Recurrent Ascendancy Feature Subset Training Model using Deep CNN Model for ECG based Arrhythmia Classification

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***Abstract*—The World Health Organization (WHO) has released a report warning of the worldwide epidemic of heart disease, which is reaching worrisome proportions among adults aged 40 and high. Heart problems can be detected and diagnosed by a variety of methods and procedures. Scientists are striving to find multiple approaches that meet the required accuracy standards. Finding the heart issue in the waveform is what an Electrocardiogram (ECG) is all about. Feature-based deep learning algorithms have been essential in the medical sciences for decades, centralising data in the cloud and making it available to researchers around the world. To promptly detect irregularities in the cardiac rhythm, manual analysis of the ECG signal is insufficient. ECGs play a crucial role in the evaluation of cardiac arrhythmias in the context of daily clinical practice. In this research, a deep learning-based Convolution Neural Network (CNN) framework is adapted from its original classification task to automatically diagnose arrhythmias in ECGs. A deep convolution network that has been used for training with most relevant feature subset is used for accurate classification. The primary goal of this research is to classify arrhythmia using a deep learning method that is straightforward, accurate, and easily deployable. This research proposes a Recurrent Ascendancy Feature Subset Training model using Deep CNN model for arrhythmia Classification (RAFST-DCNN-AC). The suggested framework is tested on ECG waveform circumstances taken from the MIT-BIH arrhythmia database. The proposed model when contrasted with the existing models exhibit better classification rate.**

***Keywords*—Feature selection; arrhythmia classification; convolution neural network; deep learning; electrocardiograms**

I. INTRODUCTION

Many international health groups, including the World Health Organization, have concluded that cardiovascular diseases are the leading cause of death around the world. More people die each year from cardiovascular disease than from any other single cause [1]. Both strokes and heart attacks account for 88% of all cardiovascular diseases. Majority of cardiac deaths worldwide occur in regions with lower or moderate incomes [2]. Untreated cardiac arrhythmias and their long-term consequences are a leading cause of deadly cardiovascular diseases. Arrhythmia is the medical term for irregular heartbeats [3]. Arrhythmias play a pivotal role in ECG abnormalities, as this is essentially a rhythm conduction problem. Electrocardiography can detect potentially fatal heart arrhythmias and other problems. During this procedure, an electrode is positioned on the patient's chest to record the rhythm of their heart's electrical activity. ECG sessions are typically used for long-term data recording and analysis by physicians and doctors to evaluate the presence or absence of a cardiac abnormality and the patient's risk for developing this condition. Time is a major factor in this undertaking. Therefore, it is crucial for doctors and medical professionals to be able to diagnose heart arrhythmia [4].

People are concerned about the global health as the prevalence of congenital heart defects increases over time. Up to this point, ECG signals have shown to be the most reliable method of determining cardiac dysfunction and abnormalities [5]. ECG and its associated terms P wave, QRS complex, T wave, and QT interval show normal heart activity [6]. By analysing these characteristics or electrical waves, the abnormality can be identified with the help of expert medical expertise. The heart diseases that affect heart rate were successfully observed using deep learning techniques [7]. It is possible that the irregular heart rate is the result of the faulty signal being too slow, too rapid, or completely unexpected. Lack of therapy can result in a heart attack or heart failure. The Normal Sinus Rhythm (NSR) represents a healthy, normal heartbeat on an electrocardiogram [8]. Congestive heart failure (CHF) represents the opposite type, a chronic condition in which the heart's ability to pump blood is impaired. Inadequate blood flow causes the heart to weaken and frequently disrupts its ability to operate [9].

Medical researchers have been motivated by the state-of-the-art uses of deep learning in the fields of pattern and image recognition. Though electrocardiograms (ECGs) are excellent at monitoring heart activity, only individuals with specialised training can read and understand the resulting tracings [10]. The distinction between symptomatic and asymptomatic arrhythmias is crucial because some potentially deadly arrhythmias can be present with no symptoms at all. Patients with symptomatic arrhythmias may experience dizziness, difficulty breathing, and an irregular heartbeat, all of which may be caused by emotional stress [11]. Extremely high blood sugar, mental stress, excessive smoking, hypertension, and other environmental and behavioural variables have all been linked to arrhythmias. A sluggish heartbeat is possible even in healthy persons, and is not always indicative of any underlying health concern [12]. Categorization results are helpful for diagnosing the risk of arrhythmias or sudden deaths, and can reveal information such as the presence of non-sustained sustained ventricular tachycardia and ventricular premature beats.

In recent years, cardiac arrhythmia data has grown to an unprecedented degree, stifling advancements in feature-extraction outcomes. This is why Deep Learning (DL) has brought about crucial outcomes in the field of arrhythmia detection. Because of their ability to automatically detect and extract features to produce clear and precise findings, deep neural networks have gained popularity in the field of heartbeat classification [13]. In order to maximise the benefits of automated feature detection and extraction, a wide variety of methods and techniques have been integrated with cutting-edge deep-learning algorithms [14]. These methods can be grounded in a variety of frameworks, including those for multiple models and hybridization. In order to incorporate multi-level features and their transformation, a deep neural network is typically designed with a hierarchical layered structure [15].

In modern medicine, the diagnosis of potentially fatal cardiac arrhythmias requires the meticulous analysis of the ECG by board-certified cardiologists. Automated cardiac arrhythmia categorization, on the other hand, has the potential to speed up diagnosis while also providing cardiologists with more objective data [16]. To classify a system automatically into one of several categories is the goal of pattern recognition [17]. An experienced cardiologist can tell only by looking at the ECG waveforms printout what kind of cardiac arrhythmia their patient has. While advanced ECG analyzers can sometimes outperform a human cardiologist, there is still a subset of ECG waveforms that cannot be reliably identified by computers at this time [18]. The purpose of this research is to lay the groundwork for the creation of a computer-aided diagnostic system that will aid specialised cardiologists in the diagnosis of ECG arrhythmias in a way that is both smart and efficient in terms of both money and time. This is done by applying state-of-the-art deep learning approaches to the problem of ECG arrhythmia pattern detection alongside more traditional methods of ECG data processing [19].

In addition, this structure aids in the improvement of feature refinement. The limitations of traditional machine-learning strategies, such as the need for manual and inaccurate feature selection, which can have undesirable effects in the context of the aforementioned applications, are being overcome by integrating neural networks such as Recurrent Neural Networks (RNN) [20], Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and hybrid models, etc. Because accurate categorization of heartbeats and arrhythmia detection necessitates a large quantity of data to work with, the downsides of hybrid techniques build as the cost and lack of quality datasets [21], which may be regarded trivial in some viable scenarios, increase over time. This research offers a deep neural network ensemble to tackle these problems head-on, with the design and merging of two networks, then training the combined model all happening in one continuous process [22]. The innovative features centre on the utilisation of a multi-model framework that combines the capability to blend different ML/DL models and generate a robust result. The suggested methodology outperforms state-of-the-art studies in heartbeat detection and categorization. This research proposes a Recurrent Ascendancy Feature Subset Training model using Deep CNN model for arrhythmia classification with better classification rate.

II. Literature Survey

ECG tracing and arrhythmia classification methodology is presented by Tang et al. [2]. The suggested system includes a front-end IC, an FPGA-based delineation technique, and an arrhythmia classification technique. The inclination of the incoming analogue ECG signal is measured by a ternary second-order Delta modulator in the front-end circuit. Without regard to the instantaneous amplitude, the circuit transforms the analogue inputs into a pulse density modified bitstream whose pulse density is proportionate to the slope variation of the input analogue signal. Within a timing inaccuracy of 3 ms, the front-end chip can detect a slope variation as small as 3.2 mV/ms2. Fabricated to use a 180 nm CMOS technology, the 0.25 mm 2 front-end IC uses just 151 nW of power at 1 kS/s sampling rate. An ECG waveform's fiducial spots can be located using a delineation technique that is informed by the slope variation received from the front-end circuit. A Spartan-6 FPGA was used to test the demarcation algorithm. The delineation system can determine 22 aspects about the QRS/PT waves based on their intervals, slopes, and shape. This information is used to classify arrhythmias such as ventricular ectopic beat (VEB), supraventricular ectopic beat (SVEB), and sinus node originated heartbeats using a rotational linear kernel support vector machine (SVM) for each individual patient.

An ECG is a non-invasive diagnostic tool for identifying heart rhythm disturbances. The literature reports numerous methods for classifying arrhythmias using a wide variety of ECG parameters. Accurate recognition and categorization of arrhythmias is proposed in this work by Zhang et al. [4] using a new approach in conjunction with a novel morphological feature. Events in the ECG signals are first identified. Then, certain sections of an ECG are extracted in order to measure their amplitude, interval, and duration, which are all parametric aspects of ECG morphology. Finally, a new clustering-based extracting features approach is proposed, along with a novel feature for assessing QRS complex morphological changes as visual patterns. At last, the feature vectors are fed into a neural network, a support vector machine, and a K-nearest neighbours classifier so that an automatic diagnosis can be made. Using the MIT-BIH arrhythmia database, which includes all fifteen heartbeat types recommended by the Association for the Advancement of Medical Instrumentation, the proposed method was evaluated, and with the help of the combined parameterized and visual pattern features of ECG Morphology, it achieved the best accuracy rate of 97.70% based on KNN.

An automatic method of detecting arrhythmias from a 12-lead ECG signal is a vital tool in the early detection and prevention of cardiovascular disorders. Previous research on automatic arrhythmia diagnosis often involved combining data from 12 ECG leads into a matrix, which was then fed into a number of feature extractors or deep neural networks. As the data from each lead of a 12-lead ECG interacts with one another during training, these approaches were able to extract comprehensive properties of the full ECG. Poor information acquisition for 12-lead ECG was the result of ignoring the diversity of lead-specific properties across those leads. The information fusion of extensive features with consistency and lead-specific characteristics with variety should be considered to maximise the information learning of multi-lead ECG. In this paper, Wang et al.[5] presented a new Multi-Lead-Branch Fusion Network (MLBF-Net) architecture for arrhythmia classification by jointly learning the variety and integrity of multi-lead ECG through the use of multi-loss optimization. There are three parts to the MLBF-Net system: It consists of three parts: multiple lead-specific branches for learning the variety of multi-lead ECG; cross-lead features blending by appending the output feature maps of all branches for learning the integrity of multi-lead ECG; and multi-loss co-optimization for all the different branches and the concatenated network.

The ECG is the gold standard for diagnosing heart conditions. However, due to the volume of patient ECG data, human interpretation is laborious and time-consuming. Since there is a severe scarcity of medical personnel, intelligent ECG recognition technology is crucial. For the first time, this research provides an arrhythmia classification algorithm that makes use of ECG data fragments that each contain information on three whole cardiac processes across several ECG leads. Using the MIT-BIH arrhythmia database as training examples, the THML ECG data pre-processing algorithm is developed. To get the best possible integrated classification effect, Tang et al. [7] build four arrhythmia classification models using a 1D-CNN and a priority model integrated voting technique. Ablation trials demonstrate the viability and efficacy of THML ECG data, and the experiments were conducted using the inter-patient system proposed by the Association for the Advancement of Medical Instrumentation (AAMI).

Arrhythmia is a life-threatening kind of cardiovascular disease. ECG analysis using artificial intelligence is a powerful tool for the detection, diagnosis, and treatment of arrhythmia in its earliest stages. Commonly, many types of arrhythmia will be diagnosed in a single patient based on their ECG waveform. Despite this, the focus of the majority of the research done now is on multiclass approaches for dealing with the multi-label problem, which leads to information loss by disregarding the links between diseases. Therefore, Singh et al. [10] proposed an ECG-based multi-label feature selection method (MS-ECG) designed an evaluation criterion of ECG features based on kernelized fuzzy rough sets in order to select the best feature subset and maximise the ECG feature space. The author developed a multi-objective optimization model and proposed a multi-label classification algorithm for arrhythmia based on ECG. To reliably and automatically assign various labels to a single ECG signal, this sparsity-constrained method investigates the relationships between different arrhythmia disorders and examines the mapping link between ECG features and arrhythmia diseases.

Deaths from cardiovascular disease (CVD) now outnumber all others. ECG monitoring is currently included in wearable devices and is a common approach for diagnosing CVD. An ECG delineation and arrhythmia classification (EDAC) system prototype for wearable ECG biosensors is presented in this research by Sohail, et al. [12]. The system is made up of a Delta-modulator-based analog-to-feature converter (AFC), a linear kernel support vector machine (SVM) classifier, an automated gain controller (AGC) block, and an algorithm for detecting, delineating, and extracting features from an ECG. In order to recognise QRS complexes, localise fiducial sites, and extract feature vectors for each pulse in the DDF block, the AFC digitises the slope and slope variation of the input analogue signal. On the basis of the detected QRS complex, the AGC then sends a gain control signal to the front-end amplifier. Finally, arrhythmia classification is handled by the SVM block. The MIT-BIH arrhythmia database is used to assess the efficacy of the EDAC system.

Qian et al. [15] introduced a low-overhead method for extracting key characteristics from ECG signals. Additionally, real-time algorithms are proposed to categorise arrhythmias based on these features. Two delta-sigma modulators with a 250 Hz sampling rate and three wave detection algorithms are the basis of the proposed feature extraction system. Essential information about each heartbeat is extracted and encoded into 68 bits of data, which is only 1.48 percent as much as other comparable approaches. Random forests are used as classifiers, and they are trained to distinguish between two common categories of arrhythmias. There are two types of ectopic beats: supraventricular (SVEB) and ventricular (VEB). Comparable to state-of-the-art approaches, the arrhythmia classification achieves F1 scores of 81.05% for SVEB and 97.07% for VEB. This technique offers a dependable and precise means of analysing ECG readings.

Performing an ECG signal analysis is a process that can be laborious, time-consuming, and prone to human error. That's why it's about time Pławiak et al. [16] had an automated study to help cardiologists spot issues in the heart faster and more reliably. While deep learning (DL) models have made remarkable strides and demonstrated impressive arrhythmia classification capabilities recently, their "black-box" nature makes it difficult to employ them in the medical field. This article presents a strong explainability approach to help explain how deep neural networks (DNNs) make decisions and to give feedback on biases that may be used to better train DNNs. In order to accomplish these goals, a DL model is first trained and tested using the MIT-BIH Arrhythmia Database. Post-hoc explanation techniques like SHapley Additive exPlanations (SHAP), local interpretable model-agnostic explanations (LIME), and gradient-weighted class activation mapping (Grad-CAM) are used to make sense of the classification results by deciphering the decision-making process. Several limitations are identified after evaluating these methods for ECG arrhythmia classification, including a lack of ability to identify the significance of a feature when that feature occurs multiple times in a signal and the fact that SHAP and LIME perform random perturbations, which can lead to unreliable explanations. Therefore, a unique K-GradCam approach is proposed to address the limitations of conventional post-hoc explainability techniques for time-series data.

Suitable for low-quality ECG data, Wang et al. [17] proposed a rapid and accurate denoising and classification method. In order to accomplish this, the author proposed a novel attention-based convolutional denoising autoencoder (ACDAE) model that uses a skip-layer and attention module to reliably reconstruct ECG signals from high-noise environments. A lightweight, efficient channel attention (ECA) module is used to efficiently update key characteristics obtained through cross-channel interaction, and skip-layer connections are used to reduce information loss while reconstructing the original signal. Four public databases are used for training and testing the model. Additive white Gaussian noise (AWGN) with amplitudes between 20 and 20 dB is used to evaluate the signals, along with noise from the MIT-Beth Israel Hospital Noise Stress Test Database (NSTDB) with amplitudes between 6 and 24 dB.

III. Proposed Model

The electrical activity of the heart can be measured and recorded with the use of ECG. The interpretation of ECG signals is vitally important for the diagnosis of arrhythmias. Cardiologists typically employ visual recognition to diagnose and detect various arrhythmias based on brief ECG data [23]. The QRS complexes will show any irregularities in the electrical signal. Detailed information about the signal's nature can be gleaned from the QRS complexes from the ECG signal. When it comes to categorizing ECG signals [24], feature extraction presents a substantial challenge. Most techniques based on deep learning for autonomous categorization of cardiac arrhythmia can be broken down into two categories: feature engineering and classification. To be more specific, researchers first manually retrieved a significant number of medically relevant ECG components, such as wavelet features. Integrated performance of P, Q, R, and S, plus T, a statistical feature of HRV, morphological features and a statistical feature of higher order mathematical techniques such as enhanced principal component analysis are used to reduce the dimensions of an ECG and thereby extract its features [25]. Artificial features are analysed using deep learning methods, self-organizing maps, and clustering, following feature engineering to yield a prediction result. Deep learning has several potential uses in the classification of cardiac arrhythmias for scientific research, however some issues remain to be resolved [26]. For instance, feature engineering that relies on subjective considerations can result in the removal of potentially relevant features, which in turn can have an impact on the overall classification performance.

The accuracy of ECG-based diagnostics for cardiovascular diseases has been shown to be improved with the help of deep learning models. They lead to steadily better neural networks by leveraging the cascade of mixed layers of neural networks to extract progressively higher-level features. In many applications of AI algorithms, deep neural networks have finally reached their full potential. This research proposes a unique framework for ECG analysis and classification, one that can represent the signal in a form that is portable between tasks. In order for this to occur, a deep neural network design is proposed that provides high abilities to learn such representations. Since this network has indeed been trained to identify arrhythmias, it is reasonable to presume that the model has picked up all the relevant features information about the ECG's structure.

A CNN is the first model that this framework supports. It has three hidden layers, one flattening layer, two dense layers, and a batch normalization layer. A n1 matrix is what the CNN expects to see when it starts up. Additionally, a convolution layer and a pooling layer make up all hidden layers. Data type and quantity inform the best pooling strategy selection among options like min-pool, max-pool, and average-pool. Both the average and the maxpool methods are commonly employed for heartbeat categorization. With this goal in mind, max-pooling is used in the deployed CNN, which takes the item in the list from each unit of the feature map. The proposed model framework is shown in Fig. 1.

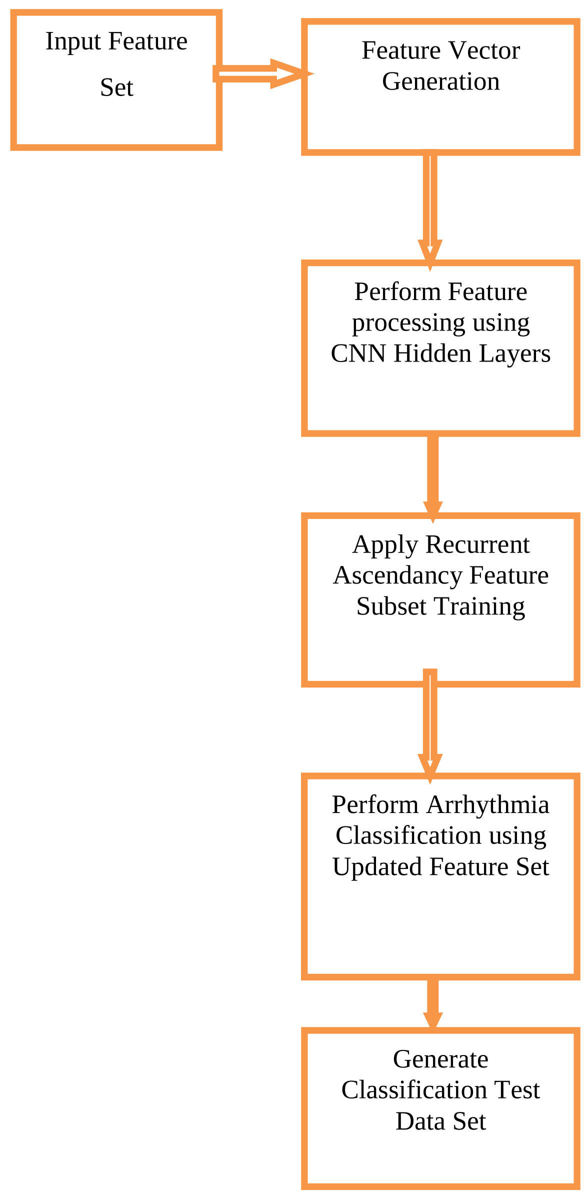

Fig. 1. Proposed model framework.

All of the convolution layers here are one-dimensionally applying convolution in time, and each of those layers has 32 kernels of size 3. Furthermore, all pooling layers employ maximum pooling with a pool size of 5, and a stride of 3. Output class probabilities are predicted by a predictor network made up of five residual blocks, two fully-connected layers of 32 neurons each, and a softmax layer. First, an ECG signal is segmented into 15-second windows, and then one of those windows is chosen. Scaling all amplitude values to fall between 0 and 1. The next step is to identify all local maxima using zero-crossings of the first derivative. Then using a 0.9 threshold on the normalized value of the local maxima, identify a set of potential R-peak locations in an electrocardiogram. Using the middle value of R-R intervals as the window's standard heart rate, pick a section of the signal with a length of 1T for each R-peak. Adding leading zeros to each segment chosen until their total length is the same as some fixed value as set. In particular, the proposed beat extraction technique is simple to apply and produces reliable results when applied to signals of varying morphologies, making it ideal for use in applications requiring the extraction of R-R intervals. This research proposes a Recurrent Ascendancy Feature Subset Training model using Deep CNN model for Arrhythmia Classification.

Algorithm RAFST-DCNN-AC

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Input: Feature Set {F_{set}}

Output: Arrhythmia Classification Set {AC_{set}}

Step-1: The feature set is considered and the features are analyzed for processing for accurate classification. The feature vector generation is performed based on the independent attribute correlation range. The feature vector generation of independent feature set is generated as

$$FVset(Fset(M)) = \sum_{f=1}^{M}\left(getattr(Fset(f)) + \frac{max(FSet(f+1))}{len(Fset(f))} + avg(f, f+1) - min(getattr(Fset(f))\right)$$

Here f is the feature considered and f+1 is the neighbor dependant feature.

Step-2: Hidden layer is situated between the input and output layers. An activation function is used to convert a set of weighted sources into an output. Since it is neither the input nor the output layer, this layer is referred to as the hidden layer. The processing layer called hidden layer is where everything actually occurs. The feature processing using hidden layers is performed for removing the irrelevant features still and to update the feature vector for better classification rate. The process of hidden layer process is performed as

$$HiddLayer(f, f+1, M) = \sum_{f=1}^{M} FSet(sim(f, f+1)) + \frac{\min(Rec(j,i)) + \max(Fset(f))}{\sum_{f=1}^{M} actvF(\max(f+1), \min(f))}$$

Step-3: After feature processing is done, Recurrent Ascendancy Feature Subset Training is performed to train the model with the processed feature vector for accurate Arrhythmia Classification that is performed as

$$FTrain(Fset(M)) = \sum_{f=1}^{M} \frac{\max(HiddLayer(f)) + \sum_{f=1}^{M} \mathrm{maxrange}(\mathrm{HiddLayer}(f+1, f))}{sizeof(HiddLayer(M))}$$

Step-4: The updated feature set is generated and then the test data processing will be done for Arrhythmia Classification that is used for accurately classifying the disease or not as multiple sets. The Arrhythmia Classification is performed as

$$ArClassupdate(Fset(M)) = \sum_{f=1}^{M} \sum_{f=i}^{len(FTrain)} FTrain(f) + \sum_{f=1}^{M} \frac{\mathrm{G(max(Ftrain(f))}}{\lambda}$$

Here G is the function that identifies the similarity of the feature attribute comparison. λ is the threshold value considered for comparison.

Step-5: The classification set is generated and maintained for further identification of grade of the disease and the process of classification set generation is performed as

$$ClaSet(\mathrm{ArClassupdate}(f)) = \sum_{f=1}^{M} getrange(f, f+1) - min(ArClas\,sup\,d\,ate(f)) + \frac{\sum_{f=1}^{M-f} max(FTrain(f+1))}{max(FTrain(f))}\}$$

IV. Results

The significance of ECG classification is quite high important due to many contemporary clinical applications in which this problem can be expressed. The analysis and classification of ECG data is currently supported by a plethora of machine learning methods. The primary drawbacks of these ML outcomes, however, are the shallow feature learning architectures and the reliance on heuristic hand-crafted or manipulated features. The difficulty stems from the fact that it is possible that the best features for this ECG classification problem will not be found. One proposed solution is to employ deep learning architectures in which the initial layers of convolutional neurons operate as feature extractors and the last layers of fully-connected neurons are used to decide between ECG classes. In order to categorize cardiac arrhythmias, this research work makes use of freely available dataset from kaggle available in the link https://www.kaggle.com/datasets/shayanfazeli/heartbeat. The MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database are two well-known sources of heartbeat signals that were used to compile this dataset. Both datasets have sufficient sample sizes for use in deep learning network training. Deep neural network architectures for heartbeat classification have been investigated and the possibilities of transfer learning have been observed utilising this dataset. Electrocardiogram (ECG) waveforms of heartbeats (in both the normal case and the instances affected by various arrhythmias and myocardial infarction) are reflected in the signals. Each segment of these signals represents a single heartbeat during preprocessing. There are 87554 samples in all, and 10 features to analyse. The dataset is divided into 80% and 20% ratios, used for training and testing.

There are ECG recordings from multiple people included in the dataset. The dataset collects its own unique collection of features, and these differences have been taken into account independently of one another in the training and testing. This research proposes a Recurrent Ascendancy Feature Subset Training model using Deep CNN model for Arrhythmia Classification (RAFST-DCNN-AC). The proposed model is compared with the traditional ECG Delineation and Arrhythmia Classification System Using Slope Variation Measurement by Ternary Second-Order Delta Modulators (DACS-SVM-TSDM) model. The proposed model exhibits better performance in accurate classification when contrasted with the traditional models.

The technical hurdle for applications like speech recognition, image classification, strategy games, and medical diagnosis has been dramatically raised in recent years because to DNNs' powerful feature extraction capabilities and incremental learning methodologies. Since DNNs can recognise patterns and acquire important features from raw input data without requiring considerable human intervention in the form of custom rules and feature engineering, they are well-suited for decoding ECG data as opposed to standard machine learning approaches. Some studies have looked into the feasibility of using DNNs for automatic classification of cardiac arrhythmia using a single or multiple lead ECG.

ECG arrhythmia diagnosis using computers relies heavily on feature extraction. To this end, feature selection seeks out the most informative characteristics that can be used to distinguish between groups. The goal of feature extraction is to generate fewer features from the same dataset. When this new set of streamlined features is used, it should be able to effectively summarize the original set of features' worth of data. By combining the original features in this way, a condensed version of the full set can be made. The feature extraction accuracy rate of the proposed and existing models are shown in Fig. 2.

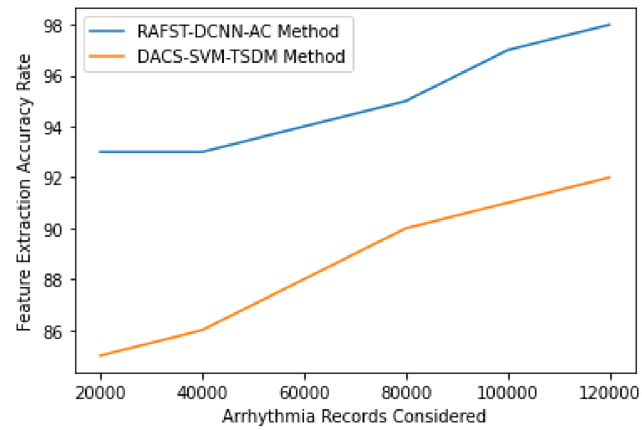

Fig. 2. Feature extraction accuracy rate.

The process of reducing the number of dimensions that a dataset occupies involves a number of steps, one of which is feature extraction. As a result, processing will be less of a hassle. A key feature of these massive datasets is the abundance of variables they contain. Extensive computational resources are needed to process these variables. By selecting and merging variables into features, feature extraction aids in getting the best features from those large data sets. The proposed model in less time generates the feature vector. The feature vector generation time levels of the proposed and existing models are shown in Fig. 3 and the accuracy levels of the feature vector generation is shown in Fig. 4.

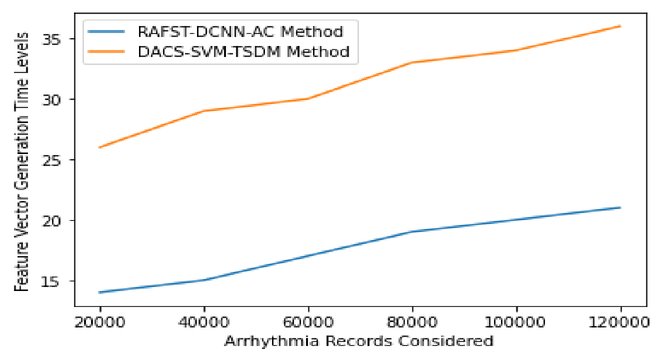

Fig. 3. Feature vector generation time levels.

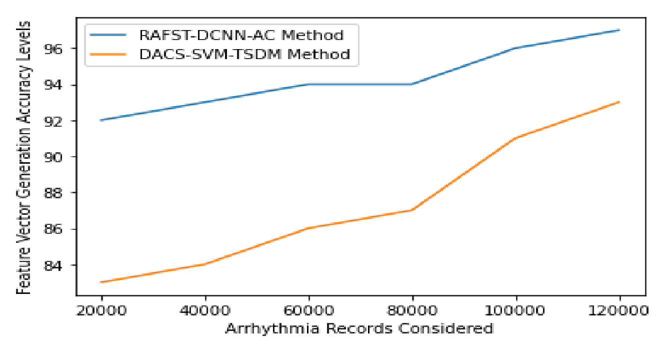

Fig. 4. Feature vector generation accuracy levels.

Hidden layers in a CNN typically include convolutional layers, pooling layers, fully connected layers, and normalization layers. In this case, it simply implies that convolutional and pooling functions are utilised as activation functions rather than the conventional activation functions stated above. CNNs typically have convolutional layers, max pooling, fully connected layers, and normalising layers as their hidden layers. In this case, it just implies that users not utilising the standard activation functions specified earlier, but rather convolution and pooling functions. The hidden layer processing time levels of the proposed and existing models are shown in Fig. 5.

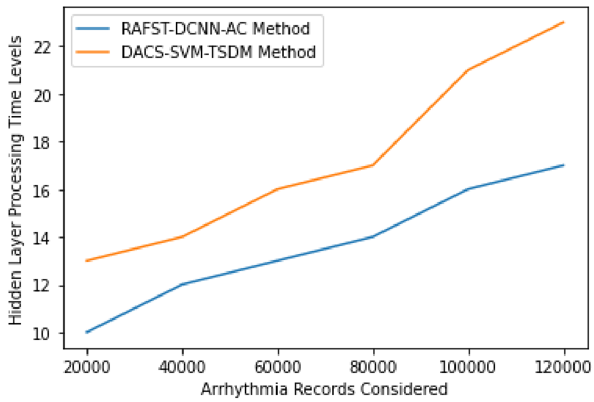

Fig. 5. Hidden layer processing time levels.

An activation function is used as the output of a neural network, which has a hidden layer in between its input and output. The function applies weights to the inputs. In a nutshell, the hidden layers alter the network's inputs in a nonlinear way. The number of hidden layers and the weights assigned to those levels can change based on the task being performed by the neural network. In a nutshell, hidden layers are a series of mathematical operations with the same goal in mind but different inputs. Squash functions are an example of a type of hidden layer. These functions take an input and return a value between zero and one, the range for defining probability, making them handy when the algorithm's expected result is a probability. The hidden layer processing accuracy levels of the proposed and existing models are shown in Fig. 6.

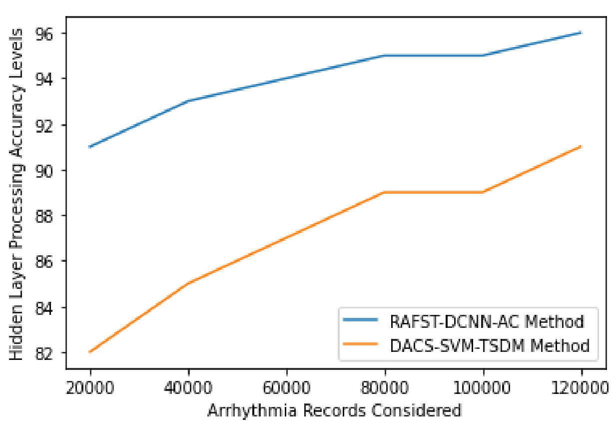

Fig. 6. Hidden layer processing accuracy levels.

There are two main types of arrhythmia, both of which are characterised by the patient's heart rate: bradyarrhythmias and tachyarrhythmias. They are further classified by their aetiology, mode of transmission, and resulting clinical symptoms. The ECG is a crucial tool in the detection of cardiac disorders. Arrhythmias, which include Atrial Fibrillation, Ventricular Tachycardia, Ventricular Fibrillation, and so on, are irregular rhythms in the ECG signal. The primary goal of this research is to identify and categorise patients with cardio-vascular arrhythmias. The Arrhythmia Classification Time Levels of the existing and proposed models are shown in Fig. 7.

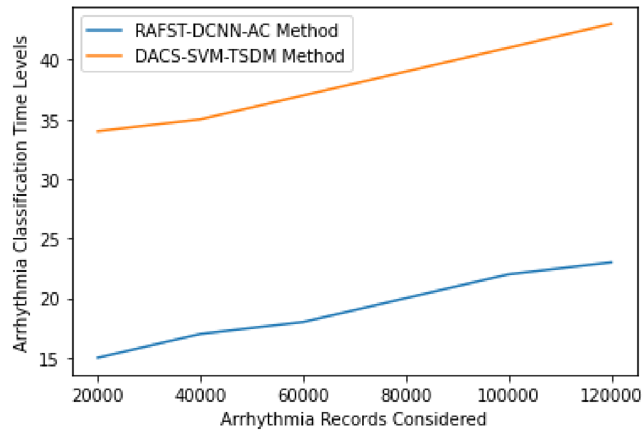

Fig. 7. Arrhythmia classification time levels.

Too fast or too slow heart rates are examples of arrhythmias, often known as cardiac arrhythmias, heart arrhythmias, or dysrhythmias. It is possible for arrhythmias to present themselves with no warning signs at all. One possible symptom is experiencing a palpitation or a halt in heartbeats. In severe circumstances, users may experience dizziness, fainting, difficulty breathing, or chest pain. While most instances of arrhythmia are not life-threatening, certain types might put a person at risk for significant complications including a stroke or heart failure. Critical cardiac diseases can be helped greatly by automatic identification and classification of potentially fatal arrhythmias. The Arrhythmia Classification Accuracy Levels of the existing and proposed models are shown in Table I and Fig. 8.

TABLE I. ARRHYTHMIA CLASSIFICATION ACCURACY LEVELS

Records Considered	**Models Considered**	
	RAFST-DCNN-AC	***DACS-SVM-TSDM***
20000	91	81
40000	93	85
60000	95	86
80000	96	87
100000	97	91
120000	98	93

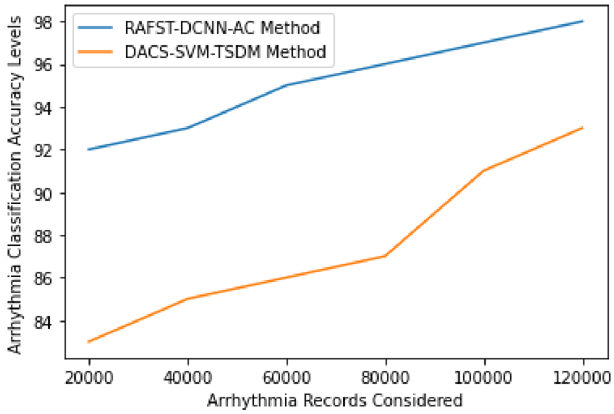

Fig. 8. Arrhythmia classification accuracy levels.

V. Conclusion

Diagnosis of arrhythmia typically involves the use of ECG because of its ease of use, lack of invasiveness, and high accuracy. Many deep neural network-based models have recently been successfully implemented for autonomous categorization of cardiac arrhythmia. However, most models, during training, separately extract the internal properties of each lead in the 12-lead ECG, leading to a deficiency in inter-lead features. The ECG is a reliable diagnostic tool for heart conditions because it measures electrical signals associated with heart muscle function. ECGs can be used to diagnose cardiac issues. Arrhythmia is a leading cause of sudden cardiac death. Heart disease, most often coronary artery disease, is the leading cause of death for persons older than 35. Today, multi-lead electrocardiogram (ECG) signals constitute the gold standard for computer-automated arrhythmia identification using deep learning models. However, due to the amplitudes of the input signals, these models supply too many parameters for practical use. In this research, we present a strategy for bridging the gap between the arrhythmia classification algorithm with multi-lead ECG signals and the arrhythmia classification algorithm with single-lead ECG signals using deep learning model to reduce the performance loss. This research proposes a Recurrent Ascendancy Feature Subset Training model using Deep CNN model for Arrhythmia Classification The purpose of this research was to determine how little of a performance hit would result from shifting from arrhythmia classification based on multi-lead ECG signals to classification based on single-lead ECG signals. The intention was to take advantage of the high precision approaches based on multi-lead ECG signals in order to give the low computational cost offered by the approaches based on single-lead ECG signals. In future feature dimensionality reduction can be applied to reduce the feature vector size and also to use hybrid models integrated with optimization techniques for enhancing the classification rate.

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