve Bayes, RFrest, Artificial Neural Network, etc.	Extra-tree classifier: Precision: 92.09% Sensitivity: 91.82% Specificity: 92.38%.
2021	Rohit Bharti *et al.* [41]	UCI	RF, Logistic Regression. KNeighbours, SVM, Decision Tree	Model Accuracy RF: 80.3% Logistic Regression: 83.31% KNeighbours: 84.86% SVM: 83.29% Decision Tree: 80%
2021	Zeleznik *et al.* [42]	20084 individuals from distinct cohorts	TensorFlow-GPU and Keras, and four GPUs that had a minimum of 64GB	Results based on spikes in generated graphs with no accuracy used
2022	Kaniz Fatema *et al.* [43]	ECG images c and COVID-19 patients	InRes-106 InceptionV3 ResNet50 DenseNet201 VGG19 MobileNetV2	Model Accuracy InRes-106: 98.34%, InceptionV3: 90.56% ResNet50: 89.63% DenseNet201: 88.94% VGG19: 87.87% MobileNetV2: 80.5%
2022	Mhamdi, L. *et al.* [44]	Self-created ECG dataset.	Custom CNN models, namely MobileNetV2 and VGG16	CNN Model validation accuracy above 95%
2023	Ao & He [45]	PTB-XL, CPSC, Shaoxing, Tongji	Grad-CAM	The models performed well on the ECGs from the same populations and datasets used for training
2023	Golande & Pavankumar [46]	Publicly available PTB Diagnostic ECG	LSTM classifier, dynamic handcrafted and CNN feature extraction, manifold learning for	Classification accuracy of 99.45%, F1-score of 99.83%. Outperforms state-of-the-art

Year	Author(s)	Dataset(s)	Methods	Results
			feature selection and normalization	methods in efficiency and accuracy
2023	Gadaleta, M. *et al.* [47]	Patch-based ambulatory single-lead ECG	DL model integrating ECG morphology data and demographic	AUC=0.80 for predicting AF within 14 days. Adding ECG signal data significantly improves prediction over just using demographics.
2023	M. Bukhari *et al.* [48]	MIT-BIH PTB	1D CNN for linear features, Vanilla LSTM for time-series features, Generalized Gated Pooling, SMOTE oversampling	Average accuracy of 99.14%, Recall of 95%
2023	Seyed Matin Malakouti [49]	MIT-BIH	Gaussian Naive Bayes, Logistic Regression, RF	Gaussian NB Classifier with 96% accuracy
2023	Deepika *et al.* [50]	McKinsey data set and MIT-BIH RR Interval	CNN	Diverse results; some approaches reach as high as 99.94% accuracy
2023	Hima Vijayan VP *et al.* [51]	MIT-BIH	CNN, CNN with LSTM	CNN with LSTM achieved the highest accuracy of 96.3%
2023	Cuevas-Chávez *et al.* [52]	Echocardiogram video data of 1024 patients	ML DL	CNN with 97.50% accuracy

Acknowledgment

Words cannot express my gratitude to my supervisor Asst. Prof. Dr. Mohammed S. H. Al-Tamimi for his invaluable support.

I would like to extend my gratitude to the staff in Computer Science Department - College of Science - University of Baghdad for their collaborative efforts. Their expertise has greatly benefited the study.

I would like to thank all those people who have supported me intellectually and emotionally as I worked on my project.

Conflict of Interest

There is no conflict of interest.

Funding

There is no funding for the article.

References

1. Younis, M. A.; Al-Tamimi, M. S. Preparing of ECG Dataset for Biometric ID Identification with Creative Techniques. *TEM Journal*, **2022**, *11*(*4*), 1500-1507. https://doi.org/10.18421/TEM114-10.
2. Yousiaf, T. H.; Al-Tamimi, M. S. The Role of Artificial Intelligence in Diagnosing Heart Disease in Humans: A Review. *Journal of Applied Engineering and Technological Science*, **2023**, *5*(*1*), 321-338. https://doi.org/10.37385/jaets.v5i1.3413.
3. Morris, F. *ABC of Clinical Electrocardiography*; John Wiley & Sons: **2009**, ISBN 978-1-444-31249-2.

4. Manda, Y.R.; Baradhi, K.M. *Cardiac Catheterization Risks and Complications*; Stat Pearls Publishing: Treasure Island, FL, USA, **2021**, PMID: 30285356.
5. Jørgensen, M.E.; Andersson, C.; Nørgaard, B.L.; Abdulla, J.; Shreibati, J.B.; Torp-Pedersen, C.; Gislason, G.H.; Shaw, R.E.; Hlatky, M.A. Functional Testing or Coronary Computed Tomography Angiography in Patients With Stable Coronary Artery Disease. *Journal of the American College of Cardiology* **2017**, *69(14)*, 1761-1770. https://doi.org/10.1016/j.jacc.2017.01.046.
6. Al-Tamimi, M. S. H.; Al-Tamimi, A. S. H.; Sulong, G. A new Abnormality Detection Approach For T1-Weighted Magnetic Resonance Imaging Brain Slices Using Three Planes. *Adv. Computer*, **2016**, *6(1)*, 6-27. https://doi.org/10.5923/j.ac.20160601.02.
7. Al-Tamimi, M. S. H.; Sulong, G. A New Method for Detecting Cerebral Tissues Abnormality in Magnetic Resonance Images. *Modern Applied Science*. **2015,** *9(8)*, 363-379. https://doi.org/10.5539/mas.v9n8p363.
8. Syed,I.S.; Glockner,J.F.; Feng,D.; Araoz,P.A.; Martinez,M.W.; Edwards,W.D.; Gertz,M.A.; Dispenzieri, A.; Oh,J.K.;Bellavia,D. Role of Cardiac Magnetic Resonance Imaging in the Detection of Cardiac Amyloidosis. *JACC Cardiovascular Imaging*. **2010**, *3(2)*, 155–164.
9. Pannu,J.; Poole,S.; Shah,N.; Shah,N.H. Assessing Screening Guidelines for Cardiovascular Disease Risk Factors using Routinely Collected Data. *Scientific Reports* **2017**, *7(1)*, 6488. https://doi.org/10.1038/s41598-017-06492-6.
10. Iragavarapu, T.; Radhakrishna, T.; Babu, K.J.; Sanghamitra, R. Acute Coronary Syndrome In Young—A Tertiary Care Centre Experience With Reference To Coronary Angiogram. *Journal of the Practice of Cardiovascular Sciences*. **2019**, *5(1)*, 18-25. https://doi.org/10.4103/jpcs.jpcs_74_18.
11. Rafie, N.; Kashou, A.H.; Noseworthy, P.A. ECG Interpretation: Clinical Relevance, Challenges, and Advances. *Hearts*. **2021**, *2(4)*, 505–513. https://doi.org/10.3390/hearts2040039.
12. Al-Tamimi, M. S. H. A Survey on The Vein Biometric Recognition Systems: Trends and Challenges. *Journal of Theoretical and Applied Information Technology*. **2019,** *97(2)*, 551-568.
13. Cook, D.A.; Oh, S.Y.; Pusic, M.V. Accuracy of Physicians' Electrocardiogram Interpretations. *JAMA Internal Medicine* **2020**, *180(11)*, 1461-1471. https://doi.org/10.1001/jamainternmed.2020.3989.
14. Higueras, J.; Gómez-Talavera, S.; Cañadas, V.; Bover, R.; P, M.L.; Gómez-Polo, J.C.; Olmos, C.; Fernandez, C.; Villacastín, J.; Macaya, C. Expertise in Interpretation of 12-Lead Electrocardiograms of Staff and Residents Physician: Current Knowledge and Comparison Between Two Different Teaching Methods. *Journal Caridology Current Research.* **2016**, *5(3)*, 00160. https://doi.org/10.15406/jccr.2016.05.00160.
15. Abd-Alzhra, A. S.; Al-Tamimi, M. S. Image Compression Using Deep Learning: Methods and Techniques. *Iraqi Journal of Science*. **2022**, 1299-1312. https://doi.org/10.24996/ijs.2022.63.3.34.
16. Schläpfer, J.; Wellens, H.J. Computer-interpreted electrocardiograms: benefits and limitations. *Journal of the American College of Cardiology* **2017**, *70(9)*, 1183-1192. https://doi.org/10.1016/j.jacc.2017.07.723.
17. Martínez-Losas, P.; Higueras, J.; Gómez-Polo, J.C.; Brabyn, P.; Ferrer, J.M.F.; Cañadas, V.; Villacastín, J.P. The Influence of Computerized Interpretation of An Electrocardiogram Reading. *The American journal of emergency medicine* **2016**, *10(34)*, 2031-2032. https://doi.org/10.1016/j.ajem.2016.07.029.
18. Dey,S.; Pal,R.; Biswas,S. Deep Learning Algorithms for Efficient Analysis of ECG Signalsto Detect Heart Disorders. *In Biomedical Engineering*; Intech Open: London, UK, **2022.** https://doi.org/10.5772/intechopen.103075.
19. Abed, R. M.; Abdulmalek, H. W.; Yaaqoob, L. A.; Altaee, M. F.; Kamona, Z. K. Genetic Polymorphism of TLR5 and TLR6 in Iraqi Patients with Heart Failure Disease. *Iraqi Journal of Science.* **2023,** *64(4)*, 1662–1674. https://doi.org/10.24996/ijs.2023.64.4.9.
20. Moini, J. *Anatomy and physiology for health professionals*; Jones & Bartlett Publishers: **2015**.
21. Al-Juboori, R. A. L. Contrast Enhancement of the Mammographic Image Using Retinex with CLAHE methods. *Iraqi Journal of Science*. **2017,** *58(1B)*, 327–336.

22. Rahma, M. M.; Salman, A. D. Heart Disease Classification–Based on the Best Machine Learning Model. *Iraqi Journal of Science*. **2022**, *63(9)*, 3966–3976. https://doi.org/10.24996/ijs.2022.63.9.28.
23. Sadiq, A. T.; Mahmood, N. T. A Hybrid Estimation System For Medical Diagnosis Using Modified Full Bayesian Classifier And Artificial Bee Colony. *Iraqi Journal of Science*. **2014,** *55(3A)*, 1095-1107.
24. Park, J.; An, J.; Kim, J.; Jung, S.; Gil, Y.; Jang, Y.; Lee, K.; young Oh, I. Study on the Use of Standard 12-lead ECG Data for Rhythm-Type ECG Classification Problems. *Computer Methods Programs Biomed*. **2021**, *21*, 106521. https://doi.org/10.1016/j.cmpb.2021.106521.
25. Rath, A., Mishra, D., Panda, G.; Sat apathy, S. C. Heart Disease Detection Using Deep Learning Methods From Imbalanced ECG Samples. *Biomedical Signal Processing and Control*. **2021,** *68*, 102820. https://doi.org/10.1016/j.bspc.2021.102820.
26. S., C. V.; Ramaraj, E. A Novel Deep Learning based Gated Recurrent Unit with Extreme Learning Machine for Electrocardiogram (ECG) Signal Recognition. *Biomedical Signal Processing and Control*. **2021,** *68*, 102779. https://doi.org/10.1016/j.bspc.2021.102779.
27. Shkara, A. A.; Hussain, Y. Heartbeat Amplification and ECG Drawing from Video (Black and White or Colored Videos). *Iraqi Journal of Science*. **2018,** *59(1B)* ,408-419. https://doi.org/10.24996/ijs.2018.59.1B.21.
28. Vasconcellos, M. M. E.; Ferreira, B. G.; Leandro, J. S.; Neto, B. F. S.; Cordeiro, F. R.; Cestari, I. A.; Gutierrez, M. A.; Sobrinho, Á.; Cordeiro, T. D. Siamese Convolutional Neural Network for Heartbeat Classification Using Limited 12-Lead ECG Datasets. *IEEE Access*. **2023,** *11*, 5365–5376. https://doi.org/10.1109/ACCESS.2023.3236189.
29. Wang, M.; Rahardja, S.; Fränti, P.; Rahardja, S. Single-Lead ECG Recordings Modeling for end-to-end Recognition of Atrial Fibrillation With Dual-Path RNN. *Biomedical Signal Processing and Control*. **2023,** *79*, 104067. https://doi.org/10.1016/j.bspc.2022.104067.
30. Yoneyama K; Naka M; Harada T; Akashi Y. Creating 12-Lead electrocardiogram Waveforms Using A Three-Lead Bedside Monitor To Ensure Appropriate Monitoring. *Journal of Arrhythmia*. **2020,** *36(6)* ,1107. https://doi.org/10.1002/joa3.12441.
31. Saad NM; Abdullah AR; Low YF. Detection of Heart Blocks In ECG Signals By Spectrum And Time-Frequency Analysis. In: *2006 4th Student Conference on Research and Development. Piscataway, New Jersey, United States: IEEE;* **2006**; 61-65. https://doi.org/10.1109/SCORED.2006.4339309.
32. Ozyilmaz L; Yildirim T. Artificial Neural Networks for Diagnosis of Hepatitis Disease. In: *Proceedings of the International Joint Conference on Neural Networks*. **2003,** 1, 586-589. https://doi.org/10.1109/IJCNN.2003.1223422.
33. Mao WB; Lyu JY; Vaishnani DK; Lyu YM; Gong W; Xue XL. Application of Artificial Neural Networks in Detection and Diagnosis of Gastrointestinal and Liver Tumors. *World Journal of Clinical Cases (WJCC)*. **2020**, *8(18)*, 3971-3977. https://doi.org/10.12998/wjcc.v8.i18.3971.
34. Krizhevsky A; Sutskever I; Hinton GE. ImageNet Classification With Deep Convolutional Neural Networks. *Communications of the ACM*. **2017**, *60(6)*, 84-90. https://doi.org/10.1145/3065386.
35. Sunny MAI; Maswood MMS; Alharbi AG. Deep Learning-Based Stock Price Prediction Using LSTM and Bi-Directional LSTM Model. In: ***2020** 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES). Piscataway, New Jersey, United States: IEEE*; **2020**, 87-92. https://doi.org/10.1109/NILES50944.2020.9257950.
36. Mansoor, M.; Al Tamimi, M. Plagiarism Detection System In Scientific Publication Using LSTM Networks. *International Journal Technical and physical problems of engineering*. **2022,** *4(4)*, 17-24.
37. Yu X; He J; Zhang Z. Facial Image Completion Using Bi-Directional Pixel LSTM. *IEEE Access*. **2020**, *8*, 48642-48651. https://doi.org/10.1109/ACCESS.2020.2975827.
38. Rawshani, A. The ECG Leads: Electrodes, Limb Leads, Chest (Precordial) Leads, 12-Lead ECG (EKG). Available online: https://ecgwaves.com/topic/ekg-ecg-leads-electrodes-systems-limb-chest-precordial .
39. Ribeiro, A.H.; Ribeiro, M.H.; Paixão, G.M.M.; Oliveira, D.M.; Gomes, P.R.; Canazart, J.A.; Ferreira, M.P.S.; Andersson, C.R.; Macfarlane, P.W.; Meira, W. Automatic Diagnosis of the 12-lead ECG Using A

Deep Neural Network. *Nature communications*. **2020**, *11(1)*, 1760-1772. https://doi.org/10.1038/s41467-020-15432-4.

40. Muhammad, Y.; Tahir, M.; Hayat, M.; Chong, K.T. Early and Accurate Detection and Diagnosis of Heart Disease Using Intelligent Computational Model. *Scientific Reports*. **2020,** *10(1)*, 19747. https://doi.org/10.1038/s41598-020-76635-9.
41. Rohit Bharti; Aditya Khamparia; Mohammad Shabaz, Gaurav Dhiman; Sagar Pande; Parneet Singh; Prediction of Heart Disease Using a Combination of Machine Learning and Deep Learning. *Computational Intelligence and Neuroscience*. **2021,** Article ID 8387680. https://doi.org/10.1155/2021/8387680.
42. Zeleznik, R.; Foldyna, B.; Eslami, P. Deep Convolutional Neural Networks To Predict Cardiovascular Risk From Computed Tomography. *Nature communications.* **2021,** *12(1)*, 715-726. https://doi.org/10.1038/s41467-021-20966-2.
43. Fatema K; Montaha S; Rony MAH; Azam S, Hasan MZ; Jonkman M. A Robust Framework Combining Image Processing and Deep Learning Hybrid Model to Classify Cardiovascular Diseases Using a Limited Number of Paper-Based Complex ECG Images. *Biomedicines*. **2022**, *10(11)*, 2835-2848. https://doi.org/10.3390/biomedicines10112835.
44. Mhamdi, L.; Dammak, O.; Cottin, F.; Dhaou, I.B. Artificial Intelligence for Cardiac Diseases Diagnosis and Prediction Using ECG Images on Embedded Systems. *Biomedicines*. **2022**, *10(8),* 2013. https://doi.org/10.3390/biomedicines10082013.
45. Ao R; He G. Image Based Deep Learning in 12-lead ECG Diagnosis. *Frontiers in Artificial Intelligence.* **2023**, *5*, 1087370. https://doi.org/10.3389/frai.2022.1087370.
46. Golande, A.L.; Pavankumar, T. Optical electrocardiogram Based Heart Disease Prediction Using Hybrid Deep Learning. *Journal Big Data*. **2023,** *10(1)*, 139-150. https://doi.org/10.1186/s40537-023-00820-6.
47. Gadaleta, M.; Harrington, P.; Barnhill. Prediction of Atrial Fibrillation From At-Home Single-Lead ECG Signals Without Arrhythmias. *NPJ Digital Medicine*. **2023,** *6(1)*, 229. https://doi.org/10.1038/s41746-023-00966-w.
48. M. Bukhari; S. Yasmin; S. Naz; M. Y. Durrani; M. A Smart Heart Disease Diagnostic System Using Deep Vanilla LSTM. *Computers, Materials & Continua*. **2023,** *77(1)*, 1251–1279. https://doi.org/10.32604/cmc.2023.040329.
49. Seyed Matin Malakouti. Heart Disease Classification Based on ECG Using Machine Learning Models. *Biomedical Signal Processing and Control*. **2023,** *84,* 104796. https://doi.org/10.1016/j.bspc.2023.104796.
50. Deepika, S.; Jaisankar, N. Review on machine learning and deep learning-based heart disease classification and prediction. *The Open Biomedical Engineering Journal* **2023**, *17(1)*. https://doi.org/10.2174/18741207-v17-e230110-2022-HT27-3589-17.
51. Hima Vijayan VP; Reshma S, R; Sathyanjan; Vaishnavi Geetha. Integrating Deep Learning Architectures for Improved Arrhythmia Detection in electrocardiogram Signals. *International Journal of Science and Research Archive.* **2023**, *08(02),* 704–715. https://doi.org/10.30574/ijsra.2023.8.2.0332
52. Cuevas-Chávez, A.; Hernández, Y.; Ortiz-Hernandez, J.; Sánchez-Jiménez, E.; Ochoa-Ruiz, G.; Pérez, J.; González-Serna, G. A Systematic Review of Machine Learning and IoT Applied to the Prediction and Monitoring of Cardiovascular Diseases. *Healthcare*. **2023**, *11(16)*, 2240. https://doi.org/10.3390/healthcare11162240.