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Analysis of Electrocardiogram Signals Using Machine Learning Techniques – A Review

Prerana M[1], Stavelin Abhinandithe[2], Sridhar Ramachandran[3] & Balasubramanian Somanathan[4]

[1]*Research Scholar, Division of Medical Statistics, School of Life Sciences, JSS AHER, Mysuru, Karnataka, India.*

[2]*Assisstant Professor, Division of Medical Statistics, School of Life Sciences, JSS AHER, Mysuru, Karnataka, India.*

[3]*Head, MCA, Ramakrishna Mission Vidyalaya, Coimbatore, Tamil Nadu, India.*

[4]*Former, Director Research, JSSAHER, Mysore, Karnataka, India.*

Corresponding Author - Prerana M

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Abstract:

According to the most recent survey, 60% of patients die as a result of heart disorders, which accounts for a major cause of death in this century. Electrocardiogram (ECG) signals can be used to diagnose these conditions. Electrical activity that the heart produces is captured in an ECG signal. Building a model to do automatic ECG categorization has piqued interest in the analysis of the ECG signal for more than ten years. This research's major objective is to examine and provide a summary of using modern classification techniques such artificial neural networks (ANN), convolutional neural networks (CNN), discrete wavelet transforms (DWT), support vector machines (SVM), and K-Nearest Neighbour (KNN). The final product includes effective comparisons of classification techniques, feature extraction methods, datasets, contributions, and other factors. The outcome also demonstrates that the CNN has been the most popular method for classifying ECGs since it has a greater success rate than the remaining classification approaches.

Keywords:* *ANN, CNN, DWT, SVM, KNN, ECG.

Introduction:

Electrocardiogram (ECG) is a simple recording of the heart's electrical activity [1]. All the related data are recorded by an ECG machine and displayed on paper [2]. An ECG is a medical test that is used to identify cardiac abnormalities, examine electrical activity generated by the heart [3]. Small electrical impulses generated by the heart travel throughout the heart muscle [4]. Once this information has been interpreted by a medical professional, an irregular cardiac rhythm can be found and the reason of chest pain symptoms found [5]. Aside from the atrial depolarization, which creates a minor turn prior to atria contraction as the activation (depolarization) wave-front will propagate from the Sino atria node across the atria, there are a total of five principal turns in an ECG signal, counting P, Q, R, S, and T waves [6]. After P wave, Q wave deflects downward [7]. S wave follows the R wave, which deflects upward, while the R wave deflects downward [8]. Together, Q, R, and S waves point to a single event [9]. As a result, they are typically regarded as QRS complexes, which is shown in the Fig. 1 [10], [11]. One of the most effective aspects to analyse ECG is based on QRS complex [12]. Currents produced when the ventricles depolarize before contracting are what induce the QRS-complex [13]. Atrial depolarization precedes ventricular depolarization, but because the later waveform—the QRS-complex—has a much higher amplitude, it cannot be observed on an ECG. Ventricular depolarization, or the T wave, which comes after S wave, is when the heart muscle gets ready for subsequent ECG cycle [14]. U wave, which is the final deflection, instantly follows the T wave. Typically, T wave and U wave are travelling in the same direction.

QRS complex contains majority of the energy in an average ECG tracing of the cardiac cycle/heartbeat, whereas T and U wave contain very little energy and are frequently missed in 50-75% of ECGs due to being hidden by the T wave and impending new P wave [15]. Different wave types and the activities that create them are summarised in Table I.

Electrocardiogram's baseline is made up of the PR segment, flat horizontal segments, and the segment between TP segments. The isoelectric line (0 mV) serves as a baseline in the heart that is normally healthy. However, because of the flow of damage currents in this conduction period of the TP and PR intervals, when ventricles are resting, baseline in a heart with a disease may be increased (for example, in cardiac ischemia) or depressed (for example, in myocardial infarction) relative to the isoelectric line. In most cases, baseline drift brought on by patient breathing, 50/60 Hz power line interference, faulty electrodes, incorrect electrode location drastically degrades the ECG signal and makes it difficult or even impossible to detect QRS complexes. To effectively and precisely detect QRS complexes, numerous researchers have created various methods and algorithms. To find the QRS complexes, Trahanias employed mathematical morphology, Dr. Li presented the wavelet transforms approach, Mehta and Lingayat [16] presented the SVM approach.

A single or series of irregular heartbeats is known as an arrhythmia. A classification technique can be used to determine the type of arrhythmia. These include artificial neural network-based classification, self-organizing maps, fuzzy neural networks, Hermite functions coupled, wavelet analysis and radial basis function neural networks. Within these techniques, several elements were retrieved from the ECG waveform of each beat in order to categorise various arrhythmic kinds.

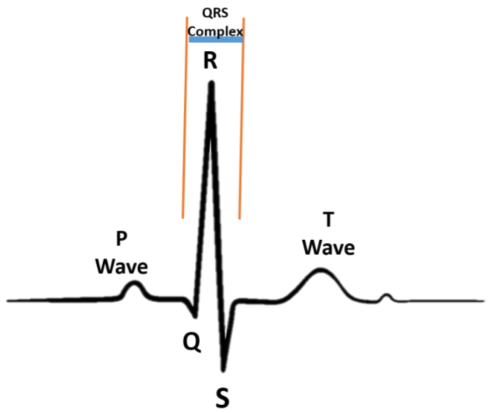

Fig. 1: ECG signal

Fig. 2: Classification of ECG

Our paper's primary goal is to review the majority of the typical methods that have been applied often since 2010 - 2023. Additionally, as many parts of the methodology are covered, the study can help other researchers to figure out problems with ECG classification, if any; and in analysing the topic of research.

Table 1: Types of waves and their actions

Wave	Action
P – wave	Atrial depolarization
Q – wave	Anterioseptal region activation of the ventricular myocardium
R – wave	Ventricular myocardium depolarization
S – wave	Posteriobasal portion activation of the ventricles
T – wave	Rapid repolarization of the ventricles

The paper is sectioned as follows: Classification, discussion and conclusion.

Classification:

By analysing the ECG signal, a patient's heart activities can yield a wealth of pathological data [17]. Heartbeat classification has undergone a great deal of development because it is crucial for the identification of arrhythmias [18]. Arrhythmias can be segregated into 2 categories: Those that endanger life and those that do not. Since a long-term ECG classification is needed to diagnose non-life-endangering arrhythmias, it can be impractical and time-consuming. In these cases, automatic algorithms are helpful. As a result, one of the areas of study that is most worthwhile worldwide is automatic ECG classification of arrhythmias [19].

Different classifiers have been employed in the task of classifying ECGs. The most popular ECG classification methods that have been proposed between 2016 and 2020 are discussed in this work. These classification methods may primarily be classified based on the classifiers into several groups, like ANN, KNN, CNN, DWT, and SVM.

There are many features in the ECG signal that may be recovered, hence several classification methods are studied to classify ECG data under the variance features. Below, few of the classification techniques are discussed:

1. *Artificial Neural Networks (ANN):*

Based on how the human brain works, ANN is a special class of machine learning algorithm. This means that the ANN can learn from the data similarly to how the neurons in our nervous system can learn from previous data and produce responses in the form of forecasts or classifications.

By presenting a complex relationship between inputs and outputs, ANNs seek to discover fresh patterns (Fig. 3). These ANNs are engaged for a variety of tasks, like machine translation, speech recognition, medical diagnosis, and picture recognition.

A significant advantage is that ANN can learn from sample data sets. As a crude approximation of a random function, ANN is used the most frequently. These technologies make it possible to define the distribution's solutions in a practical way. An ANN can also provide results using a sampling of the data rather than the entire dataset. ANNs can be utilised to enhance the efficiency of current data analysis techniques because of their sophisticated predicting capabilities.

For a variety of issues, including estimation, classification, clustering analysis, sample recognition, and others, Artificial Neural Networks (ANN) are effectively employed as a substitute for statistical methods. Since ANN models are typically nonlinear, they provide superior application estimates [20].

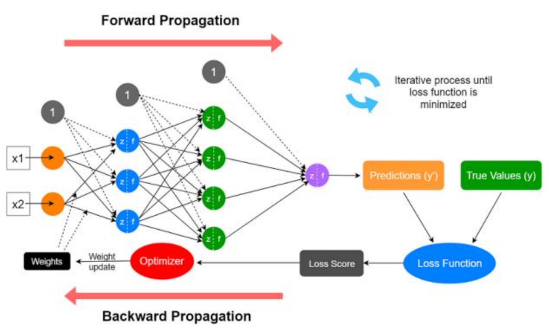

Fig. 3 Artificial Neural Network

In order to categorise ECG waveforms, Gaurav Kumar Jaiswal and Ranbir Paul [21] introduced an ANN-based approach that can help identify the optimum neural network topology for categorising the anomalies of cardiac illnesses. Focus was placed on the five ECG signal characteristics (P, Q, R, S, and T). The MIT-BIH arrhythmia database provided 12 files. According to simulation results, classification of ECG beats produces the best results at roughly 97.14%. It was determined that significant ECG abnormalities had a stronger predictive value for CVD and CHD death than recognised cardiovascular risk factors.

A heart attack prediction system was presented by Amit S. Wale et al. [22] with the aid of neural networks & genetic algorithms. This approach determined the number of nodes that are hidden for a neural network, trained with appropriate neural network architecture and initialization using a global genetic algorithm optimisation. They collected the male and female normal and abnormal ECG signal datasets from MIT-BIH arrhythmia dataset webpage. By enhancing performance and utilising optimised neural network architecture, genetic neural network-based heart disease forecast for patients determines if the patient has heart disease or not. Additionally, research the likelihood of a heart attack depending on heart activity.

The ANN tool was used by Prachi Garg and Ajeet Sharma [24] to distinguish between abnormal and normal ECG signals. They discussed the use of an ANN technique to detect MIT-BHI normal sinus ECG database signals and MIT-BHI supraventricular ECG database signals. The proposed ANN mode provides 100% accuracy for detecting normal ECGs and 96.65% accuracy for detecting abnormal ECGs. The suggested ANN model is quite effective in categorising the normal and abnormal ECG signals in our research; we have taken 10 seconds to finish the ECG, including many ECG bits are taken for analysis. Classification accuracies and the results produced by the ANN validated this.

2. Convolutional Neural Network (CNN):

More precise representations of image data can be generated with the use of CNN model of neural networks. The raw pixel data from the picture is the starting point for CNN, which trains the model before automatically extracting the features to categorize better (Fig. 4). This is in contrast to the traditional image recognition that necessitates that we describe the image characteristics ourselves. CNNs are a subset of deep neural networks, which often employ in deep learning for the processing of visual input. It employs a special technique called convolution [25].

The three CNN layers are generally fully connected, convolutional, and pooling.

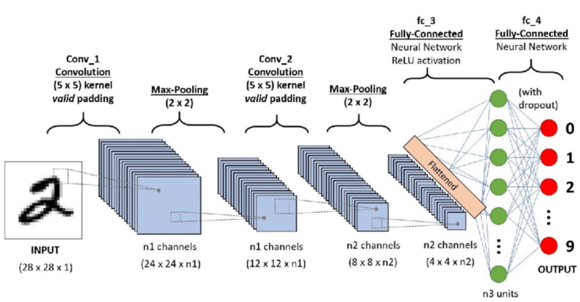

Fig. 4 Image taken from [22]

Convolutional neural networks (CNNs) were used to train a new ECG pattern classifier approach that Shubham Srivastava et al. [26] created and examined in order to speed up and minimise the complexity of classifying an ECG signal. Python served as the platform for a variety of operations. Their artificial neural network was trained using machine learning and the back propagation algorithm on the MIT-BIH database. Python was chosen over Matlab because it has more libraries, more community support, and more user-friendly tools to implement machine learning effectively. Their artificial neural network was trained to an accuracy of 96%, which can be increased by expanding the network's training cycles.

Implementation of Deep CNN that technically is a challenging architecture, was the main emphasis of Ritesh Sharma et. al.'s study [27]. A dataset from the MIT-BIH dataset website was used by them. The 187 columns in the dataset gathered related to the moment in time when the heartbeat was detected. They got a precision of 98.18% in the training phase and 95.56% in the testing phase after putting the Deep CNN model that was suggested in this study into practise. To obtain automatic and precise findings, the presented methodology can be implemented in embedded systems along with numerous biotechnological devices.

A 2D CNN deep learning model was created by Muayed S. Al-Huseiny et al. [28] to successfully identify a cardiovascular problem among 17 marked types of heart arrhythmia in long-term (10-s) ECGs. The suggested method calls for creating a convolution neural network (2D-CNN) that was trained using pictures of ECG signals gathered from the MIH-BIH database. The proposed method was demonstrated to be: Efficient, rapid (real-time ranking), thorough, and adaptable to additional wearable applications and devices. The outcomes of the suggested algorithm make a compelling case for the widespread adoption of deep learning-based autonomous diagnosis methods in healthcare systems. Additionally, it demonstrated how these methods can save lives by continuously and immediately updating patients' conditions; this is of great importance.

Heartbeat morphology and rhythm were combined by Jia Li et al. [29] into a two-dimensional information vector to be processed by CNNs that use biased dropout and adaptive learning rate techniques. Results showed that the suggested CNN model is effective in identifying arrhythmias or abnormal heartbeats through automatic feature extraction. The suggested model performed better than existing cutting-edge algorithms for the four and eight heartbeat categories when tested on MIT-BIH arrhythmia database (the average accuracy was 99.1% and 97%). More particularly, the presented system outperformed the current one for V beats by more than 4.3% and 5.4%, S beats by more than 22.6% and 25.9%, respectively, in terms of sensitivity and positive prediction rate.

Piyush Jain et al. [30] have presented a 2-stage deep convolutional neural network (CNN) technique for the automatic classification of low and high-risk hypertension classes that used multi-lead ECG data. The suggested DNN architecture was examined using multi-lead ECG readings from open datasets. The results demonstrated that the first stage deep CNN had average accuracy, sensitivity, specificity, F-score, and Kappa values of 99.68%, 99.51%, 100.00%, 0.997, and 0.993 respectively, to identify hypertension. The second stage deep CNN generated average values for accuracy, specificity, sensitivity, F-score, and Kappa to classify low and high-risk ECG signals of 90.98%, 85.92%, 96.00%, 0.905, and 0.819, respectively. A cloud-based framework can be used to implement the suggested two-stage deep CNN approach for automatic detection of high and low risk hypertension classes that use multi-lead ECG signals.

A hybrid approach utilising Convolution Neural Network (CNN) to automatically extract features from ECG and apply XGBoost to determine the kind of arrhythmia was proposed by Ravindar Mogili and G. Narsimha [31]. They used the MIT-BIH arrhythmia database to test our model's ability to diagnose eleven different types of arrhythmia beats, and the results were overall sensitivity of 92.61%, specificity of 99.85%, positive predictive value of 95.99%, and a precision of 99.84%. By categorising the arrhythmia beats into 5 types in accordance with the AAMI standard and contrasting the results with cutting-edge techniques, the suggested model's resilience was further demonstrated. Overall sensitivities of 94.36%, 99.44% specificities, 96.40% positive predictive values, and 99.69% accuracy for 5 AAMI classes was achieved.

A personal identification method on the basis of collective LSTM and CNN that utilises ECGs was proposed by Jin-A Lee and Keun-Chang Kwak [32]. To describe heart rate in signals utilising micro-currents and account for measurement noise, an ECG requires internal biometric data. In a pre-processing step, this noise was eliminated using filters, and the signals were then separated into cycles in regard to R-peaks for feature extraction. A 2D-CNN was used to conduct personal identification using ECG data, after 1D ECG signals have been translated into the time-frequency domain using STFT, WSST, FSST and scalogram. This pair of combined models is utilised to provide better results than LSTM or 2D-CNN. Results showed an improved performance of 1.06-3.75%.

A precise ECG classification and monitoring system employing 1D CNNs and LSTM was proposed by Lana Abdulrazaq Abdullah and Muzhir Shaban Al-Ani [33]. The CNN model's learnt features are extracted, and the LSTM model was then fed with them. The model does not need to have any handmade features in order to classify ECGs. The CNN-LSTM model's output showed superior performance than a number of state-of-the-arts that are mentioned in the results. On the PTB Diagnostics and MIT-BIH arrhythmia datasets, the proposed models are assessed. Results suggested that classification of arrhythmias and myocardial infarction is possible with an accuracy rate of 98.1% and 98.66%, respectively, using the CNN-LSTM approach.

A transfer learning strategy to detect arrhythmia and classify in cross ECG databases was put forth by Mohamad M. Al Rahhal et. al. [34]. This method uses a deep CNN that has been fully connected layers added to it and has been pre-trained on an auxiliary domain called ImageNet that has very big tagged picture datasets. According to studies published in the MIT-BIH arrhythmia, SVDB databases, and INCART, the suggested method can detect ventricular and supraventricular ectopic beats (VEB and SVEB) more accurately than state-of-the-art techniques.

To address issues with conventional methods, Allam Jaya Prakash et al. [35] propose a beat-based template that matches deep learning (DL) strategy. This suggested methodology performs ECG beat de-noising, R-peak detection, and segmentation during pre-processing phase. The suggested deep-learning technique is used to create grayscale images from these noise-free ECG beats. A publicly accessible ECGID biometric database was used to assess the network's performance, and the suggested method was contrasted with the body of previous research. According to the comparison, the suggested modified Siamese network authenticated biometrics had precision rates of 99.85%, sensitivity rates of 99.30%, specificity rates of 99.85%, and positive predictivity rates of 99.76%. Results demonstrated that the proposed approach outperforms cutting-edge methods.

*3. **Discrete Wavelet Transform (DWT):***

DWT is frequently employed in signal processing and is used to identify and diagnose ECG signals [36]. The primary benefit of DWT is a flawless time resolution [37]. Both at low and high frequencies, it has good resolution for frequency [38]. Due to its excellent temporal and frequency localization capabilities, DWT can expose input signal's local properties [39].

Today, DWT is a common tool for analysing time-series generated by various non-stationary dynamical systems. DWT has already been effectively included into the multifractal formalism [40] and displays dynamical characteristics of processed signals that obey power-like scaling laws with great precision.

The ECG categorization based on DWT has been the subject of a wide variety of published material. Below are a few of these novel ideas:

Using the Discrete Wavelet Transform, Jonathan Goodfellow et al. [41] presented a unique method for detecting ECG R-peaks. 30 AF patients who had undergone DC cardioversion at Royal Victoria Hospital in Belfast provided 18,647 beats for analysis. 3 performance metrics—Sensitivity, Accuracy and Positive Predictivity—were used to evaluate the R-peak detection algorithm's effectiveness for both regular sinus rhythm and atrial fibrillation beats. Outcomes obtained utilising the suggested R-peak detection strategy showed 99.61%, 99.88%, and 99.50% outcomes, proving that using DWT to aid peak detection was a workable technique. The ability of the DWT R-peak detection approach to distinguish between individuals with normal sinus rhythm and the ones with AF was also found to be useful in practise.

The application of the DWT was suggested by Rachid Haddadi et. al. [42] to detect ECG signal's QRS complex. The ECG is distinguished by a recurring wave sequence of P, QRS, and T-waves. Localization is offered by the Wavelet Transform in both time and frequency. Baseline drift in the ECG signal was removed during the pre-processing stage using DWT. The standard MIT-BIH (Massachusetts Institute of Technology, Beth Israel Hospital) Arrhythmia database was used to assess the performance of the QRS detection algorithm. The achieved average QRS complexes detection rate is 98.1%.

A modified method to detect cardiac irregularities and QRS complexes using machine learning and support vector machine (SVM) classifiers was presented by Ali Rizwan et al. in their study published in 2017 [43]. The proposed technology detected an error rate of 0.45% for cardiac abnormalities, and thus surpassed current methods in terms of both sensitivity and specificity. The method supported vector machine classifiers with 98.39% accuracy for MLP-BP and 96.67% accuracy for MLP-BP. The SVM classifier can potentially be very useful in the analysis of cardiac problems, according to the results. Additionally, the SVM classifier classifies ECG beats based on DWT traits gleaned from ECG signals.

In order to clean up the noise in the ECG, Sagar Singh Rathore et al. [44] utilised a wavelet transform-based filter. In order to choose the best wavelet, various wavelet types have been compared. Meyer and Symlet wavelet help increase SNR. The record from the MIT-BIH's arrhythmia database was utilised to test the method. Appearance of de-noising in the ECG plays a critical role in the identification of the component and in diagnosis of the disease. The research that was presented indicated that the Meyer wavelet is the optimum solution for removing power line interference and base line wander. Symlet produces higher SNR output when reducing high-frequency noise. Additionally, Symlet's reaction to power line interference and base line wandering noise filtration is acceptable. Therefore, the optimal filter for de-noising can be designed by Meyer or Symlet wavelet using a rigrsure threshold.

BW (Baseline Wandering) and 50 or 60 Hz PLI are the two types of noise that occur most frequently in the processing of ECG signals. Mustapha El Hanine [45] employed the most recent, very effective DWT (discrete wavelet transform) signal processing on ECG data that were received from the MIT-BIH Arrhythmia Database in order to remove these two primary sources of noise. The findings suggest that DWT is an effective method to filter sounds without altering the morphology of ECG signals. It can be used to process all types of ECG signals, whether they are arrhythmia-presenting or normal signals.

Both de-noising techniques were evaluated by Neelam Bhardwaj et al. [46], who confirmed that they were successful at reducing noise. The evaluation of these two methods' performance using SNR and RMSE values reveals that wavelet-based ECG signal augmentation is significantly more efficient than EEMD.

ECG signal de-noising technique utilising sub-band smoothing filter and wavelet energy was put forth by Dengyong Zhang et. al. [47]. Wavelet coefficients that need threshold de-noising are selected on the basis of wavelet energy in the proposed method, as opposed to the conventional wavelet threshold de-noising method that performs threshold processing for all wavelet coefficients. To test the suggested strategy, MATLAB software was used with the ECG signals from the common MIT-BIH database. Utilising the Signal-To-Noise ratio (SNR), Mean Square Error (MSE), and Percent Root Mean Square Difference (PRD), the performance of the suggested procedure was evaluated. Results showed that, when compared to the current methods, the suggested method can successfully eliminate noise from the noisy ECG signals.

ECG signal is affected by a variety of noises, including BLW noise and inter-line interference. Therefore, to eliminate the majority of the noise from ECG Signal, we can utilise the QRS detection & BLW Removal approach. Resources were constrained successfully during the system simulation. Although the DSP system was built using the DWT method, it has performed admirably in producing the results obtained by Ketan J. Bijwe and S. S. Vasekar [48].

Sachin Darji and Rahul Kher have tackled ambulatory ECG signal processing to identify numerous movements of body using DWT and adaptive filtering techniques [49]. The lead I configuration of the BIOPAC MP 36 data acquisition system was used to record ECG signals of 5 healthy subjects (between ages 22 and 30), when they performed a variety of body movements, such as raising and lowering their hands, twisting their waist while standing, and rising from a chair. The Gabor transform was used to extract the characteristics of the motion artefact signal, which were then supplied into the artificial neural network (ANN) being trained to categorise body movements. For motion artefacts recovered using DWT and Adaptive filtering techniques, the total classification accuracy was 93.70% and 89.07%, respectively. Accordingly, they concluded that ANN are a crucial tool for classifying body movement activities with the help of the motion artefact component of an ambulatory ECG signal.

Wavelet packet transform (WPT) was used to eliminate PLI from ECG data, whereas Asim Almumri et al. [50] employed DWT to remove baseline wander during the pre-processing stage. The noise-free ECG was examined by DWT to produce a set of approximation and detail coefficients, in addition to the position of the onset and offset of the P, T, and QRS complexes. A Haar wavelet-based analysis of lead L2 using the second detail coefficients of the reconstructed signals from the MIT-BIH

Database provides 99.88% sensitivity, 99.91% positive predictivity, and 0.215% detection error of true R peaks. The study also shown that the mother wavelet with little order outperformed the mother wavelet with greater order in the same wavelet family for the detection of R-peaks.

4. K-Nearest Neighbor (KNN):

Compared to other machine learning techniques, the KNN algorithm is a straightforward procedure [51]. The KNN algorithm is the foundation of the majority of ML algorithms [52]. All training sample vectors were stored by the instance-based KNN classifier [53]. In particular for high-dimensional issues, it is a highly straightforward and efficient approach [54]. Based on comparable training examples, it categorises the fresh unknown test samples [55]. The Euclidean distance is typically used as the similarity metric [56]. The nearest training points in the given feature space were clustered to create the K-NN classifier. Most voters gravitate towards the points of their closest neighbours [57].

Many methods for classifying ECGs using KNN have been described. Here are a few of these recent works:

Using the Dempster Shafer Theory (DST), Shameer Faziludeen and Praveen Sankaran [58] examined the automatic classification of ECG beats into two categories—Normal and Premature Ventricular Contraction. Errors can have costly consequences in biomedical signal categorization challenges. This was accomplished by identifying the ECG beats using the evidentiary K nearest neighbours (EKNN) method, based on the Dempster Shafer Theory. Features of RR intervals were applied. The MIT-BIH database was the subject of analysis. Error rates were taken into account when evaluating performance. Performance between EKNN and the conventional K nearest neighbours (maximum vote) technique was examined. Utilising training sets of various sizes, the impact of training data size is evaluated. EKNN based classification system consistently outperformed KNN based classification system.

Hany Ferdinando et al. [59] investigated emotion recognition on the basis of ECG signals from the Mahnob-HCI database using supervised dimensionality reduction, NCA (Neighbourhood Components Analysis), MCML (Maximally Collapsing Metric Learning) and LDA (Linear Discriminant Analysis). LOSO (leave-one-subject-out) validations and 10-fold cross validations were used to confirm the results. LDA, NCA, and MCML all fared better than the NCA. Results showed that, after modifying the features with projection matrices from NCA, the accuracy for valence was enhanced from 55.8% to 64.1% and for arousal from 59.7% to 66.1% using 10-fold cross validation. Valence had not improved significantly for LOSO validation, whereas arousal had improved significantly, going from 58.7% to 69.6%.

Tanatorn Tanantong [60] presented an automatic method for categorising signal quality utilising statistical ECG-based characteristics and a straightforward instance-based ML algorithm, K-Nearest Neighbour (KNN). For accuracy, sensitivity, and specificity, the average assessment results for signal quality classification were 96.87%, 84.79%, and 98.44%, respectively. The test findings demonstrated that the suggested method may be used for categorising ECG signal quality levels obtained from wireless sensors and for reducing false alarms in continuous monitoring systems.

Fei Yang et al. [61] compared the various approaches to estimate missing values in the ECG data, such as the "Zero method," "Mean method," "PCA-based method," and "RPCA-based method," before proposing a new KNN-based classification algorithm, i.e., an altered kernel Difference-Weighted KNN classifier (MKDF-WKNN), suitable to classify imbalance datasets. Results after using the UCI database showed that "RPCA-based method" could effectively handle the values that are missing in the arrhythmia dataset regardless of the values that were missing in it. They presented a classification algorithm, MKDF-WKNN, which was also greater to other state-of-the-art algorithms like DS-WKNN, KNN, KDF-WKNN, and DF-WKNN, for datasets that are uneven and that affect the classification accuracy.

The technique put forth by Ritu Singh et al. [62] intends to demonstrate the superiority of kernel capabilities of Kernel Independent Component Analysis (KICA) and Kernel Principal Component Analysis (KPCA) in the wavelet domain. Five different types of heart beats were used in this study. The effect of discrete wavelet with KICA and KPCA on extracted beats was statistically assessed using supervised classifiers such as feed-forward neural network (FNN), back propagation neural network (BPNN), and K closest neighbour (KNN). Performance assessment also contrasts the results with tried-and-true methods. The acquired results, which produced a 99.7% classification success rate, demonstrated the superiority of the wavelet, kernel, and KNN technique. The effectiveness of classifiers was evaluated using the five-fold cross-validation method.

In order to predict cardiac disease, R. Sateesh Kumar and S. Sameen Fatima [63] employed a version of the K-Nearest Neighbour (KNN) algorithm known as E-KNN and compared the outcomes with K-Nearest Neighbour (KNN), Support Vector Machine (SVM), and Classification and Regression Trees (CART). The most crucial elements were chosen using the chi-square test to increase the proposed system's efficiency. The proposed approach produced results that were more precise while using fewer attributes than all 13. Effectiveness of E-KNN when 11 attributes were used. Its accuracy score was 90.10 percent. SVM came second with 89% accuracy.

Oguzhan T. Imus and Emine Dogru Bolat devised a pattern recognition method for automated apnea diagnosis based on respiratory signals gathered from the electrocardiogram (ECG) and heart rate variability (HRV) [64]. The models for categorising the different forms of sleep apnea was developed using the KNN classifier. For the purpose of comparison, multilayer perceptron, support vector machine, and C4.5 decision tree (C4.5 DT)-based classification models have also been created. Sensitivity, accuracy, and specificity measurements were used to assess the classifiers' performance. By successfully separating 100% of apnea recordings from normal recordings, KNN classifier produced greater classification accuracy, specificity and sensitivity. It also attains a classification rate of 89% sensitivity, 97% accuracy, and 100% specificity of individuals in the test database. Most illustrative parameters for HRV were absolute deviation, median, mean, and interquartile range. These findings pointed to a considerable potential for obtaining fundamental estimates for OSAS patients.

KNN algorithm was applied by Indu Saini et al. [65] to classify the identification of QRS-complex in ECG. Two of the manually annotated standard datasets, like CSE and the MIT-BIH Arrhythmia database, were used to assess the proposed technique. The interference in the ECG signal was reduced in this study using a digital band-pass filter, and the signal's additional gradient was utilized as a feature for QRS recognition. The CSE and MIT-BIH databases both reached 99.89% and 99.81%, of detection rates respectively. For the CSE database, the QRS detector's sensitivity Se and specificity Sp were both 99.86%, while for the MIT-BIH Arrhythmia database, these values were Se = 99.81% and Sp = 99.86%. CSE and MIT-BIH Arrhythmia databases, was used to compare between the presented algorithm and other published work. These findings firmly validate the KNN algorithm as a trustworthy and accurate method of QRS identification.

For QRS detection, Runnan He et al. [66] suggested a real-time, precise, and successful approach. In the algorithm, baseline drift and PLI were initially eliminated from the signal using a proposed pre-processor with a band-pass filter. For precise detection of QRS in ECGs with various morphologies following de-noising, a technique combining K-Nearest Neighbour (KNN) and Particle Swarm Optimisation (PSO) was applied. The presented algorithm was tested and authenticated using 48 ECG records from the MIT-BIH arrhythmia database, and it showed a significant improvement over existing algorithms as described in the literature with high averaged detection accuracy, sensitivity, and positive predictivity of 99.43, 99.69, and 99.72%, respectively.

5. Support Vector Machine (SVM):

SVM is a learning algorithm with several beneficial characteristics. It recognises the pattern and is related to data analysis. Although SVM uses a linear discriminating function, non-linear classification can also be accomplished [67] by using a non-linear kernel. SVM is robust, works well in real-time, and is simple to comprehend. Comparatively speaking to other classifiers [68], a classifier must be trained before categorising any data since classifying task often involves knowledge of the data to be categorised [69]. The automatic discovery of support vectors for improved classification is one of the SVM classifier's key advantages [70]. Performance of SVM is almost always largely dependent on the choice of the impacted kernel function [71].

Various types of research articles are published on ECG classification that are based on SVM. Some of them include:

Advanced approach for automatic categorization of atrial fibrillation (A), normal rhythm (N), noisy records (P), and other rhythm (O), was developed by Radovan Smek et. al. [72]. The method's overall F1 score in Phase II of the challenge is 0.81 for the hidden challenge dataset and 0.84 for the training set, respectively. Within the hidden challenge dataset, specific F1 scores are 0.81 (A), 0.90 (N), 0.55 (P), and 0.72 (O). Within the training set, specific F1 scores are 0.91 (N), 0.85 (A), 0.76 (O), and 0.73 (P).

A very reliable support vector machine-based ECG analysis and classification method was put out by Tanu Kaistha et al. [73]. The pre-processing of the ECG data, feature selection, and classification are the three processes that make up this approach. They created a hybrid method that distinguishes between normal and abnormal ECGs. Various feature extraction techniques were used to extract various features from human ECG data. While classifying with SVM-Linear, SVM-Quad, SVM-Polynomial, or SVM-RBF, the extracted features mean and kurtosis yield 100% precision. However, when PCA features skewness & kurtosis, energy & correlation are employed using SVM, certain signals are misclassified. Although this method produces precise results, the ultimate choice is only taken after consulting with a medical expert.

With an overall accuracy rate of 95.26 percent, Ahmed Shdefat et al. [74] developed a precise and sequential technique to diagnose abnormality using the DWT, QRS complex detection, and SVM classification. SVM is a model with an associated learning method that is based on supervised learning and performs regression analysis and classification over the sampled data. DWT refers to sampling any kind of discrete wavelet transform. They examined the accuracy level for each patient who required the processing of ECG data by testing the ECG signals for 10 patients from various file formats obtained from the PhysioNet database. Results were displayed with regard to accuracy, which varied from 92.1% to 97.6%, and diagnosis status, which is divided into two categories: Normal and abnormal.

Meenakshi Pareek et al. [75] used a variety of techniques with magnetic resonance images as the input for brain tumour detection and categorization. They had experimented with 50 MRI scans from the "figshare brain data set" for tumour categorization. In order to distinguish between dangerous and non-cancerous tumours, we offer an effective method for classifying brain tumours. The proposed approach consists of three main steps. Extraction of features is followed by feature reduction and classification. The current method uses GLCM and 2D Discrete Wavelet transformation (Daubechies) to extract statistical texture information. For feature reduction, PCA (principle Component Analysis) is utilised. To determine if a tumour is benign or malignant, they created a training data set using 50 MRI scans. They then applied an SVM classifier, and evaluated the results by Kernel based SVM.

A thorough investigation on ECG signal de-noising and detection of abnormalities using various approaches was carried out by Akhil Mathew Philip and S Hemalatha [76]. ECG readings can contain annoying distortions and acoustic noise. In this study, the noise in the unprocessed ECG data was removed using the "Biassed Finite Impulse Response (BFIR)" preparatory filtering. The 'R' peak signals are segmented using the "Nonlinear-Hamilton" segmentation technique. When extracting features from the segmented ECG data, the novel "Enhanced Principal Component Analysis (EPCA)" was utilized to reduce the number of unnecessary features. For categorising the ECG data, a novel "Enhanced version of the Support Vector Machine (ESVM)" framework with a "Weighting Kernel" based technique was presented. This framework will be able to recognise the 'Q', 'R', and 'S' waves in the provided ECG data, characterising the cardiac rhythm. Evaluation metrics of the proposed EPCA-ESVM method are compared to those of our earlier EPSO methodology. The EPSO and EPCA-ESVM approaches were tested in order to estimate the outcomes for the MIT-BIH dataset, focusing on several criteria like Accuracy, F1-score, etc. The EPCA-ESVM method's final results were superior to those of the EPSO approach, which had higher accuracy despite the presence of unbalanced data.

A method for automatic classification of cardiopathies from an electrocardiogram (ECG) was reported by Dinesh D. Patil et al. [77]. This course of action is based on the identification of four cardiacopathies by the examination of specific morphological criteria. Heart arrhythmias were identified and parameterized using the Hidden Markov Model (HMM). The morphological parameters (amplitude, surface, interval, and slope) were separated into homogeneous groups. According to an analysis of the several groups, the overall performance for recognition was 98.43%. For the RBBB class, 96.75% is the worst.

On the basis of a cardiac arrhythmia dataset with missing attribute values, Maryamsadat Hejazi et al. [78] examined a multi-class problem using SVM methods, on the basis of RBF kernel method for both One-Against-All and One-Against-One approaches. The impact of pre-processing methods including mean & median imputation, PCA for managing missing data, and reduced dimensionality of imputed data on classification performance has been taken into consideration in this paper. Results showed that the OAA strategy beats the OAO approach for ECG categorization. Due to its ability to generalise, results demonstrated the use of SVM algorithms for ECG data interpretation in diagnostic applications. They often have improved classification accuracy, thanks to this feature and are less sensitive to noisy datasets.

Discussion:

The ECG classification is crucial for enhancing the patient's quality of life because it displays the heart's state and cardiovascular condition. This study's primary goal is to review the key methods for classifying ECG signals. Any ECG categorization structure can generally be separated into four stages. The first one is a pre-processing step that is important for classifying ECG signals. The most popular strategies are therefore reviewed in this study. Pre-processing phase and a combination of pre-processing approaches were used to enhance the model's performance. The second phase involves taking the most significant data out of the ECG signal that describes the condition of the heart. The action is known as a feature extraction action. The ability to effectively extract information that can be differentiated based on the ECG signal's variation status presents a significant hurdle. The model's success rate can determine whether or not the feature has meaningful knowledge about the signal. The feature selection stage is the third step. The model's time execution is a vital component that can be sped up by selecting the best features from among the available feature spaces. Dimensionality of the features has been reduced using a variety of ways. Some of the techniques were influenced by nature, while others operated according to mathematical standards. The phase that receives the most attention is choosing a machine-learning method to categorise the ECG characteristics. There have been many methods employed for this. The majority of classifier techniques are fed by the features, but since CNN is a featureless method, it is fed by the raw signal. We examined ANN, CNN, DWT, KNN, and SVM. Every article that is reviewed is downloaded from reliable sources; and the data for study have been collected from MIT-BIH and Apnea-ECG databases from the PhysioNet bank.

Conclusion:

Identifying normal and pathological heartbeats is dependent heavily on the classification of ECG data. A difficult difficulty is raising the ACC of ECG categorization. It has been interested for more than a decade, leading to the development of numerous ways. This study reviews the most recent methodologies in terms of dataset, success rate, method, and contribution. Our recommendation is to employ a hybrid model that is based on CNN and LSTM. Depending on how many convolution layers we apply, the CNN component can extract features from raw signal that could be temporal features. The LSTM component can then learn the pattern in the temporal feature, because it is better suited to time series data. Unidentified ECG signals can also be forecasted by the model. To improve classification rates, we shall fine-tune layers in the LSTM model and filters in the CNN model.

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Abbreviations:

The abbreviations are used in this manuscript are as follows:

ECG – Electrocardiogram
ANN – Artificial Neural Network
CNN – Convolutional Neural Networks
DWT – Discrete Wavelet Transform
SVM – Support Vector Machines
KNN – K - Nearest Neighbor
PLI – Power-Line Interference