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Emotion Detection Through Electrocardiogram Signal Classification in an IOT Environment with Deep Neural Networks

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Abstract: - An ECG detects the health and rhythm of the heart by measuring the electric activity of the heart. It has also been demonstrated that a person's emotions may influence the electrical activity of the heart. As a result, studying the electrical behaviour of the heart may simply determine a person's cardiac state and emotional wellness. IoT is a new technology that is quickly gaining acceptance throughout the world. Anybody, at any time, from anywhere, may connect to any network or service because to the extraordinary power and capacity of IoT. IoT-enabled devices have revolutionized the medical business by providing new capabilities such as remote patient monitoring and self-monitoring. This research proposed an IoT-based ECG monitoring system that employs a heart rate sensor to generate data and an intelligent hybrid classification algorithm to categorize the data. ECG monitoring has become a widely used method for detecting cardiac problems. The following are the primary contributions of this paper: To begin, this paper describes WISE (Wearable IoT-cloud-based health monitoring system), a one-of-a-kind system for real-time personal health monitoring. WISE makes use of the BASN (body area sensor network) technology to provide real-time health monitoring. WISE rapidly transfers data from the BASN to the cloud, and a lightweight wearable LCD may be included to enable quick access to real-time data. This model can address the issue of class imbalance in the ECG dataset, assisting in the development of an IoT-based smart and accurate healthcare system. Pre-processing, feature extraction, and classification are the three steps in any classification technique, whether it is emotion classification or heart health classification. Sensors are used to collect an ECG signal from a person's outside body. The provided ECG signal is first pre-processed using the Butterworth Filtering Method, which effectively reduces noise from the signal. Following pre-processing, the Adaptive Discrete Wavelet Transform technique is used to anticipate the signal's attributes. Lastly, a decision making classification approach based on relational weights is used to determine if the ECG signal is normal or abnormal.

Keywords: ECG monitoring, wearable LCD, WISE, IoT, BASN, Butterworth Filtering, Adaptive Discrete Wavelet Transform, weight based decision making classification.

I. Introduction

Heart disease is the main cause of mortality in both India and the rest of the globe. As a result, early diagnosis of these disorders is a focus in biomedicine research. Cardiac arrhythmias are cardiac pathologies defined by irregular heartbeat rhythms. Rhythmicity-heart conduction system anomalies are commonly responsible for the following disorders:

• Change the pacemaker of the sinus node to another place of the heart if the rhythm is abnormal.
• Blockages in the propagation of the impulse in the heart at various places.
• Heart impulse transmission channels that are abnormal.
• Almost any portion of the heart can spontaneously generate erroneous impulses.

Arrhythmias come in a variety of forms, some of which are difficult to detect while others are not. Some are asymptomatic, while others can be fatal. The ECG is the primary instrument utilized by both professionals and automated systems to detect heart arrhythmias. Understanding the shape of the curve is therefore critical for precise beat categorization. A normal pressure curved ECG is made up of P-waves, QRS complexes, and T-waves.

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The Internet of Things (IoT) stresses the interconnection of all physical and digital aspects, including sensors, smart devices, internet sensors, and more, enabling automatic and efficient data transfer and exchange over the Internet. As a result, it is considered that employing IoT in healthcare with networked medical sensors, particularly wearable or implanted sensors, is capable of offering smart, accurate, and cost-effective tailored healthcare. As part of the IoT for patients, many wearable gadgets like as fitness bands, smart watches, and other wireless-enabled devices (e.g., blood pressure monitoring, heart rate monitoring, glucometer, etc.) are available. These sophisticated devices are used for personalised monitoring. In the event of a medical emergency, the patient's information is shared with family members as well as the doctor, allowing us to make the best decision possible. Real-time information about the patient is communicated to the patient's family members in IoT for families. The primary objectives of this research are as follows:

- To offer a novel approach for effectively classifying abnormalities and emotion in patients utilizing wearable technology devices that outperforms existing algorithms in terms of accuracy.
- Using automated detection methods, identify the anomalies.
- To create an efficient classification approach for detecting various forms of arrhythmia in patients using ECG signals, as well as to assist algorithms appropriate for wearable technology devices in detecting a person's emotion.
- Classify a patient's emotion and cardiac abnormalities at the same time by integrating both ECG and respiratory data with an effective classification method.

The following is how the rest of the paper is organized: The strategy for locating relevant research was detailed in section 2. The materials and procedures were mentioned in Section 3. The implementation was explained in Section 4. Finally, in section 5, we wrap up the report and make suggestions for further research.

II. RELATED WORKS

Emotional state and posture recognition have emerged as critical subjects for detecting student involvement [7-15]. Rizwan Qureshi et al. (2017) suggested a new approach for removing numerous artefacts in an ECG signal by using a different number of transfer functions for each type of undesirable signal frequency. Yuzhen et al. [28] classified the ECG beat using the BP neural network, with a classification accuracy rate of 93.9 percent. The minimal peak prominence and minimum peak separation approaches were used to identify the peak signals [Tanushree Sharma & Kamalesh Kumar Sharma (2017)].

Moreover, efforts like SalmeronMajadas et al. strive to gather and evaluate keyboard and mouse interactions in order to assess how students perform throughout learning sessions. Other works centred on detecting student emotional states analyse and process signals from electroencephalograms (EEG), electromyograms (EMG), electrocardiograms (ECG), electrodermal activity (EDA), heart rate variability, skin temperature, blood volume pulse, respiration, or electrodermography (EDG)/galvanic skin response (GSR). With a classification accuracy score of 90.6 percent, Luo et al. used a multi-order feed forward artificial neural network to classify the ECG beat into six groups [4].

An ECG captures the natural electrical impulses that coordinate the contractions of the various segments of the heart to indicate the heart's pace, rhythm (steady or irregular), and the intensity and timing of the electrical impulses as they pass through the various regions of the heart [20]. Osowski et al. developed a classifier that cascaded the fuzzy self-organizing layer and the multi-layer perceptron, yielding seven ECG beat classifications with a classification accuracy rate of 96 percent [16]. Ceylan et al. used feed forward neural networks as the classifier and obtained 96.95 percent accuracy in detecting four different arrhythmias [3].

After extracting features with multiple discriminant and principal component analysis, Hwang used a support vector machine (SVM) to categorise the data. Deep learning has been used to recognise numbers and characters, as well as to identify faces, objects, and images. Deep learning algorithms are also effective for analysing bioinformatics signals [7]. The weights of this network's convolutional layers are passed to the emotion identification network, and two dense layers are trained to categorise arousal and valence scores [Sarkar, P., and Etemad, A., 2020]. Kumar and Kumaraswamy [11] presented a random forest tree (RFT) as a classifier using an RR interval as the only classification parameter. Park et al. proposed a K-nearest neighbour (K-NN) classifier with an average sensitivity and specificity of 97.1 percent and 98.9 percent, respectively, for recognising 17 different types of ECG beats [18].

III. METHODOLOGY

Figure 1 depicts the overall flow graph for the proposed method. The ECG signal is collected from the patient in this research utilising a body area network (BAN). These signals are sent to the cloud from the patient's location through wifi. The ECG input signal is received by the health monitoring person, such as a doctor, using their Communication device, such as a cell phone. The ECG input signal is first converted into an image using the discrete wavelet transform (DWT). This picture is utilised for additional processing and analysis. The collected ECG data is denoised using the Butterworth filtering method. Following that, the most important characteristics were extracted using the Adaptive Discrete Wavelet Transform. This information is sent to the clarification algorithm in order for it to categorise the ECG signal. The Classification module has been enhanced to improve the dimensionality and richness of the attributes. For classification in our research, relational weight based decision making is applied. This classifier determines if the area is normal or abnormal and assesses performance.

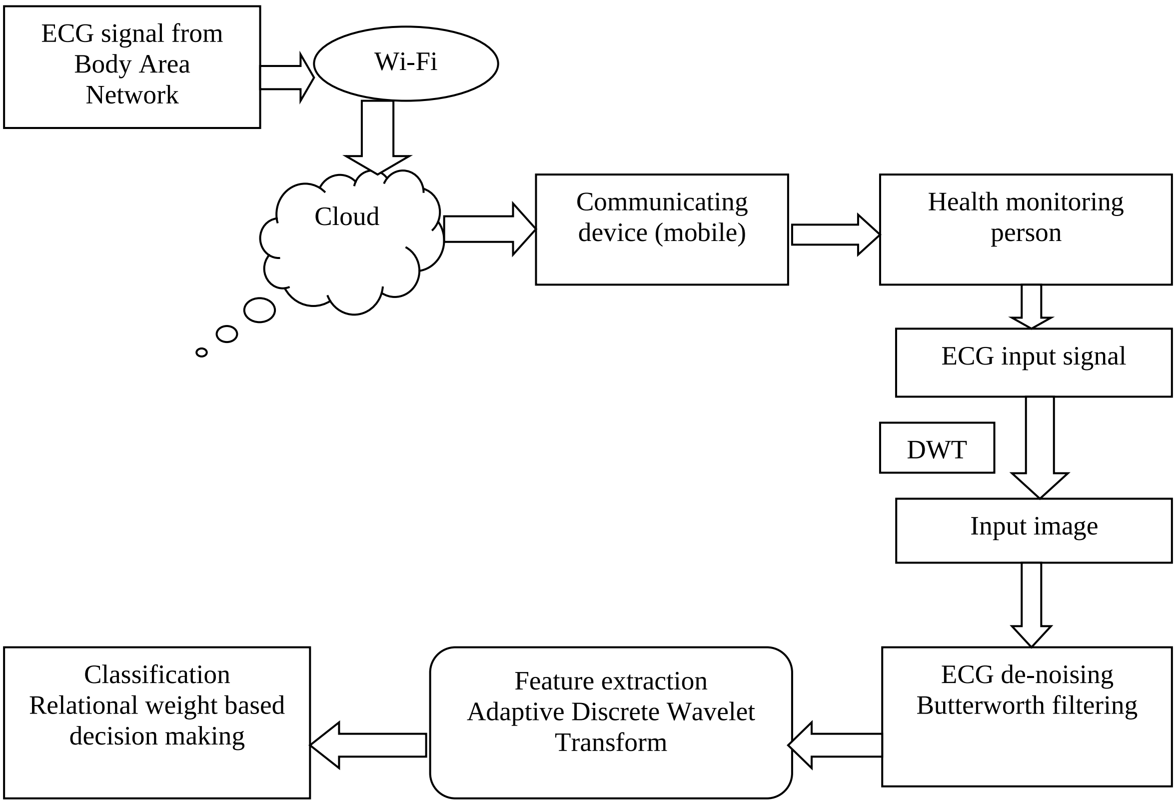

Figure 1: Proposed methodology

A. Building Dataset

This work dataset was provided by a patient who has access to the internet of things. The ECG data was downloaded from the cloud to a local computer for the research. After turning on the WISE system, the real-time data will be shown. WISE may send data straight from W-BAN to the cloud through Wi-Fi. This exercise is performed on the participants 24 hours a day, 7 days a week.

B. ECG Signal Pre-Processing

Interference from other noisy signals, such as power supply and breathing muscle artefacts, is present in the recorded ECG signal. Before processing the signal, it must be pre-processed by removing the signal's noise parts. The primary goal of signal pre-processing is to eliminate impurities from the ECG signal. The high-frequency signals were eliminated in this research by employing the Butterworth filtering approach, which passed the loss frequency signals for smoothing. As a result, the Butterworth filtering approach was utilised for ECG signal filtering and normalisation in this research. The signal S(x) was used as the input in this procedure. The low-frequency component B_((f1)) and the high-frequency componentB_((f2))) of this signal were determined.

$$B_{(f1)} = \frac{2L_{pf}}{f} \tag{1}$$

$$B_{(f2)} = \frac{2H_{pf}}{f} \quad (2)$$

Where, f represented the frequency of the signal. Lpf Indicated the low pass filter frequency coefficient and Hpf indicated the high pass filter frequency coefficient. Then, the coefficient of the Butterworth filter was calculated by estimating the bandwidth range F_w and centre frequency ω.

$$F_w = B_{(f2)} - B_{(f1)} \quad (3)$$

$$\omega = \sqrt{B_{(f2)} \times B_{(f1)}} \quad (4)$$

$$H_{(jw)} = \frac{1}{\sqrt{1+\varepsilon^2 (\frac{\omega}{F_w})^{2n}}} \quad (5)$$

Where H ((jw)) was the coefficient, that defined the filter order, ω=2πf, ε denoted the maximum pass band gain. Finally, the convolution output S_f (x) of the input signal with Butterworth filter was calculated, and is shown below,

$$S_f(x) = S(x) * H_{(jw)} \quad (6)$$

C. Feature extraction

The characteristics in the ECG signal were acquired using the Adaptive Discrete Wavelet Transform in our proposed technique. At discrete time intervals, the transform divided the input signal into multiple orthogonally aligned sets of wavelets. The precision of the wavelet transform was mostly determined by the wavelet used. The input smooth ECG signal was decomposed using a low pass filter with impulse response 'g' and a high pass filter with response 'h'. The signal was then down sampled to S samples. In this scenario, S was equal to 2.

Algorithm 1 – Feature Extraction Using Adaptive Discrete Wavelet Transform

Input: Smooth ECG Signal;

Output: QRS complex wave and ECG peak points

Step 1: Initialization of the search window.

$$T_{window} = \frac{\lambda_{max} + \lambda_{min}}{2} \quad (7)$$

Where, λ_max was the maximum eigen value in signal, λ_minwas the minimum eigen value of the signal.

Step 2: After that, the signal was downsampled using low pass and high pass filters. The wavelet coefficient was calculated using the low pass filter output.

Step 3: The formula yielded the wavelet coefficient,

$$Db_k = \frac{1}{\sqrt{k}} \int_{-\infty}^{\infty} s(t) \Psi \left(\frac{t-1}{k} \right) dt \quad (8)$$

Where, Y was the wavelet function and s(t)was the input signal, k was the level of decomposition.

Step 4: Wavelet values for various degrees of decomposition were found.

Step 5: The appropriate level for analysis was chosen after calculating the correlation coefficient between the signals using a formula.

$$C = \frac{\sum_{i=0}^{t} S(i).Db(i)}{\sqrt{\sum_{i=0}^{t} S^2(i) . \sum_{i=0}^{t} Db^2(i)}} \quad (9)$$

Step 6: The results were tallied, and the wavelet with the greatest correlation was chosen as the output.

Step 7: High peaks in the wavelet indicated low frequency components, whereas low peaks indicated high frequency components.

Step 8: Peaks were computed using these high and low frequency data.

The number of results successfully detected by the approach was defined as sensitivity. Positive predictivity indicated the likelihood of identifying peaks with the highest value.

sensitivity=TP/(TP+FN) (10)

Positive predictivity=TP/(TP+FP) (11)

D. Classification

The retrieved characteristics in the signals are utilised to determine the person's abnormal heart conditions, irregular respiratory rhythm, and mood. Anger, fear, normalcy, bewilderment, and sadness are the primary categories of a person's emotions. Sinus Bradycardia, Sinus Tachycardia, and Premature Atrial Contraction are

among the heart disorders that can be identified (PAC). The normal sinus rhythm of the heart is 60-100 beats per minute. Peak signals discovered are utilised to detect a person's heartbeat. Each form of aberration and emotion has a peak signal range that is deemed abnormal. The abnormality range for each signal was saved in internal memory and compared to the current peak value of the signal to determine the abnormality kind. In certain circumstances, two separate signals can identify various types of abnormalities. In this situation, a ranking method based on the significance of each signal to the anomaly was employed to detect the mood and abnormality.
Algorithm 2 – Classification using relational weight based decision making algorithm
Input: signal peak value and wave points;
output: abnormalities and mood of a person
Step 1: Set up each form of abnormality's behaviour.
Step 2: Save the value range in internal memory where irregularities may arise.
Step 3: compare the value of each peak signal to the abnormality database recorded in the internal memory.
Step 4: If all of the peak values are within the normal range, the output is categorised as normal; otherwise, it is labelled as abnormal.
Step 5: If any of the signals is in an abnormal range, examine the signal's priority and its impact on the irregularity.

$$S_{max} > S > S_{min} \tag{12}$$

Step 6: Each signal's abnormality range and priority value are saved and sorted in a database.
Step 7: Repeat for all of the signals.
Step 8: If the overall rank value exceeds the threshold, the individual will be advised of the type of anomaly.
This experiment was carried out using the Windows 10 operating system, and the work flow was implemented using MATLAB programming. The results demonstrate that the proposed algorithm performs admirably. The proposed strategy was shown to increase the efficiency and accuracy of clinical practice.

IV. RESULTS AND IMPLEMENTATION

Body sensors monitored the ECG signal, which was then transferred to the cloud through Wi-Fi. The signal is received by the health monitoring personnel from the cloud. Figure 2 depicts the input image.

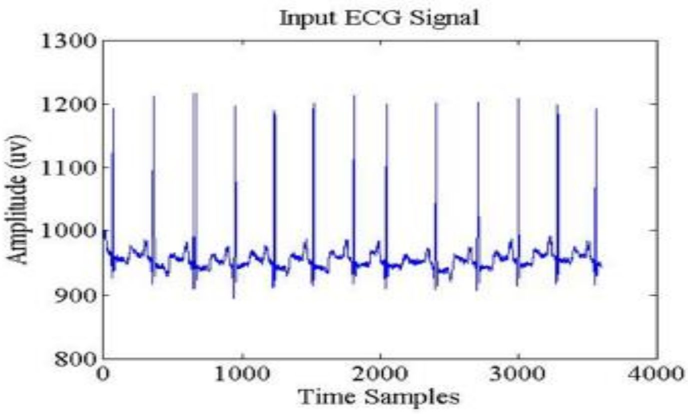

Figure 2: Input ECG signal

Butterworth filtering is used by health monitoring personnel to process the incoming signal. Figure 3 depicts the filtered ecg signal.

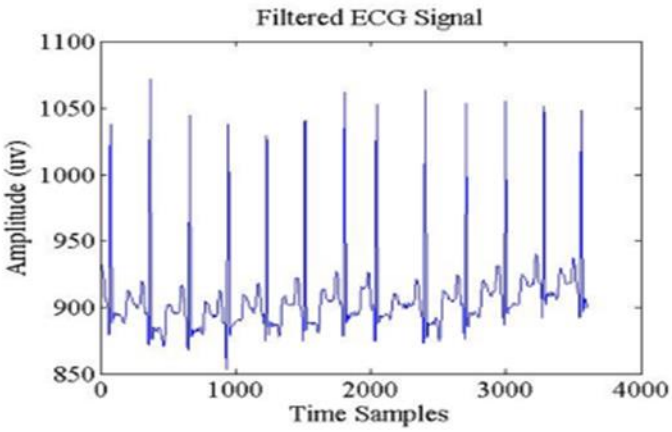

Figure 3: filtered ECG signal

Peak detection was a critical step in emotion identification. This was accomplished using the proposed adaptive discrete wavelet transform. The proposed peak detection algorithm's sensitivity and Positive Predictivity (PP) were compared to the existing Min-Max approximation method. Table 1 displays the proposed algorithm's sensitivity and Positive Predictability.

Table 1 Sensitivity and PP comparison

Sample	Total Peaks (Actual)	True Positive	False Positive	False Negative	Sensitivity	Positive Predictivity
1.	2273	2271	2	4	99.824176	99.912011
2.	1865	1864	1	6	99.679144	99.946381
3.	2187	2185	2	5	99.771689	99.908551
4.	2084	2080	4	4	99.808061	99.808061
5.	2229	2227	2	7	99.686661	99.910274
6.	2572	2569	3	3	99.883359	99.883359
7.	2027	2023	4	4	99.802664	99.802664
8.	2137	2132	5	2	99.906279	99.766027
9.	2532	2524	8	3	99.881282	99.684044
10.	2278	2273	5	2	99.912088	99.780509

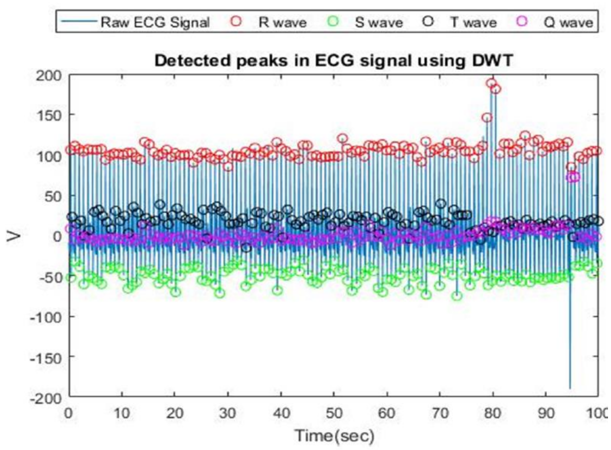

Figure 4. Detected peak signal for Anger person

The rapid increase in the peak value in Figure 4 depicts a person's mood shift. The output was formed by comparing this value to the entire QRS complex. The red dots in the image represented the peak amplitude value of the R wave, the green dots the lowest peak value of the S wave, the black dots the peak value of the T wave, and the pink dots the peak value of the Q wave. Figure 4 depicts a relationship between discrete ECG signal values and a blue line.

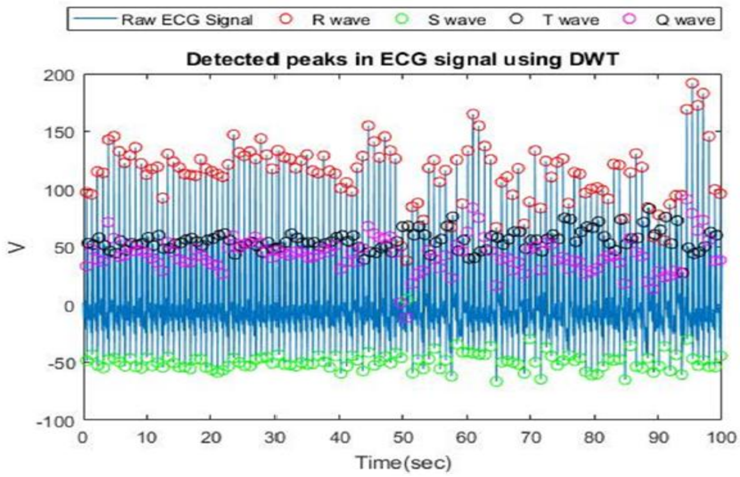

Figure 5. Detected peak signal for confused person or person with anxiety

Figure 5 depicts an individual suffering from anxiety experiencing a shift in heart rate owing to adrenaline output.

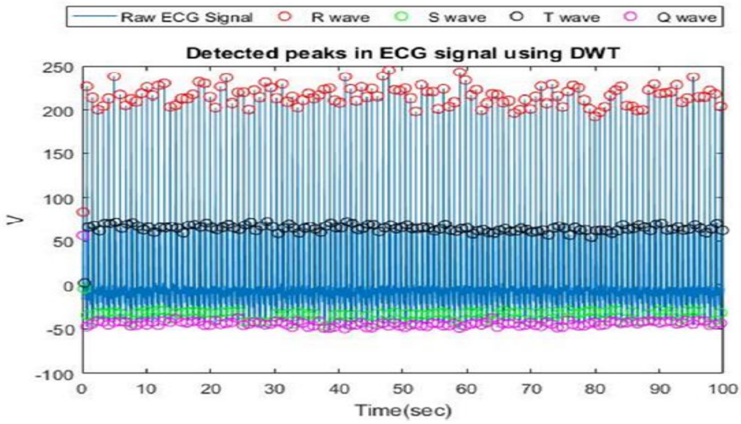

Figure 6. Detected peak signal for happy person

The person experiencing a cheerful mood had a regular RR interval and mQRS interval, and his or her blood pressure appeared to be normal, as illustrated in Figure 6. When the patient was ideal, the heart rate was uniform and there were no variations in the heart rate, but there were significant changes in the RR intervals, as shown in Figure 7.

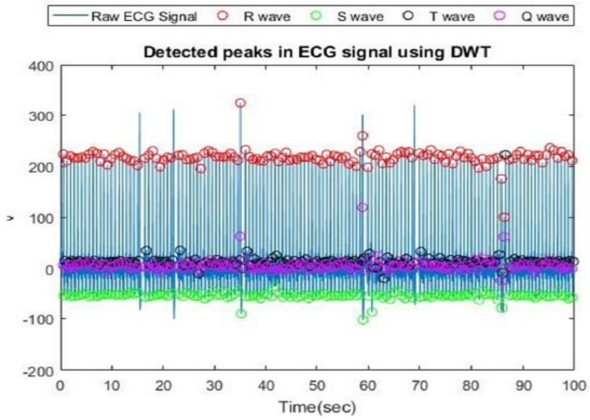

Figure 7. Detected peak signal for ideal person

Figure 7 depicts the ECG peaks of a person experiencing sadness. It was obvious that a person suffering from depression had a lower R peak value than normal persons. The amplitude value of the ECG was much lower than the usual ECG value, as illustrated in Figure 7.

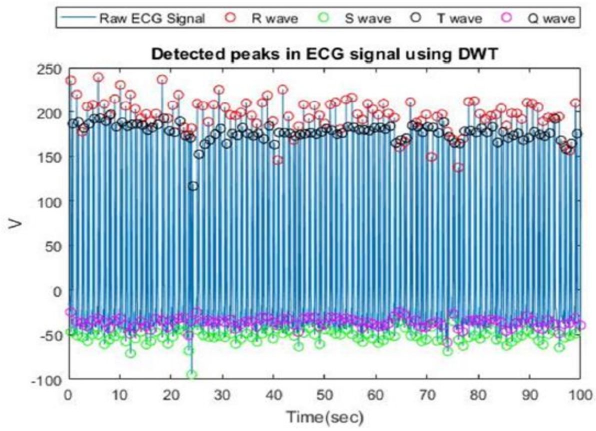

Figure 8. Detected peak signal for depressed person

Peak detection accuracy is critical for emotion categorization. Peak detection was suggested by, and the technique is presented in Figure 8. The QRS gradient and the RR interval were used to classify the anomaly. Figures 9 and 10 depict the deviation gradient of the QRS wave and the RR interval for an ECG signal.

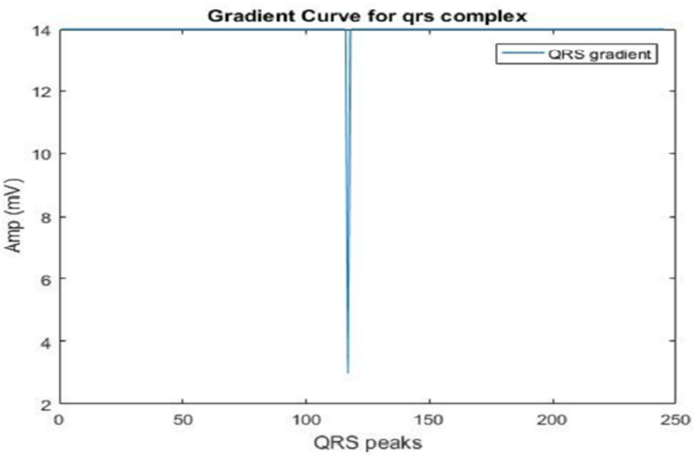

Figure 9. Gradient Curve for QRS Complex*A.Performance Testing – Classification*

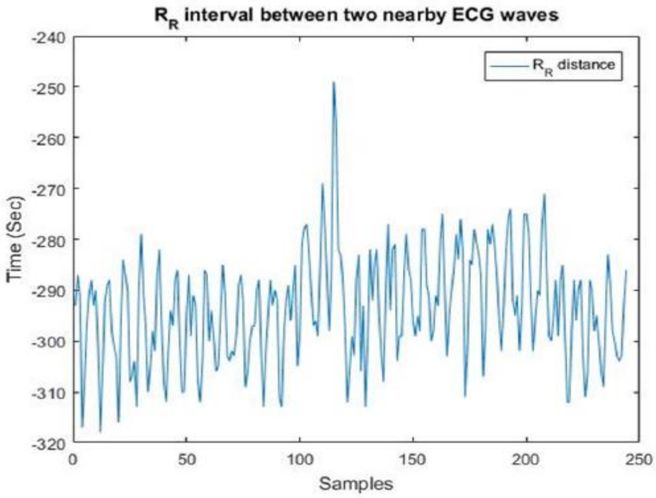

Figure 10. RR interval between two ECG waves

The proposed relational weight-based classification approach was compared to an existing algorithm in terms of classification accuracy. The identical collection of non-fiducial characteristics collected from the signals was utilised by all classifiers. Table 2 compares the classification accuracy of existing and proposed relational weight classifiers.

Table 2: Classification comparison result

Number of Sample ECG signal from Body Area Network	KNN	PSO and RBFNN	ANN	Proposed
300	87.47	89.55	88.5	90.1
400	88.02	90.6	89	94.02
500	89.07	91.87	91.28	95.17
600	90.61	92.2	92.87	96.39
700	91.3	93.4	93.63	97.46
800	92.9	94.65	94.92	98.9
900	93.9	96.3	95.2	99.2

Table 2 compares the proposed relational weight based classifier to various current approaches in terms of accuracy. The accuracy of the findings is calculated by dividing the identified abnormalities by the actual abnormalities.

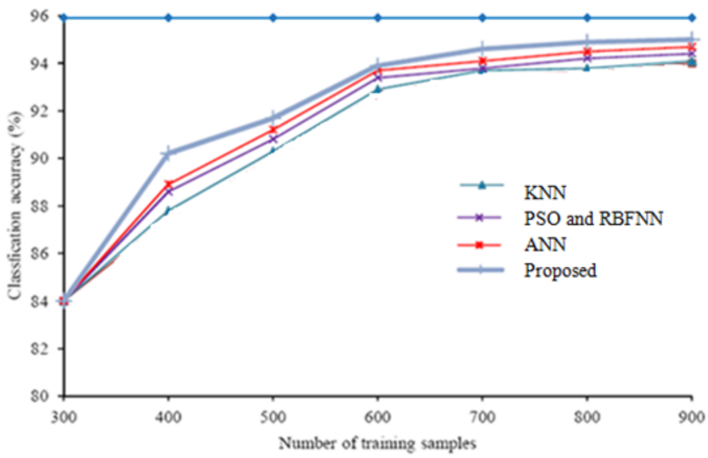

Figure 11. Classification comparison

To get the findings, the proposed technique utilised a combination of signals such as ECG and respiration value. This form of data analysis yields more accurate findings. The proposed classification approach avoided the usage of iterations, resulting in a reduction in computing time and device cost. They also avoided the usage of hidden layers and networks such as machine learning, which reduced device space. A few tests were performed to examine the outcomes of the abnormality.

V.CONCLUSION

The goal of the initiative is to develop an automatic emotion recognition approach that uses ECG signal to provide a better knowledge of a person's health. A unique strategy for noise reduction using the Butterworth filtering technique, feature extraction using the Adaptive Discrete Wavelet Transform technique, and emotion and abnormality classification using a relational based decision-making algorithm is implemented. The proposed relational weight based classifier exhibited as 99.2% efficiency, which were significantly greater than existing classification algorithms. These research algorithms lowered computing time, cost, and storage space in devices. As a result, this categorization is best suited for wearable technology applications in which patients may monitor their health via electronic devices and mobile devices. In the future, improved machine learning algorithms can be used to analyze and predict the sequence of heartbeats to obtain higher performance.

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All the authors mentioned in the manuscript have agreed for authorship, read and approved the manuscript, and given consent for submission and subsequent publication of the manuscript.
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