



## **DEEP LEARNING BASED SLEEP APNEA DETECTION AND CLASSIFICATION IN ECG SIGNAL BY ROBUST FEATURES OF RR AND CNN**

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### **ABSTRACT**

An *electrocardiogram (ECG)* is an important tool for the prediction of several diseases in human life. Hence, in this process, we implement the a machine learning for the classification framework, which is previously trained on a general signal data set is transferred to carry out automatic ECG diagnostics by classifying patient ECG's into corresponding cardiac conditions. The Statistical features are extracted from the signal and then getting the accurate detection of ECG signals with the help of detection of P, Q, R and S waveform. On the other hand, Main focus of this process is to predict the abnormal signals by means of a simple, and easily applicable machine learning technique for the Classification of the selected signals from the dataset. According to the results obtained, the best accuracy was 94%, with a sensitivity and a specificity of 100% and 89.2857%, respectively. The CNN model architecture is based on three convolutional, max pooling and dense layers which automatically extracts distinguishable nonlinear features from the ECG signals and automatically



classify them into normal or abnormal. Thus the results shows that the proposed method achieves to obtain very high performance rates.

**Index Terms** Sleep apnea, electrocardiogram, feature extraction, classification, and convolutional neural network

## 1. INTRODUCTION

Sleep apnea is a sleep problem that takes place whilst respiration is interrupted throughout sleep. There are 3 fundamental kinds of sleep apnea: obstructive sleep apnea (OSA), critical sleep apnea (CSA), and blended sleep apnea. OSA is the most not unusual place kind sleep apnea and is characterised via way of means of partial (hypopnea) or full (apnea) obstruction of the higher airways throughout sleep which limits airflow to the lungs. The apnea-hypopnea index (AHI), calculated as the quantity of apnea and hypopnea occasions consistent with hour of sleep, is used to suggest the severity of sleep apnea

Treatment of sleep apnea can opposite signs including daylight sleepiness, enhance cognitive overall performance and first-class of life, and decrease cardiovascular risk. Polysomnography is a kind of sleep have a look at used as a diagnostic device to decide sleep disorders. This multipara metric take a look at is usually completed in a single day and provides recordings of numerous physiological changes, including brain activity, eye Movement, coronary heart rhythm (ECG), muscle activity, respiration effort, nasal pressure, and blood oxygen saturation levels, at some stage in sleep. The more than one hours of polysomnography statistics are then analysed subjectively to suggest the presence or absence of OSA.



The incidence of apnea and hypopnea activities leads to coronary heart charge variations. The coronary heart charge decreases at some stage in apnea and will increase at some stage in recovery. This characteristic behaviour, coronary heart charge variability, has been used to objectively locate apnea activities the usage of sign processing and gadget gaining knowledge of strategies. Techniques for primarily based totally apnea class should be divided into time- and frequency-area analyses of the with frequency area strategies typically producing higher consequences. Various class strategies had been applied in literature with guide vector machines visible to be popular. In addition, function aggregate is a typically used method for enhancing the class overall performance. The maximum not unusual place method for that is to concatenate more than one function vectors right into an unmarried combined function vector.

However, extra recently, deep gaining knowledge of strategies have proven to outperform those complicated function extraction and choice strategies in numerous duties. The convolutional neural networks (CNN), for detecting apnea and non-apnea activities. CNN has produced encouraging consequences in image class duties and has been more and more carried out in numerous sign class applications. In this paintings, CNN is used for class of the HRV sign computed from an unmarried-lead ECG sign.

The primary contributions are as follows:

- Implementation of characteristic choice ideas aiming at to decide the maximum applicable descriptors
- Benchmark of a couple of classifiers to discover sleep apnea
- Explanatory and up to date country of the artwork on sleep apnea detection techniques.



In this process, we propose an Atrial Fibrillation in ECG signal, to automatically detect the abnormality of the heartbeats using the ECG signals. This classification model mainly consists of three sets of inputs like, Test features, Train features and labels. The Random Forest classifier is used to classify the signal. Most importantly, our proposed approach achieved favourable performances with an accuracy of above 95% in the validation set of dataset, respectively. Due to the stability of the features and less in misclassification, this process achieved the better performance.

## **11. BACKGROUND**

In current years, one of a kind strategies had been proposed with inside the literature for the analysis of sleep apnea detection. It performed a scientific evaluation on category strategies used on computerised structures for sleep apnea analysis, figuring out clusters of classifiers as follows: artificial neural networks, regression, instance-based, Bayesian algorithms, reinforcement learning, dimensionality reduction, ensemble learning, and selection trees. On the only hand, one by one of the followed classifier its accuracy is extraordinarily dependant on an effectiveness functions choice from the multitude of resets of records. On the alternative hand, for the reason that PSG calls for an exhaustive records series fused with the aid of using more than one resets of records inclusive of ECG, electroencephalogram (EEG), electrooculogram (EOG), electromyogram (EMG), an determined fashion with inside the literature is associated with the adoption of a discounted variety of physiological signals as an opportunity technique for sleep apnea detection.

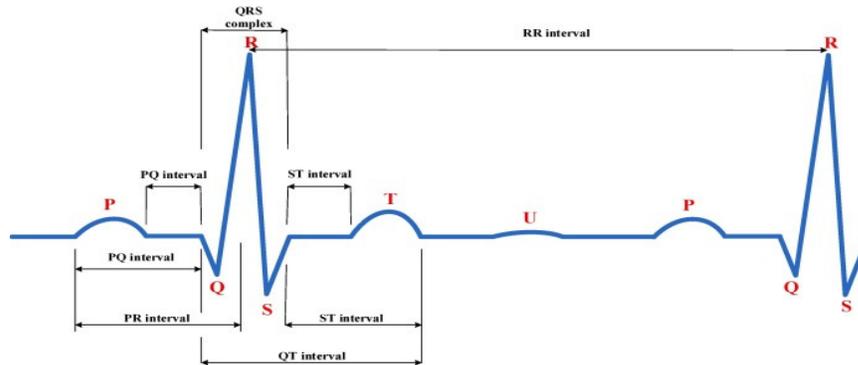


Figure: 1 the ECG Signal

Electrocardiography is the technique of manufacturing an electrocardiogram (ECG), a recording of the coronary heart's electric interest. It is an electro gram of the coronary heart that is a graph of voltage as opposed to time of the electric interest of the coronary heart the usage of electrodes located at the skin. These electrodes discover the small electric adjustments which can be an effect of cardiac muscle depolarization observed via way of means of repolarization throughout every cardiac cycle (heartbeat). Changes with inside the everyday ECG sample arise in several cardiac abnormalities, which include cardiac rhythm disturbances. Traditionally, "ECG" normally approach a 12-lead ECG taken whilst mendacity down as mentioned below.

However, different gadgets can file the electric interest of the coronary heart together with a holder display however additionally a few fashions of smartwatch are able to recording an ECG. ECG indicators may be recorded in different contexts with different gadgets. In a traditional 12-lead ECG, ten electrodes are located at the patient's limbs and at the floor of the chest. The basic value of the coronary heart's electric capability is then measured from twelve exclusive angles ("leads") and is



recorded over a length of time. In this way, the general value and course of the coronary heart's electric depolarization is captured at every second in the course of the cardiac cycle.

There are three main components to an ECG:

The P wave, which represents depolarization of the atria; the QRS complex, which represents depolarization of the ventricles, and the T wave, which represents repolarization of the ventricles

During every heartbeat, a healthful coronary heart has an orderly development of depolarization that begins off evolved with pacemaker cells with inside the sinoatrial node, spreads all through the atrium, and passes the atrioventricular node down into the package deal of his and into the Purkinje fibres, spreading down and to the left all through the ventricles. This orderly sample of depolarization offers upward push to the feature ECG tracing. To the skilled clinician, an ECG conveys a huge quantity of facts approximately the shape of the coronary heart and the feature of its electric conduction system. Among different things, an ECG may be used to degree the charge and rhythm of heartbeats, the scale and function of the coronary heart chambers, the presence of any harm to the coronary heart's muscle cells or conduction system, the outcomes of coronary heart drugs, and the feature of implanted pacemakers. [12] discussed about Reconstruction of Objects with VSN. By this object reconstruction with feature distribution scheme, efficient processing has to be done on the images received from nodes to reconstruct the image and respond to user query.

In authors provided a snooze apnea detection version the usage of each HR, and RR alerts extracted from the ECG sign. The Support Vector Machine (SVM) and the Random Forest (RF) had been implemented to categorise every day and sleep apnea episodes. The observations found out that each classifiers have yielded better



accuracies the usage of functions from HR sign compared to RR sign. In addition, the 10-fold cross-validation proven that the SVM has much less blunders price than the RF. Also primarily based totally at the ECG sign, authors in blended the RR and the EDR sign as cornerstone of a snooze apnea device. The SVM, and the Stacked Auto encoder Based Deep Neural Network (SAE-DNN) had been taken into consideration for classification. The experimental outcomes proven that SVM coupled with the Radial Basis Function (RBF) kernel plays higher compared to SAE-DNN. Similarly, authors in proposed a snooze apnea detection device primarily based totally on EDR and RR alerts. The overall performance turned into decided the usage of the bushy K-approach clustering and the SVM classifier. The experiments found out that the RBF kernel-primarily based totally SVM has yielded the very best accuracy. In authors extensively utilized the EDR sign, however this time mutually the HRV. The experimental outcomes proven that exclusive functions meet exclusive importance with inside the device overall performance. Main findings found out that the polynomial kernel primarily based totally KELM furnished better common accuracy compared to linear, RBF, and wavelet. Moreover, the inclusion of better order spectral and non-linear functions primarily based totally on EDR and HRV alerts had been endorsed.

Finally, the deep learning methods on the sleep apnea detection. In this paper, we present a technique in which consists of data pre-processing using the wavelet transform, classifying using the Euclidean Distance Classifier.

## **111. METHOD AND MATERIAL**

Based on classes discovered from the aforementioned literature we formulate the speculation that: the ECG on my own is a promising sign to apply for sleep apnea detection. In addition, a good enough function choice is preponderant for the classifier



accuracy, and the set of rules discovered its suitability to address apnea ECG signals. With the ones notions in mind, we advanced a machine to stumble on sleep apnea wherein choice function and classifiers have been bench market. The waft of the proposed version is depicted in including: pre-process, function extraction, classification, and function choice. These structure is defined in element with inside the sections below.

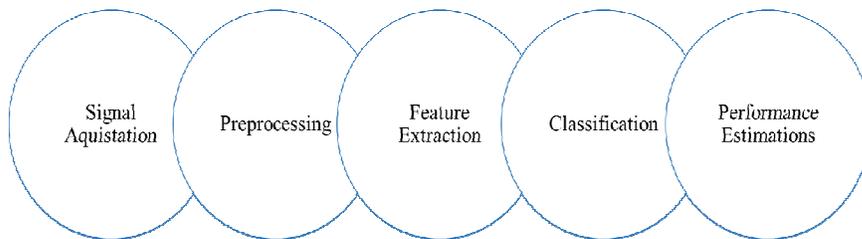


Figure: 2 Cycle diagram of ECG signal

## **A.DATABASE**

Our experiments had been primarily based totally at the Physio Net [41] database. The dataset contains 50 of 3612 ECG amplitude samples over an interval of

1000 sec. The amplitude is defined the database 50 samples. The recorded in this database selected in 7 samples.

## B.FLOW DIAGRAM

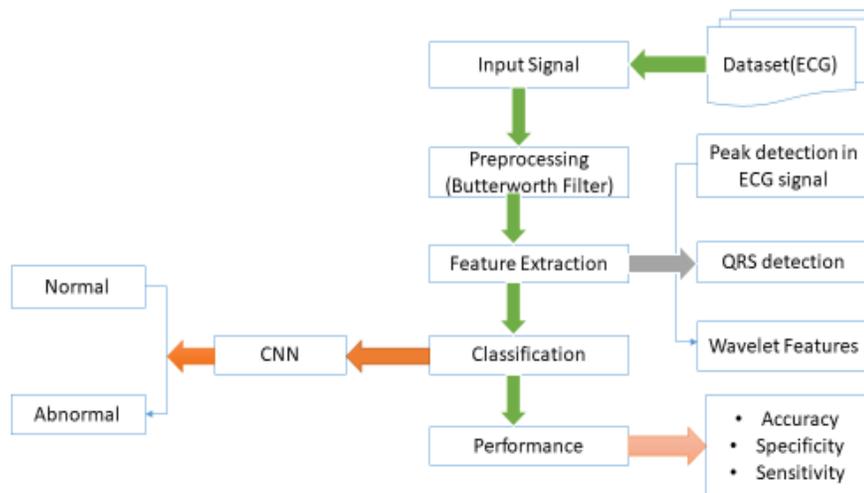


Figure: 3 Flow chart in ECG signal

## C.INPUT SIGNAL

Electroencephalography (ECG) is an electrophysiological monitoring method to record electrical activity of the brain. It is typically non-invasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used in specific applications. ECG measures voltage fluctuations resulting from ionic current within the neurons of the brain. In clinical contexts, ECG refers to the recording of the brain's spontaneous electrical activity over a period of time, as recorded from multiple



electrodes placed on the scalp. Diagnostic applications generally focus on the spectral content of ECG, that is, the type of neural oscillations (popularly called "brain waves") that can be observed in ECG signals. [10] discussed that Helpful correspondence is developing as a standout amongst the most encouraging procedures in remote systems by reason of giving spatial differing qualities pick up.

ECG is most often used to diagnose epilepsy, which causes abnormalities in ECG readings. It is also used to diagnose sleep disorders, coma, encephalopathies, and brain death. ECG used to be a first-line method of diagnosis for tumours, stroke and other focal brain disorders, but this use has decreased with the advent of high-resolution anatomical imaging techniques such as magnetic resonance imaging (MRI) and computed tomography (CT). Despite limited spatial resolution, ECG continues to be a valuable tool for research and diagnosis, especially when millisecond-range temporal resolution (not possible with CT or MRI) is required. [4] discussed that the activity related status data will be communicated consistently and shared among drivers through VANETs keeping in mind the end goal to enhance driving security and solace.

Derivatives of the ECG technique include evoked potentials (EP), which involves averaging the ECG activity time-locked to the presentation of a stimulus of some sort (visual, somatosensory, or auditory). Event-related potentials (ERPs) refer to averaged ECG responses that are time-locked to more complex processing of stimuli; this technique is used in cognitive science, cognitive psychology, and psychophysiological research.

#### **D.PRE-PROCESSING**

The database used for assessment has a extensive form of QRS complexes and P- and T-wave morphologies and the statistics have noise and artefacts that arise in a



scientific setting. In line with this, as QRS detection is primarily based totally at the time of incidence of the QRS complicated with inside the ECG sign its miles pertinent to lessen the sign noise because it has a tendency to lower the classifiers' performance. Thus, the Solway filter [36] become used to put off the baseline wander, because it decreases the accuracy of the EDR. Afterwards, the acquired sign become subtracted from the authentic to yield the waveform. With an ECG sign loose from noise, it's miles viable to hit upon the R-peaks and the QRS complicated without lacking or misclassifying a heartbeat. The TEO algorithm become implemented off-line over the sign on the idea of the discrete time domain. In addition, to hit upon the R-waves, the sign become processed in a one-2d window. An adaptive threshold at 10% of the most R amplitude become implemented because of the contrasting amplitude of the R-peaks alongside the sign. If the output at  $t_0$  exceeds the brink and no extra fee become determined with inside the subsequent 0.25 seconds, then  $t_0$  is marked as an R-peak. [8] discussed because of various appealing focal points, agreeable correspondences have been broadly viewed as one of the promising systems to enhance throughput and scope execution in remote interchanges.

### **Butterworth Filter**

The process or device used for filtering a signal from unwanted component is termed as a filter and is also called as a signal processing filter. To reduce the background noise and suppress the interfering signals by removing some frequencies is called as filtering. The Butterworth filter is a type of signal processing filter designed to have a frequency response as flat as possible in the pass band. It is also referred to as a maximally flat magnitude filter. There are various types of Butterworth filters such as low pass Butterworth filter and digital Butterworth filter.



## **E.FEATURE EXTRACTION**

The features extraction is proposed by the QRS detection, peak detection in ECG signal, Wavelet features.

### **Peak Detection in ECG signal**

Generally, the generally used automated ECG recognition strategies consist of parts: traits extraction, and waveform category and recognition. In this paper, the QRS wave detection set of rules is used because the traits extraction technique. The R wave is the maximum outstanding feature waveform in ECG indicators because it commonly has the very best or lowest cost in QRS complicated wave. The squaring method intensifies the slope of the frequency reaction curve of the spinoff and helps limitation fake positives because of T waves with better than typical spectral energies. The set of rules is capable of correctly stumble on QRS complexes with inside the presence of the intense noise. We primarily based totally all judgments of correctness upon the annotations with inside the database. Each annotation at the vicinity and morphology of a beat became decided through arbitration among cardiologists who needed to be in settlement on all beats in order for an ECG facts section to be positioned with inside the database.

### **QRS Detection**

The QRS complex is a combination of three of the graphic deflection seen on a typical ECG. This study proposes a real-time QRS detection and R point recognition method with low computational complexity while maintaining a high accuracy. The enhancement of QRS segments and restraining of P and T waves are carried out by the proposed ECG signal transformation, which also leads to the elimination of baseline wandering. In this study, the QRS fiducial point is determined based on the detected crests and troughs of the transformed signal. Subsequently, the R point can be



recognized based on four QRS waveform templates and preliminary heart rhythm classification can be also achieved at the same time.

### **Wavelet Features**

A wavelet collection is an illustration of a square-integrable (real- or complex-valued) characteristic with the aid of using a positive orthonormal collection generated with the aid of using a wavelet. This article gives a formal, mathematical definition of an orthonormal wavelet and of the crucial wavelet transform.

### **F.CLASSIFICATION**

Distance based method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time. For classification tasks, the output of the random forest is the class selected by most trees. For regression tasks, the mean or average prediction of the individual trees is returned. Decision of classification correct for decision trees' habit of over fitting to their training set. Distance based generally outperform decision trees, but their accuracy is lower than gradient boosted trees. However, data characteristics can affect their performance.

### **Convolutional Neural Networks**

In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of artificial neural network, most commonly applied to analyse visual imagery. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on the shared-weight architecture of the convolution kernels or filters that slide along input features and provide translation equivariant responses known as feature maps. Counter-intuitively, most convolutional neural networks are only equivariant, as opposed to invariant, to translation. They have applications in image



and video recognition, recommender systems, image classification, image segmentation, medical image analysis, natural language processing, brain-computer interfaces, and financial time series. [2] proposed a secure hash message authentication code. A secure hash message authentication code to avoid certificate revocation list checking is proposed for vehicular ad hoc networks (VANETs).

## G.PERFORMANCE ESTIMATION

The performance of the proposed techniques is evaluated task of apnea or non-apnea (Normal or Abnormal) classification on database. The performance following accuracy, sensitivity and specificity.

The performance of the process is measured in terms of performance metrics like Accuracy, Sensitivity, Specificity and time consumption.

TP - is the total number of correctly classified foreground (true positives).

TN - is the total number of wrongly classified foreground (true negatives).

FN - is the total number of false negatives, which accounts for the incorrect number of foreground pixels classified as background (false negatives).

FP - is the total number of false positives, which means the pixels are incorrectly classified as foreground (false positives). The performance values were calculated for each frames of the input video based on the metrics described above.

$$ACC = \frac{(TP + TN)}{(FP + TN) + (TP + FN)}$$

$$Sensitivity = \frac{TP}{(TP + FN)}$$

$$\text{Specificity} = \frac{TN}{(FP + TN)}$$

Where, P: Positive, N: Negative, TP: True Positive, TN: True Negative, FP: False Positive, FN: False Negative

#### IV.RESULT AND DISCUSSION

This work proposed the use of convolutional neural network of apnea or non-apnea detection. The dataset is downloaded from Physionet. The dataset contains 50 of 3612 ECG amplitude samples over a interval of 1000 sec.

##### Input signal

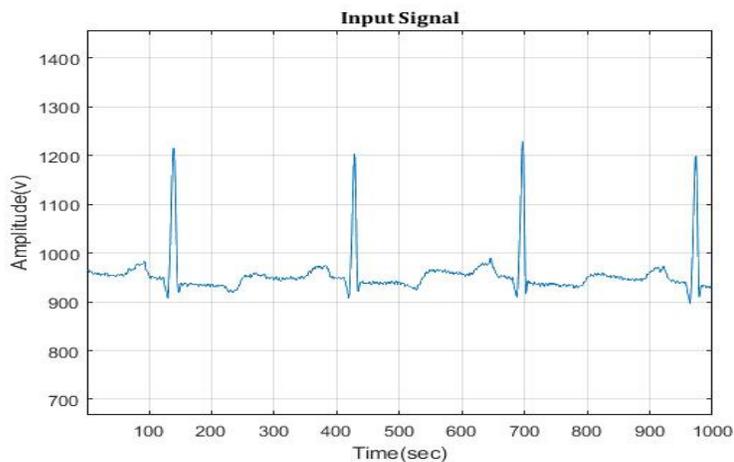


Figure: 4 Plot the input signal in 7 ECG sample



## Pre-Processing

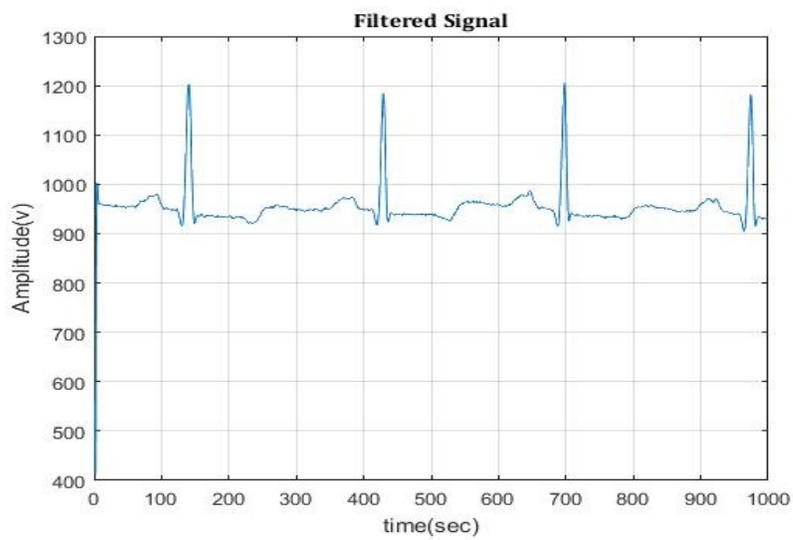


Figure: 5 Noise Removal Using Butterworth Filter

## Feature Extraction

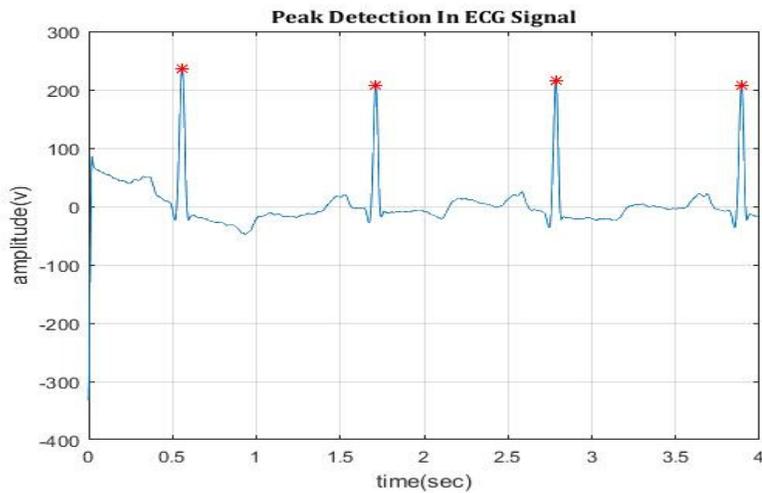


Figure: 6 Peak detection in ECG signal

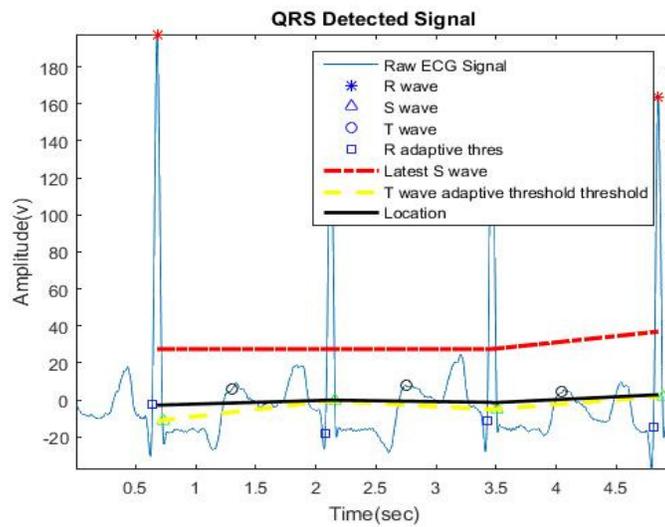


Figure: 7 QRS Detection



	1	2	3	4
1	1.9072e+03	0	-0.0919	

Figure: 8 Wavelet Feature

### **Classification**

Label (1:25) = 1; Normal Signal

CNN identified as = Normal Signal

Label (26:50) = 2; Abnormal Signal

CNN identified as = Abnormal Signal

If result = 1

CNN identified as = Normal Signal

If result = 2

CNN identified as = Abnormal Signal

### **Performance Estimation**

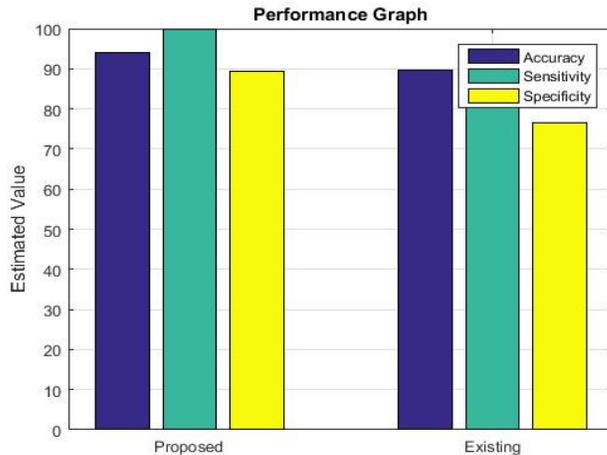


Figure: 9 proposed of ECG signal

This work proposes the use of interpolated ECG derived CNN for detecting sleep apnea epochs. With an accuracy of 94%, sensitivity of 100%, and specificity of 81.2857%, the proposed method is seen to perform better than previously used time and frequency domain features and CNN features.

## V.CONCLUSION

This paper study is particularly to find out a low load, immoderate reputation rate, and immoderate-overall performance OSA detection method. In this have a study, a multiscale feature extraction set of policies based mostly on deep studying and a classifier with weighted-loss and time-dependence were proposed for OSA detection. The CNN model was used to robotically extract multiscale competencies from the RRIS sequences, which advanced the richness of the extracted competencies just so it is able to greater effectively dig the multiscale information of HRV. The loss feature of the classifier was modified, and a weighted cross-entropy loss feature was achieved to triumph over the trouble of facts imbalance. Taking beneath neath attention the temporal dependence amongst segments, the use of advanced the general



overall performance of the classifier. In the verification check based definitely on the apnea-ECG database, the method used in this have a study obtains an accuracy of 89% this is better than some specific strategies studying the equal database. Since this method is based mostly on a single-lead ECG signal, it is able to be implanted on a wearable device to treatment the trouble of the need for OSA monitoring supplied through manner of approach of civilian cell devices or medical monitoring devices.

## **V1.FUTURE WORK**

In future, more number of dataset will be included and then to compare with the other type of machine learning or deep learning algorithms

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