Identification of Sleep Apnea using Deep Learning and Machine Learning Techniques on ECG Data

Maturi Tanuj
Department of Computer Science and Engineering
Amrita School of Computing, Bengaluru
Amrita Vishwa Vidyapeetham, India.
charantanujma63@gmail.com

Bhavana Chekuri
Department of Computer Science and Engineering
Amrita School of Computing, Bengaluru
Amrita Vishwa Vidyapeetham, India.
chekuri.bhavana@gmail.com

Preethi Reddy Mudireddy
Department of Computer Science and Engineering
Amrita School of Computing, Bengaluru
Amrita Vishwa Vidyapeetham, India.
preethir1402@gmail.com

*Suja Palaniswamy**
Department of Computer Science and Engineering
Amrita School of Computing, Bengaluru
Amrita Vishwa Vidyapeetham, India.
p_suja@blr.amrita.edu

***Abstract*— Sleep Apnea(SA) patients have regular spells of halting or decreasing airflow to the lungs for a period of time exceeding ten seconds. Determining the right medications and treatment methods requires identifying SA episodes accurately. SA is detectable through a number of methods such as polysomnography, ECG signals etc. A more efficient method, in terms of time and effort, would be a machine learning or deep learning based detection through an ECG signal. This work follows two separate methods that can predict the risk of SA for the user. The first method is a machine learning prediction based on various features such as ESS, BQ, BMI etc., based on whose values, the risk of the individual having SA can be predicted. The second method is based on ECG image data. The PhysioNet ECG SA V1.0.0 dataset which contains 50 recordings from 50 people is used in this work. The dataset is pre-processed and categorised into four classes namely, A(severe apnea), B(modelate apnea), C(normal apnea), X(non apnoeic). The VGG16-LSTM model turned out to be the best model for classification with a F1-Score of 90.83%.**

***Keywords*— SA, ECG signal. Machine learning, Deep Learning, VGG16, LSTM**

I. Introduction

SA is a serious sleep disorder that affects millions of people worldwide. It is a condition characterized by breathing pauses or shallow breathing during sleep, which can lead to negative health consequences if left untreated.This work focuses on what SA is, why it occurs, how it impacts life, the various modalities that can be used for detecting it, why early detection is important, why machine learning and deep learning techniques can be used, why polysomnography is difficult, why ECG is more preferred, what factors in an ECG signal help detect SA, how these factors or features are extracted, and the basic process to extract these features and detect SA using machine learning and deep learning approaches.

SA happens when the muscles at the rear of the larynx fail to maintain the air passages open during a sleep cycle, leading to interruptions in or shallow respiration. Severe SA and centralized SA are the two primary kinds of SA. Obstructive Sleep Apnea(OSA) happens when the respiratory tract is blocked by a soft tissue lining the throat, while central SA arises when the central nervous system fails to send the right electrical signals to the muscles that are responsible for breathing. Obesity, smoking, alcohol consumption, and genetics are some of the factors that can increase the risk of developing SA.

It is critical to identify SA early, as post corrective measures could lead to improved health outcomes and a better quality of life. It can also reduce the risk of developing other health conditions that are associated with SA, such as hypertension and heart disease. Utilizing machine learning and deep learning methods may enhance the precision of identifying SA and expedite its detection at an earlier stage.

Polysomnography is difficult to perform and can be uncomfortable for patients. ECG monitoring, on the other hand, is non-invasive and can be performed at home. ECG signals contain valuable information that is immaculate to find SA. Some of the factors in an ECG signal that help detect SA include heart rate variability, heart rate turbulence, and QT variability. These factors can be extracted using signal processing techniques and used as features in machine learning and deep learning algorithms for SA detection.

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The basic process for detecting SA using machine learning and deep learning approaches involves several steps. First, the ECG signal is pre-processed to remove noise. Then, features such as heart rate variability, heart rate turbulence, and QT (the time from the start of the Q wave to the end of the T wave) variability are extracted from the pre-processed signal. Feature selection techniques are used to select the most relevant features for classification. Different algorithms related to artificial intelligence and neural networks, including but not limited to regression models, vector machines, decision forests, and Convolutional Neural Networks(CNN) that can be used for SA, are trained on the selected features to classify the ECG signals as normal or abnormal. The performance of the algorithms is evaluated using metrics such as accuracy, F1 score, sensitivity, and specificity.

In addition, as part of this work, a website has been developed to detect SA. The website has been hosted in local system that allows users to enter their personal information such as height, weight, BMI, heart rate, pulse, and other relevant data. The website then uses this data to assess the likelihood of the user having SA. It is also capable of detecting different levels of SA by analyzing the ECG signal. The website has the option to upload the person's ECG image, which is then used to classify different intensity levels of SA as A, B, C and X.

The contributions of this work are as follows:

- Developed machine learning and deep learning models to detect SA using ECG and evaluated those. It has been identified that deep learning models performed well.
- A hybrid model has been developed which has outperformed the individual models which is higher compared to literature.

II. Literature Survey

SA is a prevalent sleep problem and is characterised by periodic cessation or reduction in breathing during sleep, resulting in low oxygen levels in the body. Diseases like heart attack, stress are caused due to this disturbance in sleep patterns[1-2]. Polysomnography (PSG) has historically been used to diagnose SA. But, it is expensive and time-consuming[3-5]. The non-invasive and reasonably priced Electrocardiogram (ECG) technology examines the electrical activity of the heart[6]. An extensive study on various literature was done on the use of ECG signal characteristics for SA identification. Al Mamun et.al [7] used audio data and employed a bandpass filter to extract the sound signal between 100 and 1000 Hz, as well as a feature extraction method based on sound interval frequency. A few research papers used single lead ECG image data for SA detection [8-10]. Bahrami et.al [11] initially pre-processed the ECG signals, and then segmented for further processing. Dey et al [12] divided the ECG recording into one-minute segments and performed the operation. Every captured wave is assumed to be composed of multiple successive sections that run in parallel for one minute. Medical professionals mark and examine each section to determine whether or not it shows an apnoeic episode. The ECG signal is then split into OSA and non-OSA classes using a DNN. Heart Rate Variability (HRV) and ECG-Derived Respiration (EDR) were extracted from each ECG signal using a Sgolay filter, and these measurements were then utilised to train, test, and validate the classifiers. Few research papers have done second-by-second signal segmentation and to train the necessary features for event identification, a 1D-CNN is used[13-14]. After pre-processing and segmenting ECG data, sleep apnoea was identified using machine learning and deep learning techniques[15]. Logistic regression, Gauss naïve Bayes', Gauss process, supporting vector machines, k-nearest neighbours, decision trees, additional trees, random forest, Ada Boost, gradient enhancement, multi-layer perceptron, and a majority vote were all traditional machine learning approaches[16]. The classification findings were improved using an HMM-based post-processing technique. ANN, ANN-HMM, SVM, SVM-HMM, Decision fusion were applied on ECG image data. The ApneaNet was proposed, which is a proprietary Deep CNN and LSTM-based model with 13 layers which outperformed the other models like SVM and MLP in terms of computing cost while maintaining accuracy at the same time[17]. For accomplishment validation, six optimal classifiers (Decision tree, NB, KNN, Deployment Assistant, ensemble DTree, and SVMs) were used. For performance comparison, four deep neural network models viz.CNNs, Long Short-Term Memory(LSTM), Recurrent Neural networks(RNNs), and CNN-LSTMs were deployed.

Overall outcomes of these works display that using ECG data to detect OSA is one of the best cost-effective techniques with good results. The deep learning classifiers outperformed the traditional classifiers in detecting OSA from ECG signals. Among the deep learning classifiers, the hybrid models achieved the greatest score, with an average score of 94.8%. Most of the existing research works were performed only on the PhysioNet dataset in which they trained on half of the data but in this work, training was done on the complete dataset. Many papers were not based on one minute segmentation of signal images. In this work, two kinds of segmentations were done, i.e, one minute and five minute segmentations according to the process adopted.

III. Proposed Methodology

Figure1 represents the process flow of how each dataset is pre processed, trained and tested for the detection of OSA. It represents two datasets. The feature dataset is processed and trained and tested to evaluate how well it performs. The PhysioNet ECG image dataset was transformed using a wavelet transform function, followed by the removal of noise in the signal images. Then, the images are segmented. Fig 2 represents how the images are segmented into five minute segments. In five minute segments, the signal segments were labeled based on the presence of R peaks. Finally, they were trained and tested using several deep learning models. Figure 3 represents how the images are segmented into one minute segments. In one minute segments, the R peaks were detected initially, followed by the extraction of time-domain, frequency-domain, and heart rate variability features. Then, training and testing was done using several machine learning models.

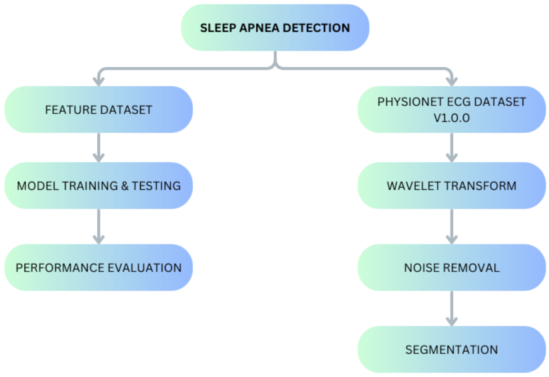

Fig. 1 Flow diagram showing the flow of process in the study of datasets.

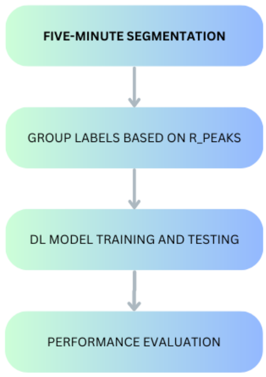

Fig. 2 Flow diagram showing the process flow for five minute segmentation

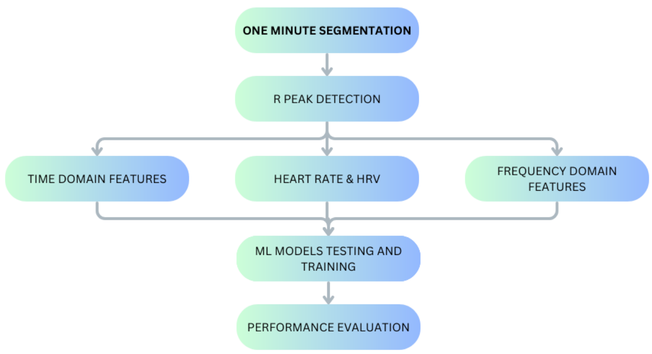

Fig. 3 Flow diagram showing the process flow for one minute segmentation

A. Feature Dataset

Feature dataset [18] and PhysioNet dataset [19] are used in this work. The feature dataset consists of 12 attributes, namely: Gender, BQ, ESS, BMI, Weight, Height, Head, Neck, Waist, Buttock, Age, AHI(Apnea Hypopnea Index). All the attributes are trained on several machine learning models to predict if the person has SA or not. This is done based on the AHI value range.

These features can only help to identify individuals with a higher risk of SA but not sufficient to diagnose the disease. The feature dataset is used to train machine learning models.

B. Signal Dataset

Implementation models were developed using PhysioNet Apnea-ECG Database v1.0.0, and their performances were compared. The database includes 70 recordings from 32 people who were separated into four groups: A, B, C, and X. These people were aged 44–11, had an AHI of 24–25, were 7 females, 175–6 in height, and weighed 86–22 pounds. In this dataset, 13 people are classified as normal if their AHI is less than 5, 13 people are classified as having severe SA if their AHI is more than 30, and 6 people have mild to moderate apnea if their AHI is between 5 and 30. The 70 recordings had almost 8 hrs of data and were digitized at 100 Hz.

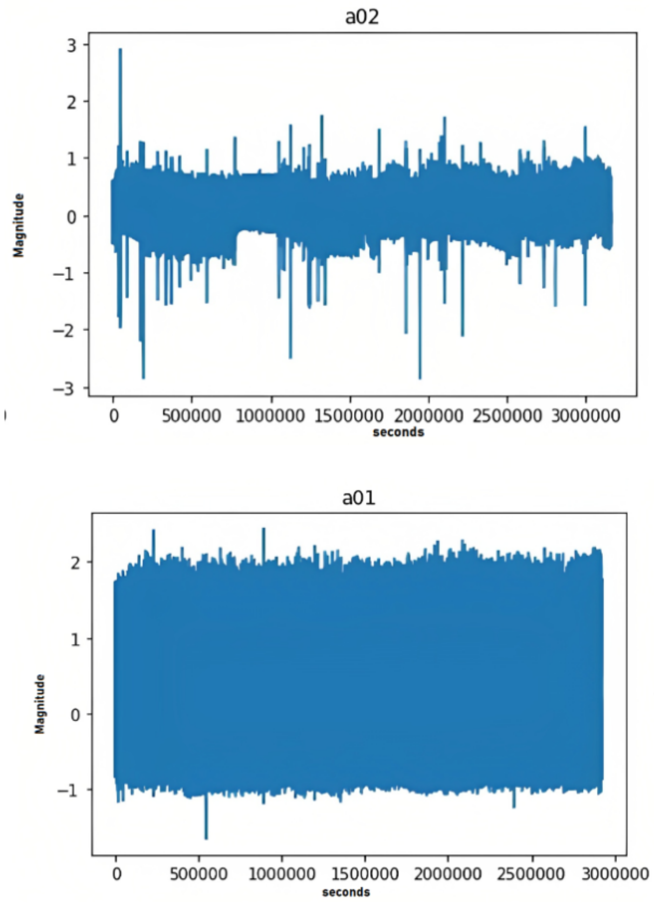

Fig. 4 Examples of the digitised signals.

The ECG Signal that is sampled at 100 Hz is first digitized by converting them to pickle files. Fig. 4 is an example of 1 minute segments of an ECG signal. Each 1-minute segment of the ECG recording contains 6000 data points (i.e., 100 samples per second * 60 seconds per minute = 6000 data points per minute). The x-axis represents time in seconds and the y-axis represents magnitude.

C. Wavelet Transform

Wavelet transform is a mathematical technique used for analysing signals or data in both time and frequency domains. Unlike the Fourier transform, which uses a fixed set of sinusoidal basis functions, the wavelet transform employs wavelets that are localized in both time and frequency. In the context of SA detection in an ECG signal using DL, wavelet transform can be used to preprocess the signal and extract relevant features. SA is a sleep disorder characterized by pauses in breathing or shallow breathing during sleep. These apnea events can manifest as distinct patterns in the ECG signal.Wavelet transform helps in detecting SA in an ECG signal by decomposing the signal into different frequency bands with varying resolutions. These features are then used as input to a DL model for classification or detection. For the purpose of this work, a continuous wavelet transform was performed to obtain a spectrogram. The mother wavelet used for this purpose is the ricker wavelet which is a part of the scipy.signal module. The signal.cwt function is then called to perform the continuous wavelet transform using the Ricker wavelet with the specified parameters.

D. Noise Removal

Noise removal is crucial in signal processing to enhance the signal quality as well as accurate detection and extraction of desired information from the signal. It also ensures no bias during the final classification. In this work, the dataset contains various files named a01, a02, ... , c05 with extensions .ecg, .apn, .qrs. The ecg files contain the recorded ecg signal of the patient. The first and last 3 seconds of the ecg signals are removed to eliminate noise. The apn folder contains a string of labels for each minute detailing apnea (A) and non apnoeic (N) moments. The first and last characters of this string are removed as they contain random characters. The similar case is performed with the qrs files.

E. Segmentation

For the purpose of this work, two types of segmentation are performed, one is where the ECG signal is segmented into one minute segments and the other is where they are divided into 5 minute segments. The files present in the qrs and apn format are divided into segments corresponding to the size of the ECG signal segmented.

F. Machine Learning Approach

The ECG segments that are one minute long are used for the purpose of classification of apnea during sleep using machine learning models. Features are extracted from these segments and then are fed to the machine learning models. The different features extracted are heart rate, time domain features and frequency domain features. To obtain the above features, the R peaks must be located.

1) *R peak Detection*: R peaks are the highest positive deflections in an ECG wave. There are multiple ways to detect these R peaks. In this work, the Pan-Tompkins algorithm [20] is used for detecting the R peaks which is shown in Fig5.

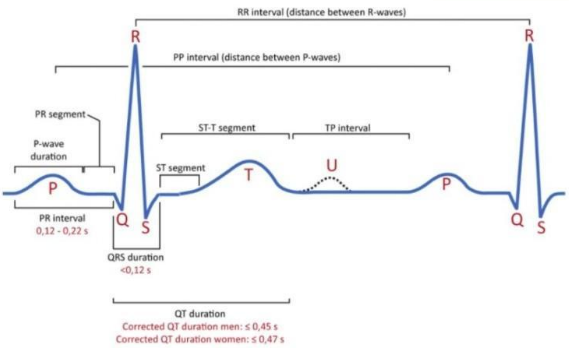

Fig. 5 Parts of an ECG signal

2) *Heart Rate*: The first feature that is extracted from the signal is the heart rate of the patient. The heart rate can be found using the above found R peaks. The first step is to find the RR intervals. The RR intervals are found using the np.diff function. It is basically the difference between two consecutive R peaks. The heart beat is calculated as the reciprocal of the RR intervals multiplied by 60 as each segment is of a minute duration.

3) *HRV*: HRV stands for heart rate variability which is the measure of variability in time intervals between consecutive heartbeats. It is calculated as 1000 multiplied by the RR interval.

4) *Time Domain Features*: Time domain features are the signal's characteristics in the time dimension. These features are calculated directly from the signal's waveform and capture properties such as amplitude, duration, and temporal changes. In this work, the time domain features that are extracted are :Mean of RR intervals, Standard Deviation of RR intervals, Difference between RR intervals, Mean of the difference between successive RR intervals, Standard Deviation of the difference between successive RR intervals, Root Mean Square of successive RR intervals, Percentage of RR intervals that differ by more than 50 milliseconds, Percentage of RR intervals that differ by more than 20 milliseconds, Coefficient of Variation of inter-beat intervals.

5) *Frequency Domain Features*: In this work, the frequency domain features like PSD are extracted using the periodogram method. After obtaining the heart rate time series using the Pan Tompkins method, the waves are resampled to a higher frequency. It is amplified by 5 Hz. This is done using an inbuilt python package called resample from the scipy library i.e., Scipy.signal.resample. Then the heart rate time series is interpolated at a fixed time duration using linear interpolation. This is done using

scipy.interpolate,intrepid function. Then the periodogram method is applied to get a Power Spectral Density (PSD) estimate which is done using the signal.periodogram function from the Scipy library. All high frequencies above 0.1 Hz are set to 0.

6) *Model Training and Testing*: The features extracted are time domain features, frequency domain features, HRV, Heart rate, the apn labels, the timestamps etc., are fed to machine learning models. The models used for this classification are :

- Logistic Regression
- SVM
- GBM: Gradient Boost method

G. Deep Learning Approach

For the deep learning approach, various deep learning and ensemble models are implemented. The five minute segmented signals are fed as input to these models.

Inception V3: Inception v3 is an image recognition model that has been shown to achieve higher than 78.1% accuracy on the ImageNet dataset. The model represents the result of several concepts explored over time by many academics. Inception v3 is a CNN that was developed as a Googlenet module to aid with picture processing and object recognition. It is the third version of Google's Inception CNN, which was first unveiled as part of the ImageNet recognition challenge.

VGG16: VGG-16 is a 16-layer

. A pre-trained version of the network trained on over a million photos from the ImageNet database may be loaded [1]. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals. It is regarded as one of the best vision model architectures to date. The most distinguishing feature of VGG16 is that instead of a huge number of hyper-parameters, they concentrated on having convolution layers of 3x3 filter with stride 1 and always utilised the same padding and maxpool layer of 2x2 filter with stride 2.

VGG19: VGG19 is a VGG model version that consists of 19 layers (16 convolution layers, 3 Fully connected layers, 5 MaxPool layers and 1 SoftMax layer). Other VGG variations include VGG11, VGG16, and more. VGG19 has a total of 19.6 billion FLOPs. VGG19 is a sophisticated CNN with pre-trained layers and a strong grasp of what constitutes an image in terms of form, colour, and structure. VGG19 is a highly deep neural network that has been trained on millions of photos with challenging classification tasks.

MobileNet: A CNN built for mobile and embedded vision applications. They are based on a simplified design that uses depthwise separable convolutions to construct lightweight deep neural networks with reduced latency for mobile and embedded devices. MobileNets are a subset of CNNs that are tiny, low-latency, and low-power models that may be used for categorization, detection, and other common tasks. Because of their compact size, these deep learning models are ideal for application on mobile devices.

ZFNet: ZFNet is a traditional CNN. Visualizing intermediate feature layers and the functioning of the classifier inspired the design. When compared to AlexNet, the filter widths and stride of the convolutions are lowered. It had five shared convolutional layers, four max-pooling layers, three dropout layers, and three fully connected layers. In the first layer, it employed a 77 size filter and a lower stride value. The softmax layer is ZFNet's last layer.

AlexNet: AlexNet is an 8-layer CNN. A pre-trained version of the network trained on over a million photos from the ImageNet database may be loaded. The pretrained network can categorise photos into 1000 different item categories, including keyboards, mice, pencils, and other animals. The Alexnet includes eight levels of parameters that may be learned. The model is composed of five layers, the first of which is a max pooling layer, followed by three fully connected layers, and each of these levels, save the output layer, uses Relu activation.

LSTM: It is a kind of RNN that may learn long-term dependencies, particularly in sequence prediction tasks. LSTMs use a number of 'gates' that regulate how information in a data sequence enters, is stored in, and exits the network. A typical LSTM has three gates: a forget gate, an input gate, and an output gate. These gates function as filters and each have their own neural network.

BiLSTM: A bidirectional LSTM (BiLSTM) layer learns the bidirectional long-term relationships between time steps in a time series or sequence data. When you want the network to learn from the whole time series at each time step, these dependencies might be advantageous. More particular, it was discovered that BiLSTM models outperform ARIMA and LSTM models in terms of prediction. BiLSTM models were likewise shown to attain equilibrium substantially slower than LSTM-based models. Forecasting is an important yet difficult aspect of time series data research.

Gated Recurrent Unit (GRU): The GRU functions similarly to a LSTM with a forget gate, but with fewer parameters since it lacks an output gate. The GRUis a form of RNN that offers benefits over LSTM in certain instances. GRU consumes less memory and is quicker than LSTM, although LSTM is more accurate when utilising datasets with longer sequences.

IV. Results and discussion

All the models implemented in this study are evaluated on the four basic metrics of evaluation: Accuracy, Precision, Recall and F1-Score. The average of the scores from all classes are considered for the evaluation. Out of 70 recordings, all of them were used for training and testing respectively.

Table I shows the various machine learning models used for classification based on the feature dataset.

TABLE I
Comparison of Models for Feature Dataset

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1 score**
LR	66.64%	64.22%	62.19%	62.75%
LDA	95.91%	93.04%	90.19%	91.99%
GNB	71.30%	68.17%	65.99%	77.07%

SVM	68.07%	64.71%	59.48%	62.01%
QDA	93.81%	90.88%	88.61%	89.73%
DT	77.57%	74.70%	72.89%	73.79%
RF	87.33%	84.14%	82.90%	83.52%
AD	76.61%	73.46%	71.61%	72.51%
KNN	52.48%	50.73%	53.35%	56.41%
GB	66.17%	62.97%	60.87%	61.91%
MR	76.87%	73.58%	70.71%	72.61%

As seen in Fig. 6, Linear Discriminant Analysis(LDA) was the best-performing model among the others, followed by Quadratic Discriminant Analysis(QDA) and Random Forest. The LDA model has a function which maximises the distance between classes and performs well in classification problems. This could be a contributing factor towards its performance.

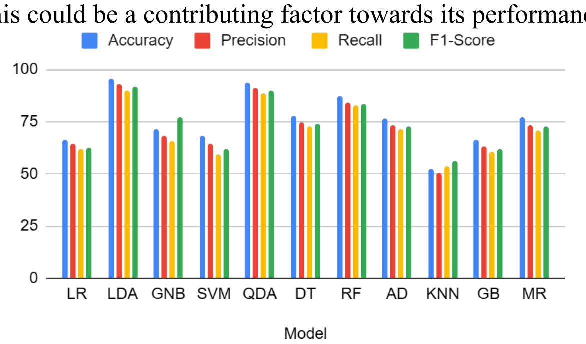

Fig.6 Flow diagram showing the flow of process in the study.

Table II details the performance of the machine learning models in the classification using the PhysioNet ECG signal dataset. It can be seen that the SVM model has the best performance with an accuracy of 83%.

TABLE II
PERFORMANCE METRICS OF MACHINE LEARNING MODELS FOR THE PURPOSE OF CLASSIFYING THE PhysioNet ECG SIGNAL DATASET.

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	82%	78.11%	74%	76%
SVM	83%	78.03%	76%	77%
GBM	81%	80%	71%	75%

It is also observed in Fig. 7 that all models have performed in an almost similar manner where accuracy is the metric which gained the greatest score. But when closely compared, SVM performed the best. SVM can easily handle nonlinearity of ECG signals with the help of a sigmoid kernel function.

VGG16 is a deep CNN capable of learning hierarchical representations from raw image data without feature extraction. Which could be a contributing reason for the accuracy of the models to be the greatest with an accuracy of 87.62%. This can be seen in Table III.

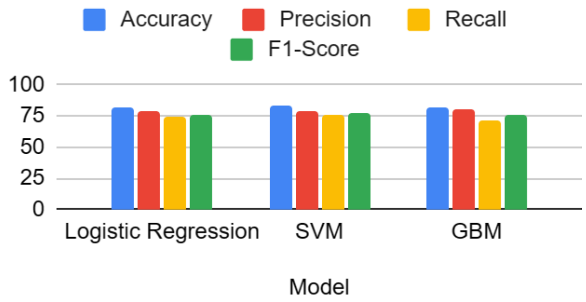

Fig. 7 Flow diagram showing the flow of process in the study.

TABLE III
PERFORMANCE METRICS OF DEEP LEARNING MODELS FOR CLASSIFYING THE PHYSIONET ECG SIGNAL DATASET

Algorithm	Accuracy	Precision	Recall	F1 Score
AlexNet	86.49%	83.67%	81.64%	82.20%
Inception	85.36%	82.49%	79.64%	81.44%
VGG 16	86.26%	83.33%	81.06%	82.18%
VGG 19	85.75%	82.62%	80.44%	81.52%
LSTM	81.52%	78.16%	72.93%	75.46%
GRU	81.93%	80.18%	72.80%	75.86%
VGG16+LSTM	87.62%	84.15%	82.34%	83.24%
VGG16+GRU	86.78%	83.59%	82.35%	82.97%
VGG19+LSTM	86.06%	82.90%	81.06%	81.96%
VGG19+GRU	85.62%	82.42%	80.32%	81.36%
AlexNet+LSTM	86.32%	83.03%	80.16%	82.06%
AlexNet+GRU	86.11%	80.82%	83.98%	82.37%

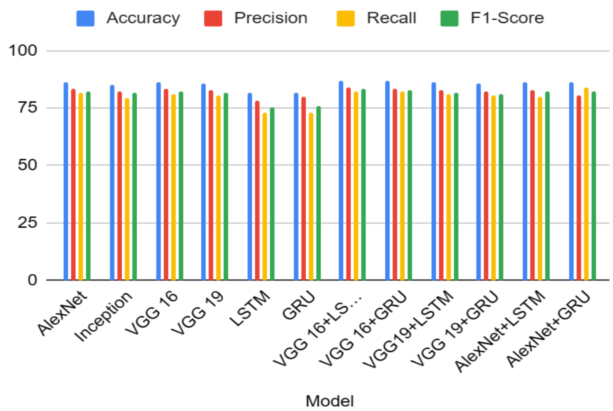

Fig 8. Flow diagram showing the flow of process in the study.

It is observed from Fig. 8 that LSTMs are good at analysing the temporal dynamics of ECG signals. They model sequential data and this shows that a hybrid model outperformed individual models.

V. Conclusion and Future Scope

In this study, a thorough evaluation of several machine learning and deep learning methods has been presented for the identification of SA from single-lead ECG in a unified framework. CNN-based deep learning models outperform DRNNs in our implementation, which handled brief segments of ECG (one minute). The best detection results were obtained using the inception V3 using adam optimizer, followed by VGG-LSTM and VGG16-GRU. Based on the findings, the usage of hybrid deep neural networks or an inception model for SA diagnosis using ECG is advocated. This study will help researchers who work on SA to create and choose suitable machine learning and deep learning algorithms for the identification of the same. The future work will include improving the accuracy of the predictions. In addition, exploring other sources of data, such as EEG signals or breath analyzers, physiological signals associated with sleep episodes could be considered.

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