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Recognition and Evaluation of Heart Arrhythmias via a General Sparse Neural Network

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Abstract: In clinical use, an electrocardiogram (ECG) is an essential medical tool for assessing heart arrhythmias. Thousands of human beings worldwide are affected by different cardiac problems nowadays. As a consequence, studying the features of the ECG pattern is critical for detecting a wide range of cardiac diseases. The ECG is a test which assesses the intensity of the electrical impulses in the circulatory system. In the present investigation, detection and examination of arrhythmias in the heart on the system using GSNNs (General sparsed neural network classifier) can be carried out[1]. In this paper, the methodologies of support vector regression(SVR), neural mode decomposition(NMD), Artificial Neural Network (ANN), Support Vector Machine(SVM) and are examined. To assess the suggested structure, three distinct ECG waveform situations are chosen from the MIT-BIH arrhythmia collection. The main objective of this assignment is to create a simple, accurate, and simply adaptable approach for classifying the three distinct heart diseases chosen. The wavelet transform Db4 is used in the present paper to obtain several features from an ECG signal. The suggested setup was created using the MATLAB programme. The algorithms suggested are 98% accurate for forecasting cardiac arrhythmias, which is greater than prior techniques.

Keywords : Artificial neural networks, General Sparsed Neural Network, heart rhythm disorders, QRS complex average filter, Electrocardiograph, Db4 Wavelet Transform.

I. INTRODUCTION

Cardiovascular arrhythmias are abnormal heartbeats that may make it difficult for the heart to beat regularly. Electrocardiogram (ECG) signals offer important data for the investigation and categorization of various arrhythmia types. For this job, generalised sparse neural networks (GSNNs) may be helpful. To learn the patterns and characteristics that identify various types of arrhythmias, the GSNN model is trained using a dataset of ECG signals with known arrhythmia classifications. Here is a broad explanation of how cardiac arrhythmia analysis and classification using GSNNs can be carried out. The The electrocardiogram (ECG) is a widely used procedure in cardiologist for examining patients' heart health. ECGs may be easily collected by placing surface electrodes on the patient's limbs or chest. In its simplest form, an ECG is an electromagnetic depiction of the muscular contractions of the heart. One of the most well-known and often utilised biological signals in the world of medicine is the ECG[3]. By measuring the peak values of R of the ECG signal throughout a single minute of monitoring (It is straightforward to calculate the heart's rhythm in beats per minute (bpm; see Fig. 1 for a specific ECG waveform). Understanding the ECG signal is essential for diagnosing cardiac illness and for understanding how the heart works in various situations. According to the American Heart Association, 70 million individuals worldwide suffer from cardiovascular disease. An electrode placed on the skin is used in the electrocardiogram (ECG), a testing technique, to gauge the electrical activity of the heart. The shape and pace of a human heartbeat reveal the condition of the heart. It is a less intrusive device that is used to assess cardiac issues and determines a waveform mostly on the skin's surface of a person [4]. Any alterations to the architectural pattern or any anomalies in heart rate or rhythm, which are indications of cardiac arrhythmia, can be seen in an ECG waveform analysis. The length and amplitude of the P-QRS-T wave provide crucial information on the type of cardiac disease. The existence of Na+ and K+ ions in the blood causes the electrical wave. One of the most important elements of the body is the heart. Through the blood, it gives the patient's body oxygen. The heart functions like a muscle pump. A complex network of arteries, veins, and capillaries links the heart to the rest of the body[5]. The electrocardiogram (ECG) consists of a variety of biopotential signals from human heartbeats. The electrodes are placed on the patient's epidermis to record these biopotential signals. It visibly displays the electrical activity of the heart's muscles. ECG facilitates the transmission of information about the heart and circulatory system. It is a vital and fundamental method for dealing with heart problems. It is a valuable and crucial tool for figuring out how serious a heart condition is. The electrical activity of the cardiac muscles is represented by the ECG waveform, which is made up of distinctive electrical depolarization-repolarization patterns[2]. The ECG signal

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continuously records the direction and magnitude of the electrical activity caused by the depolarization and repolarization of the atria and ventricles of the coronary heart. Arrhythmias include both changes in the morphological pattern and problems with the charge or rhythm of the coronary heart. The selection process takes longer when applying the guiding statement to assess the recorded ECG waveform. As a result, a detection and classification system based on artificial intelligence (AI) is used [6].

The goal of this study is to create a computer-assisted diagnosis method that offers knowledgeable, affordable, and efficient ECG arrhythmia diagnosis to professional cardiologists. This objective is accomplished by combining traditional ECG signal processing methods with cutting-edge deep learning algorithms to recognise ECG arrhythmia patterns. (RBBB) Right Bundle Branch Blocks, a kind of cardiac arrhythmia, may be explicitly distinguished from Paced Beats and Normal (Healthy) Beats by the proposed approach as it stands. Where, Healthy adult human ECG waveforms are considered normal beats; Paced beats are artificial heartbeats produced by a pacemaker, a QRS duration between 0.10 and 0.11 Apart from these, the method may also be simply modified to categorise additional, diverse cardiac rhythms that are comparable to these. To mention a few, cardiac scarring, excessive alcohol consumption, drug misuse among diabetics, coffee consumption, heart disease, hypertension, mental stress, and thyroid illness. Arrhythmias are categorised as 1[7]. atrial flutter, 2. A regular sinus beat, 3. Bradycardia, 4. Tachycardia, 5. Early atrial contraction, 6. Atrial fibrillation, 7. a premature contraction of the ventricles, 8. AVBlock of the first degree, 9. ventricular tachycardia, 10.ventricular fibrillation, etc.

The remainder of the essay is structured as follows: In section 2, a brief summary of recent recommended techniques for ECG arrhythmia identification is provided. The suggested approach is then thoroughly defined in part 3, and trials and results are discussed in section 4. In conclusion, the suggested method's current status is evaluated, and future research directions are given.

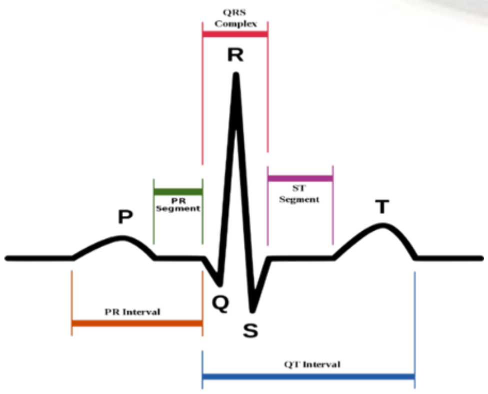

Figure 1: ECG Beats and intervals

The three tier structure of the study effort is depicted in the second figure. The entire system is divided into three parts, including feature extraction, classification, and input ECG signal. Higher order statistics and the discrete wavelet transform are used to determine the ECG pulses. As a result of their adaptability, these non-linear approaches are being employed for obtaining the ECG beats more effectively than others[9]. The primary cardiac rhythm signal is separated into its both low and high frequencies components in the time space for the Higher order statistics and discrete wavelet transform in order to eliminate the baseline and noise, respectively, and to derive the function from the ECG signals.

II. The suggested strategy

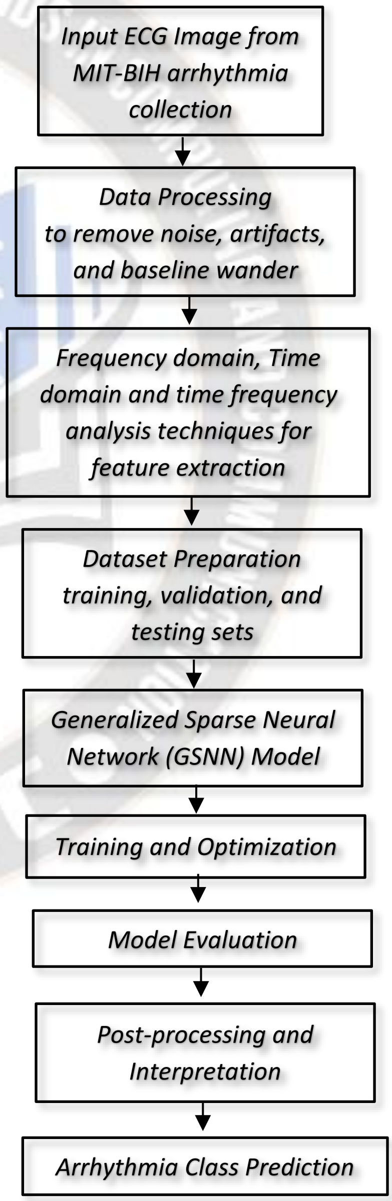

Figure2:detail flow chart of Arrhythmia classification

The ECG signal's sample frequency is 360 Hz.The categorization of normal and pathological arrhythmia activities

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is done on the ECG beats' extracted function in the last stage. The categorization of normal and pathological arrhythmia activities is done on the ECG beats' extracted function in the last stage. ECG beats are categorised before being uploaded to the cloud. It is appropriate for patient monitoring around-the-clock. The achieved categorization accuracy is more than 98% in practically all instances[11].

2.1 Collecting information for ECG

The MIT-BIH Arrhythmia database (MIT-BIH ECG database, 2017) provided the ECG data for this investigation.

An online database called the Arrhythmia database at MIT-BIH was created utilising over 4000 long-term ECG Holter recordings. These recordings were acquired from patients for around 60% of the time. The entire database includes 25 records (numbered from 200 to 234) picked at random from the same collection as the 23 records, in order to encompass a range of uncommon but clinically significant events. These 48 tracks total a little more than 30 minutes in length[14]. Cardiologists with extensive knowledge have annotated each waveform seen in these recordings. Each of these records has two leads (two signals collected from various chest angles) and a sampling frequency of 360 Hz. As a final stage, one of the channels is eliminated, leaving the system with just one channel (channel MLII) for each recording[13].

Bolts to the yield sign stream of the neuron (O) indicate that the sign stream from information sources B1,, Bn is seen as unidirectional. The following is the O input for neuron output

$$O = f(net) = f\left(\sum_{i=1}^{n} A_i B_i\right) \quad (1)$$

where Ai , Bi are the weight vector, while f (net) is the capacity.

As a scalar consequence, the weight and information vectors define the variable network.

$$net = A^T B = A_1 B_1 + A_2 B_2 \dots A_n B_n \quad (2)$$

where T is a transposition of a matrix.

O is determined as the value as Eq. (3)

$$O = f(net) = \begin{cases} 1, & if\ A^T x \geq \theta \\ 0, & otherwise \end{cases} \quad (3)$$

where the term "type of node" refers to a linear threshold unit and "range" is referred to as the limit. The inner activity of the neuron model is controlled by

$$v_k = \sum_{i=1}^{p} A_{ki} B_i \quad (4)$$

The output of the neuron yk would then be the outcome of any activation function on the value of vk.

2.2 Pre-processing of Signals

Baseline drift, artefacts, and noise are all removed during preprocessing of the ECG data. Resampling, baseline correction, and filtering are common preprocessing methods. Even though it is projected that ECG data obtained over the MIT-BIH network would not include as much distracting noise as ECG data obtained directly from a patient, there is still some noise present that has to be reduced in order to maximise the system's later stages. As a result, the goal of the signal pre-processing stage is to eliminate noise from ECG records[15].

The dc noise that exists in the ECG signals is removed in the first stage using mean removal. By subtracting the average of the ECG recording from each sample point, the unwanted dc component is removed and the signal baseline amplitude is returned to level zero. Nearly all recordings of electrocardiograms also include high- and low-frequency noise, which can be caused by a number of variables including muscular contractions, breathing movements, inadequate sensor contact, and the presence of other external equipment. A 10-point moving average filter is used to filter the signals, passing low frequencies but attenuating high frequencies, to eliminate high frequency vibration, that is mostly brought on by patients' muscular contractions during recording. Once the high frequency distortion has been eliminated, the next step is to remove the low frequency noise components[16]. This noise of low frequencies manifests as baseline wandering, which is mostly brought on by the patient's breathing. Power line interference, which is caused by electricity current flowing through cables and power lines, is another type of noise that can be seen in ECG data. Power line interference results in harmonics and 60Hz pickup in the ECG measurements. A filter should be employed to isolate the 60Hz frequency and its harmonics from the surrounding frequencies since the ECG frequency range, which is normally between 0.05 and 150 Hz, overlaps with that of 60Hz. Using a comb filter, a band-stop filter that attenuates a certain band of frequencies and their harmonics, the ECG signals are cleansed of 60Hz power line interference and its harmonics. The aforementioned processes are applied to all training and test ECG data, and filtered ECG signals are obtained in order to set up the future QRS detection phase[17].

The pre-processing of signals typically involves a series of steps to prepare the data for further analysis or modeling. The specific equations used in signal pre-processing depend on the nature of the signals and the desired processing techniques. Here are some common equations used in signal pre-processing:

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1. Signal normalization: Signal normalization is often performed to bring the signal amplitudes to a consistent scale. One common technique is to normalize the signal between 0 and 1 using min-max scaling. The equation for min-max scaling is: x_normalized = (x - min(x)) / (max(x) - min(x))

2. Signal smoothing: Signal smoothing is used to reduce noise or fluctuations in the signal. One popular smoothing technique is moving average smoothing, which replaces each sample with the average of itself and its neighboring samples. The equation for a moving average is: y[i] = (x[i] + x[i-1] + x[i+1]) / 3

3. Signal filtering: Signal filtering is used to remove unwanted noise or isolate specific frequency components in the signal. Filters can be implemented using a variety of methods, including FIR (Finite Impulse Response) or IIR (Infinite Impulse Response) filters, including low-pass, high-pass, and band-pass filters. The equations for these filters depend on their specific design parameters and coefficients.

4. Signal resampling: Signal resampling is performed to change the sampling rate or the number of samples in a signal. The equation for resampling involves interpolation or decimation techniques, depending on whether the new sampling rate is higher or lower than the original rate.

5. Signal normalization: The process of signal normalisation reduces the signal's mean and standard deviation to a specified range, usually zero mean and one variance. The equation for signal normalization is: x_normalized = (x - mean(x)) / std(x)

6. Signal detrending: Signal detrending is used to remove trends or drifts in the signal. A common method is linear detrending, which fits a straight line to the signal and subtracts it. The equation for linear detrending is: y[i] = x[i] - (a * i + b)

Where a and b are the slope and intercept of the fitted line, and i is the index of the sample.

These are just a few examples of the equations used in signal pre-processing. The choice of specific pre-processing techniques and equations depends on the characteristics of the signals and the objectives of the analysis or modeling task.

2.3 Feature extraction for ECG

To capture the characteristics of various arrhythmias, pertinent features are retrieved from the preprocessed ECG data. Techniques for feature extraction may use Time domain, frequency domain, and time frequency analysis are all examples of time domain analysis. RR interval statistics, heart rate variability measurements, spectral features, wavelet coefficients, etc. are a few examples of features. Investigating the ECG data at hand reveals that the characteristics that clearly define each class are located between the R-T interval. Additionally, it is simple to see that every member of a class exhibits the same pattern throughout this time[18].

In this regard, 200 sample points are recovered after each R-peak (see Fig. 3) and fed into the transferred deep learning-based feature extractor. This number of samples roughly corresponds to the R-T interval with a sampling frequency of 360Hz. All unnecessary components are subsequently removed from the ECG waveforms[19].

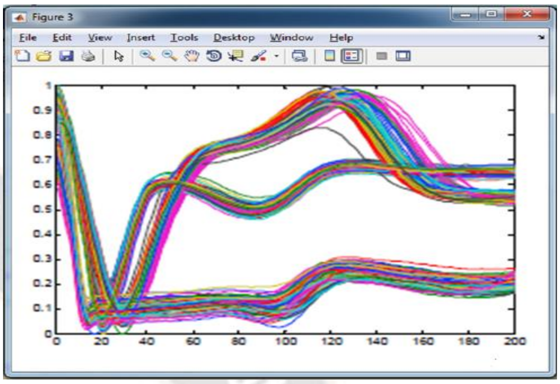

Fig.3 All training ECG data R-T intervals are represented graphically

The ImageNet dataset's 1.2 million RGB pixels with high resolution photographs used as the training data for the convolutional neural network-based deep learning system AlexNet (Krizhevsky et al., 2012). With cutting-edge performance, our system can categorise those photos into 1000 separate categories. Eight layers make up the architecture of the AlexNet CNN, five of which are convolutional and three of which are fully linked. These layers were developed using ImageNet's generic pictures as training data.

In this regard, characteristics for the supplied ECG inputs for the proposed ECG classification system may be extracted from the outputs of the deeper layers of the pre-trained AlexNet[20].

In order to describe the underlying heart activity, feature extraction for electrocardiogram (ECG) signals entails removing pertinent details or traits from the raw ECG data. Many signal processing methods are available in MATLAB to do feature extraction on ECG data. The following are some typical feature extraction methods and the accompanying MATLAB equations:

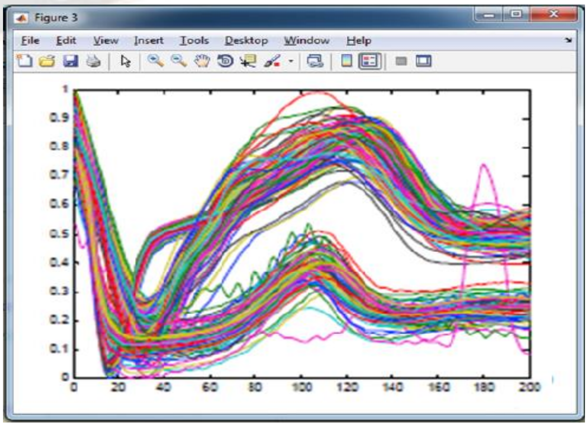

Fig.4 All test ECG data R-T intervals are represented graphically.

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In this regard, the outputs of the deeper layers of the pre-trained AlexNet may be retrieved as features for the provided ECG inputs for the proposed ECG classification system[20].

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R Peak Detection: For the analysis of ECG data, R peak detection is essential. The R peaks, which show the depolarization of the ventricles, correlate to the QRS complex's maximum amplitude points. For R peak identification, MATLAB offers a number of techniques, including the Pan-Tompkins approach. Here is an illustration of the 'findpeaks' function in use:

How to Calculate Heart Rate (HR): An important metric generated from ECG readings is heart rate. It serves as a representation of heartbeats per minute. By counting the intervals between successive R peaks and translating the results to beats per minute (BPM), the HR may be calculated:

QRS Duration: The QRS duration shows how long it takes for the heart to depolarize. Normally, it is measured from the start of the Q wave to the conclusion of the S wave. The R peak positions, along with the Q and S wave locations, may be used to compute the QRS duration:

Analysis of Heart Rate Variability (HRV): HRV analysis measures the variability in the space between succeeding R peaks. It sheds light on how the heart rate is the autonomic nervous system controls. MATLAB contains functions like hrv and pnn50 to determine HRV features like the standard deviation of NN intervals (SDNN) and the percentage of successive NN intervals that differ by more than 50 ms (pNN50):

Frequency Domain Analysis: Using methods like the Fourier Transform or the Welch method, frequency domain analysis describes the ECG signal in terms of its frequency content. For spectrum analysis, MATLAB offers tools like the fft and pwelch functions. You may extract frequency domain characteristics like dominant frequency, power spectral density, or spectral entropy:

2.4 Creating the data set:

Training, validation, and testing sets are created using the preprocessed ECG signals and the associated arrhythmia markers. It's crucial to check if the dataset is balanced and accurately represents the various forms of arrhythmia.

2.5 Using General Sparsed Neural Network Regression

General Sparsed Neural Network regression keeps all of the beneficial characteristics of support vector machines. A curve is sought for using ECG features. General Sparsed Neural Network(SVR) seeks a correspondence between a vector and the location of the curve as opposed to employing a classification problem's curve as a decision boundary [22]. This is a regression scenario, after all. Additionally, support vectors are used to determine which ECG characteristics best fit the actual function that they represent [7]. With the use of sparse connection patterns, GSNNs are neural network models that can effectively learn from high-dimensional input.

The GSNN model can have a variety of architectural configurations, but it commonly has an input layer, hidden layers with sparse connections, and an output layer that represents various kinds of arrhythmia. Based on the particular GSNN model architecture, activation functions, regularisation methods, and optimisation algorithms are selected[23].

The equations for a general sparsed neural network classifier can be described using the following notation:

Input: Let x be the input vector of size n, where n is the number of input features.

Hidden Layers: Let z^(l) be the weighted sum at layer l, where l = 1, 2, ..., L denotes the layer index. Let a^(l) be the activation at layer l.

The weighted sum z^(l) at layer l is computed as: z^(l) = W^(l) * a^(l-1) + b^(l)

The activation a^(l) at layer l is computed using a non-linear activation function g: a^(l) = g(z^(l))

Output Layer: Let k be the number of output classes. Let z^(L+1) be the weighted sum at the output layer. Let a^(L+1) be the activation at the output layer.

The weighted sum z^(L+1) at the output layer is computed as: z^(L+1) = W^(L+1) * a^(L) + b^(L+1)

The activation a^(L+1) at the output layer depends on the type of problem:

For binary classification (k = 1), you can use a sigmoid activation function: a^(L+1) = sigmoid(z^(L+1))

For multiclass classification (k > 1), you can use a softmax activation function: a^(L+1) = softmax(z^(L+1))

Regularization: To induce sparsity in the network, you can use L1 regularization. The L1 regularization term is typically the loss function has been added and encourages the weights to be close to zero. The loss function can be defined as: loss = empirical_loss + lambda * sum(abs(W))

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Where lambda is the regularization parameter and abs(W) is the element-wise absolute value of the weight matrix.

Training: The neural network is trained by minimizing the loss function using an an optimisation technique like gradient descent. The biases and weights are updated iteratively using the backpropagation algorithm and the gradients relating the weights and biases to the loss function.

Each layer's weights and biases may be updated using the following equations: W(l) = W(l) - learning_rate * db(l) - learning_rate * db(l) = W(l) b(l)

Where dW^(l) and db^(l) are the gradients of the loss function with respect to the weights and biases at layer l.

These equations form the basis for implementing a general sparsed neural network classifier. The specific implementation details and variations may vary depending on the software or programming framework being used.

2.6 Training and Optimization:

The labelled ECG signals from the training set are used to train the GSNN model.

The ECG signals are sent into the network during training, and the output is computed and compared to the actual arrhythmia labels. The model parameters are updated and the classification error is minimised using optimisation methods like stochastic gradient descent or Adam. To enhance model performance, hyperparameter adjustment may be done using the validation set.

2.7 Model Evaluation:

On the testing set, the performance of the trained GSNN model is tested. To assess the classification outcomes, Accuracy, precision, recall, and F1 score are common performance metrics used. Confusion matrices and ROC curves can offer further information on how well the model performs for various arrhythmia types.

2.8 Post-processing and Interpretation:

To get the final findings for arrhythmia classification, post-processing techniques like thresholding or filtering may be used to the model's output probabilities. The learnt sparse connections or feature significance weights can be visualised to improve the GSNN model's interpretability.

2.9 Arrhythmia Class Prediction

The ECG's QRS complex waveform is the most notable. The moment it occurs as well as its shape offer important clues regarding the current condition of the heart because it displays electrical activity that occurs when the heart is beating. In that regard, practically all automated ECG analysis methods are built on the foundation of QRS detection. Additionally, earlier studies (Ozbay and Karlik, 2001) demonstrated that automated ECG categorization works best when concentrating on the shape of the R-T interval (of the ECG), which also holds true for rbbb and timed beats. Rpeaks must be successfully recognised using QRS detection in order to derive the R-T interval from the ECG[24]. The QRS detection is done using the well-known Pan-Tompkins method (Pan and Tompkins, 1985). The algorithm consists of a number of techniques for detecting the incorporating derivative, squaring, integration, adaptive thresholding, and search methods for R-peaks in the ECG signal.

III. The Findings and Comments

Three separate techniques are used to pre-process ECG data taken from the MIT-BIH database, identify QRS complexes, and extract characteristics from R-T intervals. After completing all of these procedures, three distinct networks are created, trained, tested, and assessed for pattern identification and classification of ECG data for three distinct cardiac diseases. Each network uses these various properties as inputs. The assessment findings for the three distinct networks are summarised in the section that follows.

3.1 Results of General Sparsed Neural Network method

The five separate kinds of ECG beat annotations are described by the proposed technique as follows:

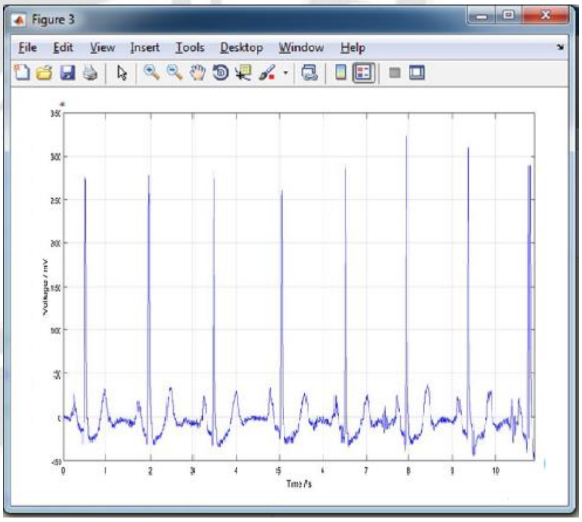

Fig. 6. Normal ECG sample.

Q - Fusion of Paced and Normal
F - Fusion of ventricular and normal
V - Ventricular Ectopic beats
S - Supraventricular Ectopic Beats
N - Normal

We extract Time and Frequency based characteristics from the ECG data in Figure 6.

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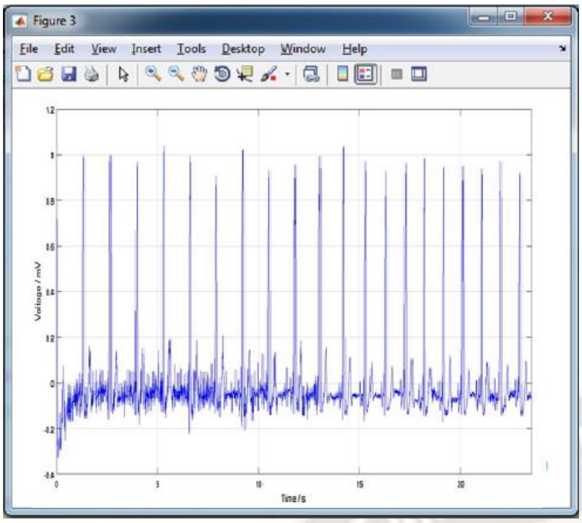

Fig. 7. Supra-ventricular premature ECG sample

The GSNN is used to categorise those characteristics. Although junctional untimely beats (also known as supraventricular untimely beats) can start from either the atria or the atrioventricular hub, the vast majority of supraventricular untimely beats originate from the atrium. The Supra-Ventricular Premature signal is shown in Figure 7 with the intention of extracting time and frequency-based features and classifying them using GSNN.

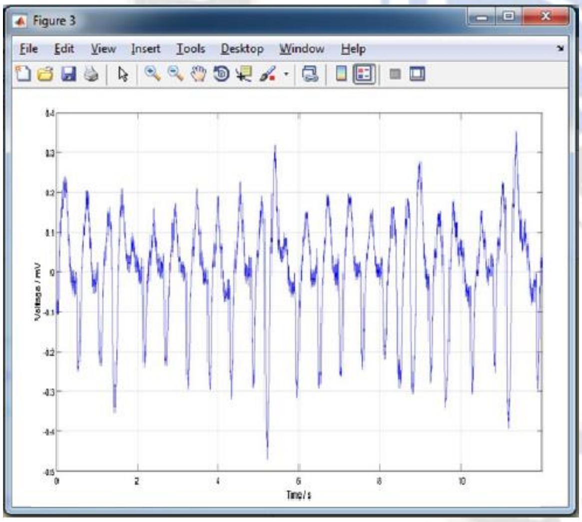

Fig. 8. ECG sample for premature ventricular contraction

The GSNN is used to categorise those characteristics. Although junctional untimely beats (also known as supraventricular untimely beats) can start from either the atria or the atrioventricular hub, the vast majority of supraventricular untimely beats originate from the atrium. The Supra-Ventricular Premature signal is shown in Figure 7 with the intention of extracting time and frequency-based features and classifying them using GSNN.

PVCs, The ventricular myocardium causes premature ventricular beats, premature ventricular depolarization, or ventricular extra systoles under a variety of conditions. PVCs are pervasive and present in all ages and socioeconomic groups[24]. A premature ventricular contraction ECG sample from the combined dataset is shown in Figure 8. Figure 8 displays the signal for premature ventricular contraction in order to extract time and frequency-based characteristics and classify those features using GSNN.

A fusion beat occurs when multiple electrical driving forces simultaneously follow the same area of the heart. Atrial combination beats are produced by altering flows in the atrial chambers, whereas ventricular combination beats are identifiable if they persist into the ventricular chambers[25]. The Ventricular and Normal signals in Figure 9 are combined to create time- and frequency-based characteristics, which are subsequently categorised using GSNN. When the ventricles are somewhat depolarized by both the normal beat and the pacemaker improvement beat, a hybrid QRS complex is produced[27].

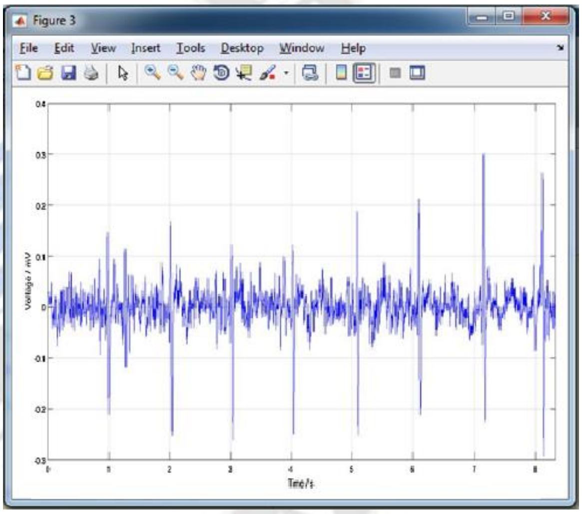

Fig. 9. combining ventricular and healthy ECG data.

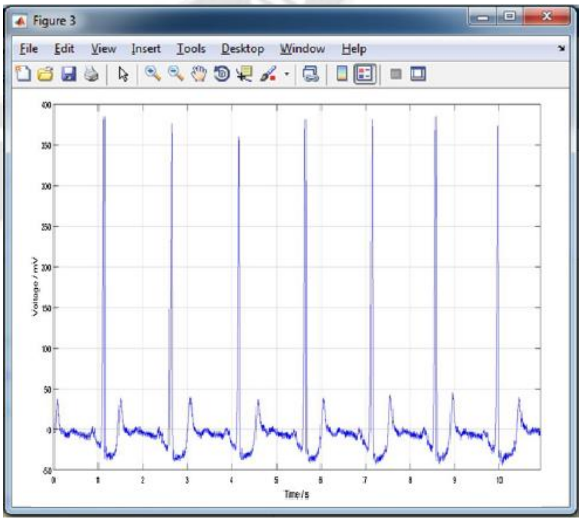

Fig. 10. Combining a timed and unpaced ECG sample

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The Fusion of Paced and Normal Signals in Figure 10 is used to extract time- and frequency-based characteristics and classify those features using GSNN.

3.2 Results of General Sparsed Neural Network method

Table 1 shows the performance of proposed system with several other methods (ANN,SVM KPCA and GSNN) to evaluate the precision, recall and F1 score. The sparsed neural network has been evaluated successfully; it is found that accuracy level of network is 98%

Table.1 Comparison of many approaches for accuracy

Sr.No	***Accuracy***	***Precision***	***Recall***	***F1 score***	***Method***
1	*89.00*	*91.12*	*92.30*	*90.21*	*ANN*
2	*90.75*	*89.83*	*92.79*	*91.70*	*SVM*
3	*88.75*	*90.33*	*92.23*	*91.83*	*KPCA*
4	*98.00*	*98.12*	*96.30*	*97.21*	***GSNN***

IV. Conclusion

In medical settings, cardiac monitoring systems are essential for identifying problems with heart arrhythmias. In this study, a model to identify multiple abnormal cardiac rhythms was developed. The computational analysis of ECG recordings uses the 16 distinct subclasses of the MIT-BIH arrhythmia dataset. They are reducing the noise and obtaining the QRS beats by using the adaptive threshold technique. The gathered traits are added to a standard back propagation neural network in order to classify the input ECG beats. The suggested system's generic sparsed neural network achieves a final accuracy level of 98%. It is shown that the universal sparsed neural network is capable of accurately categorising and forecasting the various arrhythmia situations. Arrhythmia illness has been implemented with remarkable precision and speed thanks to the general sparsed neural network (GSNN). The created model would be extremely beneficial to medical professionals in reading the ECG signal to provide additional information about the cardiac issues.

Future research will involve performance improvement by analysis and comparison of the ECG beat classification algorithm's classification accuracy with that of other deep learning classifiers.

References

[1] https://ecgwaves.com/topic/ecg-normal-p-wave-qrs-complex-st-segment-t-wave-j-point/

[2] Zubair M, Kim J, Yoon C (2016) An automated ECG beat classification system using convolutional neural networks. In: 2016 6th International conference on IT convergence and security (ICITCS), Prague, pp 1–5. https: //doi.org/10.1109/icitcs.2016.77403 10

[3] Bhagyalakshmi V, Pujeriand RV, Devanagavi GD (2018) GB-SVNN: genetic BAT assisted support vector neural network for arrhythmia classification using ECG signals. J King Saud Univ Comput Inf Sci. https ://doi.org/10.1016/j.jksuc i.2018.02.005

[4] Isin A, Ozdalili S Singh P, Pradhan G (2021) A new ECG denoising framework using generative adversarial network. IEEE/ACM Trans Comput Biol Bioinform. https://doi.org/10.1109/TCBB.2020.297 6981

[5] Kovács P (2012) ECG signal generator based on geometrical features. Ann Univ Sci Budapestinensis de Rolando Eötvös Nominatae Sect Computatorica 37

[6] Danandeh Hesar H, Mohebbi M (2021) An adaptive kalman filter bank for ECG denoising. IEEE J Biomed Health Inform. https://doi.org/10.1109/JBHI.2020.2982935

[7] Maaroof Maaroof, M. A. ., & Naimi, S. . (2023). Developing Adaptive Project Construction Cost Control Using Multi-Nonlinear Regression Engineering Techniques. International Journal of Intelligent Systems and Applications in Engineering, 11(4s), 579 –. Retrieved from https://ijisae.org/index.php/IJISAE/article/view/2729

[8] Wang Z, Zhu J, Yan T, Yang L (2019) A new modified wavelet-based ECG denoising. Comput Assist Surg 24(sup1):174–183. https://doi.org/10.1080/24699322.2018.1560088

[9] Mourad N (2019) New two-stage approach to ECG denoising 13(6):596–605. https://doi.org/1049/iet-spr.2018.5458.Print ISSN 1751-9675, Online ISSN 1751-9683

[10] Kim J, Shin HS, Shin K, Lee M (2009) Robust algorithm for arrhythmia classification in ECG using extreme learning machine. BioMed Eng 8:31

[11] Singhal A, Singh P, Fatimah B, Pachori RB (2020) An efficient removal of power-line interference and baseline wander from ECG signals by employing Fourier decomposition technique. Biomed Signal Process Control 57:101741. https://doi.org/10.1016/j.bspc.2019.101741

[12] Savalia S, Emamian V (2018) Cardiac arrhythmia classification by multi-layer perceptron and convolution neural networks. Bioengineering (Basel, Switzerland) 5(2):35. https ://doi.org/10.3390/bioen ginee ring5 02003 5

[13] Kelwade JP, Salankar SS (2015) Prediction of cardiac arrhythmia using artificial neural network. Int J Comput Appl 115(20):0975–8887

[14] Ayushi D, Nikita B, Nitin S (2020) A survey of ECG classification for arrhythmia diagnoses using SVM.In: Balaji S, RochaÁ,ChungYN(eds) Intelligent communication technologies and virtual mobile networks. ICICV 2019. Lecture notes on data engineering and communications technologies, vol 33. Springer, Cham. https://doi.org/10.1007/978-3-030-28364-3_59

[15] Kevin Harris, Lee Green, Juan Garcia, Juan Castro, Juan González. Intelligent Personal Assistants in Education: Applications and Challenges. Kuwait Journal of Machine Learning, 2(2). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/185

[16] Fariha MAZ, Ikeura R, Hayakawa S, Tsutsumi S (2019) Analysis of Pan-Tompkins algorithm performance with noisy ECG signals. J Phys Conf Ser 1532. In: 4th ınternational conference on engineering technology (ICET 2019) 6–7 July

2019. Darul Iman Training Centre (DITC), Kemaman, Terengganu, MALAYSIA

[17] Bazi Y, Alajlan N, Hichri H, Malek S (2013) Domain adaptation methods for ECG classification. In: International conference on computer medical applications. IEEE

[18] Kiranyaz S, Ince T, Gabbouj M (2016) Real-time patient-specific ECG classification by 1-D convolutional neural networks. IEEE Trans Biomed, Eng

[19] Mustaqeem A, Anwar SM, Majid M (2018) Multiclass classification of cardiac arrhythmia using improved feature selection and SVM invariants. Comput Mat Methods Med 2018:10. https: //doi.org/10.1155/2018/73104 96

[20] Sanamdikar ST, Hamde ST, Asutkar VG (2020) Analysis and classification of cardiac arrhythmia based on general sparsed neural network of ECG signal. SN Appl Sci 2(7):1–9. https://doi.org/10.1007/s42452-020-3058-8

[21] Degadwala, D. S. ., & Vyas, D. . (2021). Data Mining Approach for Amino Acid Sequence Classification . International Journal of New Practices in Management and Engineering, 10(04), 01–08. https://doi.org/10.17762/ijnpme.v10i04.124

[22] Qin Q, Li J, Zhang L et al (2017) Combining low-dimensional wavelet features and support vector machine for arrhythmia beat classification. Sci Rep 7:6067. https://doi.org/10.1038/s41 598-017-06596-z

[23] Huang J, Chen B, Yao B, He W (2019) ECG arrhythmia classification using STFT-based spectrogram and convolutional neural network. IEEE Access 7:92871–92880. https://doi.org/ 10.1109/ACCESS.2019.2928017

[24] Gualsaquí MMV, Vizcaíno EIP, Flores-Calero MJ, Carrera EV (2017) ECG signal denoising through kernel principal components. In: 2017 IEEE XXIV ınternational conference on electronics,electrical engineering and computing (INTERCON). Cusco, pp 1–4. https://doi.org/ 10.1109/INTERCON.2017.8079670

[25] Sanamdikar ST,Hamde ST,AsutkarVG(2021) Classification and analysis ofECGsignal based on ıncremental support vector regression on IOT platform. Biomed Signal Process Control 1–9. https://doi.org/10.1016/j.bspc.2020.102324

[26] Andrew Hernandez, Stephen Wright, Yosef Ben-David, Rodrigo Costa, David Botha. Predictive Analytics for Decision-Making: Leveraging Machine Learning Techniques. Kuwait Journal of Machine Learning, 2(3). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/193

[27] Hanbay K (2019) Deep neural network based approach for ECG classification using hybrid differential features and active learning. IET Signal Process 13(2):165–175. https ://doi.org/10.1049/ iet-spr.2018.5103

[28] Jambukia SH, Dabhi VK, Prajapati HB (2018) ECG beat classification using machine learning techniques. Int J Biomed Eng Technol 26(1):32–53

[29] Chaouch H, Ouni K, Nabli L (2018) Statistical method for ECG analysis and diagnostic. Int J Biomed Eng Technol 26(1):1–12

[30] MIT-BIH Arrhythmia database. http://www.physi onet.org

[31] Mondéjar-Guerra VM, Novo J, Rouco J, Gonzalez M, Ortega M (2018) Heartbeat classification fusing temporal and morphological information of ECGs via ensemble of classifiers. Biomed Signal Process Control 47:41–48. https ://doi.org/10.1016/j. bspc.2018.08.007

[32] Shukla DS (2012) a survey of electrocardiogram data capturing system using digital image processing: a review. Int J Comput Sci Technol 3:698–701.