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"Integrating Machine Learning and Deep Learning Techniques for Sleep Apnea Detection Using Single-Lead ECG"

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ABSTRACT: *Sleep apnea (SA) is a sleep disorder characterized by snoring and chronic sleeplessness, potentially leading to severe conditions such as high blood pressure, heart failure, and cardiomyopathy (enlargement of heart muscle tissue). Electrocardiogram (ECG) signals play a vital role in detecting SA as they can reveal abnormal cardiac activity. Recent studies on ECG-based SA detection have focused on feature engineering techniques that extract specific characteristics from multi-lead ECG signals and use them as inputs for classification models.*

This research applied various machine learning and deep learning algorithms for SA detection. Conventional machine learning methods included linear and quadratic discriminant analyses, logistic regression, Gaussian naïve Bayes, Gaussian process, support vector machine, K-nearest neighbor, decision tree, extra tree, random forest, AdaBoost, gradient boosting, multi-layer perceptron, and majority voting. In the domain of deep learning, models such as InceptionV3, convolutional networks (e.g., AlexNet, VGG16, VGG19, ZFNet), recurrent networks (e.g., LSTM, bidirectional LSTM, gated recurrent unit), and hybrid convolutional-recurrent networks were employed.

The dataset was split into training, validation, and test sets to optimize model parameters, tune hyperparameters, and evaluate model generalizability. A 5-fold cross-validation strategy was utilized to ensure that each recording appeared once in the test set. Among machine learning models, the Voting Regressor (VR) achieved the highest accuracy of 78.95%. In the deep learning category, InceptionV3 outperformed all others with an accuracy of 98.31%.

This study highlights the comparative performance of machine learning and deep learning algorithms in detecting sleep apnea and offers a foundation for extending these approaches to identify other sleep-related events..

Keywords: Machine Learning, Deep Learning, Sleep Apnea, Single Lead ECG, Sleep apnea

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I. INTRODUCTION

Sleep significantly influences health and quality of life, occupying nearly one-third of a human's lifespan. The sleep cycle consists of two primary phases: rapid eye movement (REM) and non-rapid eye movement (NREM). Compared to NREM, REM sleep is marked by increased sympathetic activity, cardiac instability, and hemodynamic fluctuations. NREM sleep is characterized by reduced oxygen consumption, heart rate, and blood pressure, whereas REM sleep sees an increase in these parameters. Sleep apnea can occur during any sleep phase but is more prevalent during REM sleep, primarily due to the heightened relaxation of upper airway muscles during this period.

The prevalence of sleep disorders is on the rise, affecting an estimated 70 million individuals in the United States alone. These disorders are linked to increased morbidity and mortality rates. Common sleep disorders include insomnia, sleep-breathing disorders, central hypersomnolence disorders, circadian rhythm sleep-wake disorders, parasomnias, and movement disorders, with sleep-breathing disorders (SBDs) being the most prevalent.

SBDs are categorized into four types: obstructive sleep apnea (OSA), central sleep apnea (CSA), sleep-related hypoventilation, and sleep-related hypoxia. OSA, caused by upper airway obstruction, affects approximately one billion people worldwide, making it the most common form of sleep apnea. CSA, less prevalent, arises when the brain fails to effectively communicate with the breathing muscles. While OSA can occur in both REM and NREM phases, it is generally more severe during REM sleep. In contrast, CSA is predominantly associated with the NREM phase

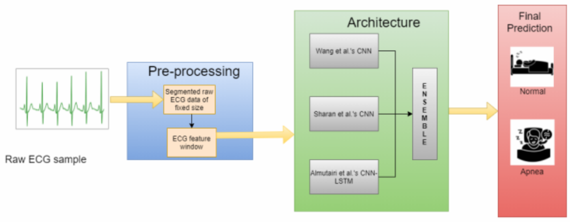

Fig.1: Example figure

Accurate, inexpensive, and portable devices that identify and monitor sleep episodes are necessary to prevent and treat cardiovascular, behavioural, and other health concerns associated with sleep apnea. There has been a significant amount of study on the creation of automated algorithms for the diagnosis of sleep apnea using a range of physiological signals, with ECG showing the most promising results in terms of both convenience and accuracy [2, 4], [5]. Apnea detection with a single-lead electrocardiogram (ECG) opens up the possibility of designing and developing wearable devices based on a single sensor.

II. LITERATURE REVIEW

Detection of sleep apnea from single-lead ECG: Comparison of deep learning algorithms:

Apnea is a common sleep condition that has a negative influence on human health and quality of life. Accurate automated sleep apnea detection methods are required for assessing long-term sleep data and monitoring and managing its side effects and repercussions. Deep learning algorithms are of special relevance among diverse techniques for autonomous identification of sleep apnea using biosignals because, unlike standard machine learning algorithms, they do not depend on expert-crafted characteristics. We created and tested a variety of deep learning models for detecting sleep apnea from a single-lead electrocardiogram (ECG) data in this study. The R-peak amplitude and R-R intervals from the ECG were extracted, and power spectral analysis was used to align the R-peak amplitude and R-R intervals in frequency domain. Convolutional neural network (CNN), long short-term memory (LSTM), bidirectional LSTM, gated recurrent unit, and deep hybrid models were built and tested. Deep learning techniques were tested on an apnea-ECG dataset of 70 recordings, which was separated into a learning set of 35 records and a test set of 35 records. With a hybrid CNN and LSTM network, the best accuracy, sensitivity, specificity, and F1-score on the test data were 80.67%, 75.04%, 84.13%, and 74.72%, respectively. Deep learning studies offer potential for better apnea detection.

Classifier precision analysis for sleep apnea detection using ecg signals:

This article details a research on the effectiveness of developing classifiers for the identification of sleep apnea moments based on a minute-to-minute Electrocardiogram (ECG) signal, comparing the accuracy of several classifiers. A Sgolay filter was used to each ECG signal to extract the Heart Rate Variability (HRV) and ECG-Derived Respiration (EDR), which were then utilised for classifier training, testing, and validation. In a second step, the same traits were expanded to determine if all of the categorised features were relevant. The greatest accuracy was 82.12%, with sensitivity and specificity of 88.41% and 72.29%, respectively, according to the data. This research demonstrates the significance of selecting the best classifier for a certain issue, as well as selecting and using the best features for improved accuracy. These intriguing early-stage findings may lead to more research to enhance the classifiers for potential real-world applications. The suggested model's performance was compared to previous techniques for detecting sleep apnea.

A novel approach osa detection using single-lead ECG scalogram based on deep neural network:

Obstructive sleep apnea (OSA) is the most prevalent and severe breathing disorder that commonly causes breathing to stop for more than 10 seconds while sleeping. The traditional method for treating OSA detection is polysomnography (PSG). However, this method is expensive and time-consuming. To address the aforementioned issue, an acceptable and new approach for interpreting sleep apnea utilising ECG were recording is being developed. For many years, the approaches for OSA analysis based on ECG have been studied. Early study focused on extracting traits, which are fully dependent on the expertise of human professionals. This research looks at a unique strategy for predicting sleep apnea condition based on a convolutional neural network (CNN) and a pre-trained (AlexNet) model. The 2D scalogram pictures are obtained after filtering a per-minute segment of a single-lead ECG recording using continuous wavelet transform (CWT). Finally, a CNN-based deep learning method is used to improve classification performance. The suggested model's efficiency is compared to earlier approaches that employed the same datasets. The proposed CNN-based technique achieves 86.22% accuracy and 90% sensitivity in per-minute segment OSA classification. Our study successfully classifies all aberrant apneic recordings with 100% accuracy based on per-recording OSA diagnosis. Our OSA analysis model using a time-frequency scalogram achieves good independent validation performance with several cutting-edge OSA categorization techniques. The experimental findings shown that the suggested strategy offers great performance outcomes while being minimal in cost and complexity.

Obstructive sleep apnea detection using convolutional neural network based deep learning framework:

This letter describes a high-accuracy automated obstructive sleep apnea (OSA) diagnosis approach based on a deep learning framework that employs a convolutional neural network. The proposed work creates a system that analyses single lead electrocardiography data from patients and diagnoses the patient's OSA status. The findings reveal that the suggested technique has several benefits in addressing such problems, and it greatly outperforms the current methods. The current technique removes the need for separate feature extraction and classification algorithms to identify OSA. The proposed network performs feature learning as well as supervised feature classification. The system is computationally demanding, but it can reach a very high degree of accuracy—a margin of more than 9% on average when compared to other published material to date. The approach is also resistant to noise contamination of the signals. Even with pessimistic signal-to-noise ratio estimates in mind, the previously described approaches cannot outperform the current method. The software for the algorithm described here might be a strong candidate for inclusion in a module for a portable medical diagnostic system.

III. METHODOLOGY

The first automated approaches for detecting apnea events were standard machine learning algorithms. Due to the intricacy of physiological inputs and the limited feature extraction capacity of traditional machine learning approaches, recent research has developed toward more difficult deep learning models. Because of advancements in computing power, deep learning algorithms have outperformed their classical machine learning counterparts by being able to automatically extract the bulk of representative characteristics. The performance of the algorithms is difficult to compare owing to the range of algorithms built for the detection of sleep apnea, the numerous datasets and physiological signals used to train them, the various validation procedures, and the performance metrics used to evaluate the algorithms.

Disadvantages:

1. It is impossible to compare the algorithms' efficacy.
2. Because of the complexity of physiological data and the limitations of traditional machine learning algorithms in extracting features, current research has shifted toward more difficult deep learning models.

In this article, we give a fair and impartial assessment of several conventional machine learning and deep learning algorithms for detecting the occurrence of sleep apnea using a single-lead ECG. All tests are run using the same dataset and circumstances to correctly analyse and compare the performance of different algorithms. In contrast to most research, we employed three sets of data to adjust the model hyperparameters: a training set to train the model parameters, a validation set to determine the model's optimal hyperparameters, and a test set to verify the generalizability of the produced models on unseen data.

Advantages:

1. It was revealed that hybrid deep models with the highest accuracy, sensitivity, and specificity perform the best in terms of detection.
2. Deep learning models outperform traditional machine learning approaches.

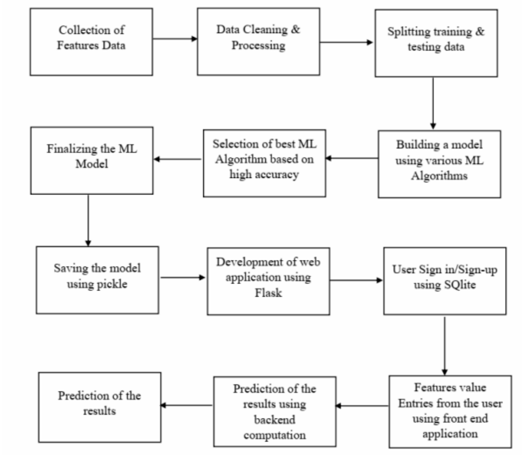

Fig:2 System architecture for Feature data

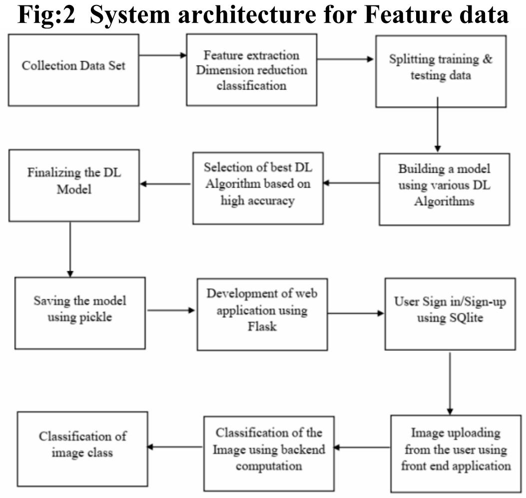

Fig:3 System architecture for Image data

Sl No	Machine Learning Model (Algorithm)	Accuracy of the model %	5-Fold cross validation mean accuracy %
1.	Linear Regression (LR)	52.16	38.61
2.	Random Forest (RF)	60.26	35.78
3.	ElasticNet (EN)	51.06	38.67
4.	Decision Tree (DT)	26.43	-38.50
5.	Majority Rule/Voting Regressor (VR)	**78.95**	**41.33**
6.	Naïve Bayes (NB)	51.91	38.97
7.	Gaussian Process (GP)	51.50	39.27
8.	Support Vector Machine (SVM)	48.16	32.18
9.	KNeighbors (KN)	44.76	14.11
10.	AdaBoost (AB)	24.96	0.73
11.	Multilayer Perceptron (MLP)	54.90	40.34
12.	Gradient Boosting (GB)	59.61	40.17
13.	Stacking Regressor (SR)	11.38	9.78

Table:1 Accuracy and 5-Fold Cross validation accuracy comparison of various ML models

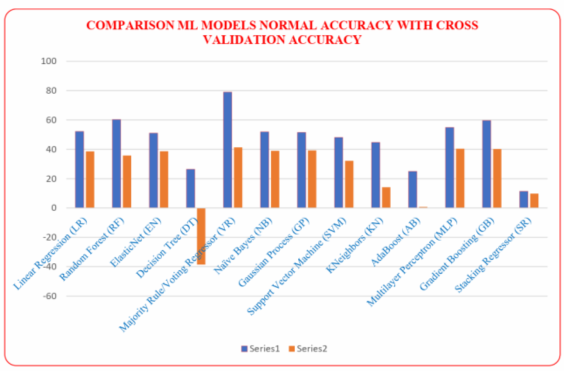

Fig:4 Comparison ML Models Normal Accuracy with Cross Validation Accuracy

Sl No	Deep Learning Model (Algorithm)	Training		Validation	
		Loss	Accuracy	Loss	Accuracy
1.	InceptionV3	**7.09**	**98.31**	**6.01**	**98.62**
2.	VGG16	95.73	76.56	95.30	74.53
3.	VGG19	88.97	77.03	92.11	75.00
4.	MobileNet	29.61	94.22	31.48	78.28
5.	ZFNet	0	0.31	0	0.31
6.	AlexNet	86.62	96.25	135.4	82.34
7.	LSTM with CNN using Xception	0	1	0	0.65
8.	BiLSTM	0	0.50	0	10.06
9.	GRU	0	0.56	0	10.06
10.	Hybrid ZFNet + LSTM	0	0.44	0	10.06
11.	Hybrid ZFNet + BiLSTM	0	0.31	0	10.06
12.	VGG16 + LSTM	0	0.81	0	10.06
13.	VGG16 + BiLSTM	0	0.88	0	10.06
14.	VGG16 + GRU	0	0.81	0	10.06
15.	VGG19 + BiLSTM	0	0.94	0	10.06

Table:7.3 Deep learning models training and validation details

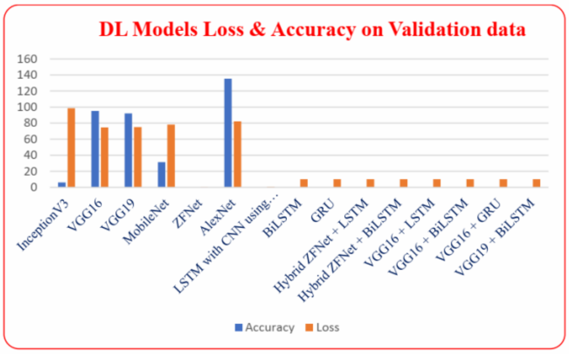

Fig:5 DL Models Loss & Accuracy on Validation data

MODULES:

To implement aforementioned project we have created the modules listed below

1. Linear regression, Random forest, Elastic net, decision tree, nave bayes, SVM, KNN, Adaboost,MLP, Gradient boosting, Guassian process, Stacking regressor, Majority rule/Voting classifier, Linear discriminant analysis, Quadratic discriminant analysis for feature data.
2. Inceptionv3, VGG16, VGG19, MobileNet, ZFNet, AlexNet, LSTM, BiLSTM, GRU, Hybrid ZFNet (LSTM, BiLSTM, GRU), Hybrid AlexNet (LSTM, BiLSTM, GRU), Hybrid VGG16 (LSTM, BiLSTM, GRU), Hybrid VGG19 (LSTM, BiLSTM, GRU), Hybrid VGG19 (LSTM, BiLS (LSTM, BiLSTM, GRU) for image based data.

This model Inceptionv3 and voting classifier Regressor are used to forecast user input since they provide improved accuracy.

IV. IMPLEMENTATION

ALGORITHMS:

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 convolutional neural network that was developed as a Googlenet module to aid with picture processing and object recognition. It is the third version of Google's Inception Convolutional Neural Network, which was first unveiled as part of the ImageNet Recognition Challenge.

VGG16: VGG-16 is a 16-layer convolutional neural network. A pretrained 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 layer, 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 convolutional neural network (CNN) built for mobile and embedded vision applications. They are based on a simplified design that use depthwise separable convolutions to construct lightweight deep neural networks with reduced latency for mobile and embedded devices. MobileNets are a subset of convolutional neural networks 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 convolutional neural network. 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 convolutional neural network. A pretrained 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: LSTM is an abbreviation for long short-term memory networks, which are utilised in Deep Learning. It is a kind of recurrent neural networks (RNNs) 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.

GRU: Gated recurrent units (GRUs) are a recurrent neural network gating technique established in 2014 by Kyunghyun Cho et al. The GRU functions similarly to a long short-term memory (LSTM) with a forget gate, but with fewer parameters since it lacks an output gate. The Gated Recurrent Unit (GRU) is a form of Recurrent Neural Network (RNN) that offers benefits over long short term memory (LSTM) in certain instances. GRU consumes less memory and is quicker than LSTM, although LSTM is more accurate when utilising datasets with longer sequences.

V. EXPERIMENTAL RESULTS

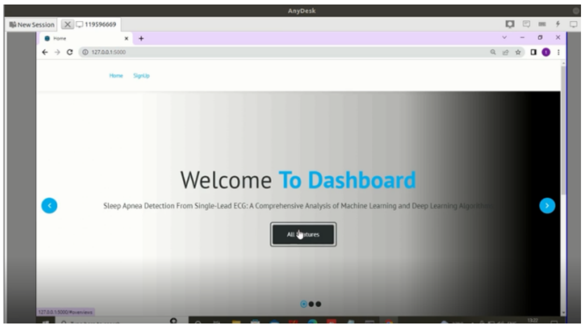

Fig.3: Home screen

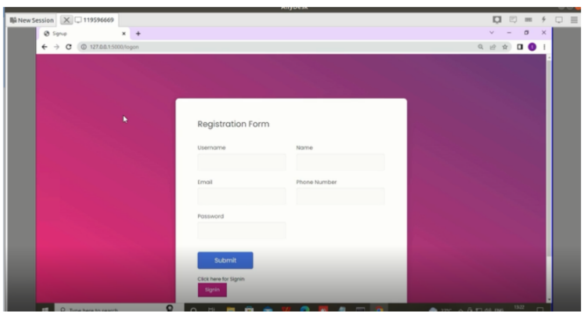

Fig.4: User registration

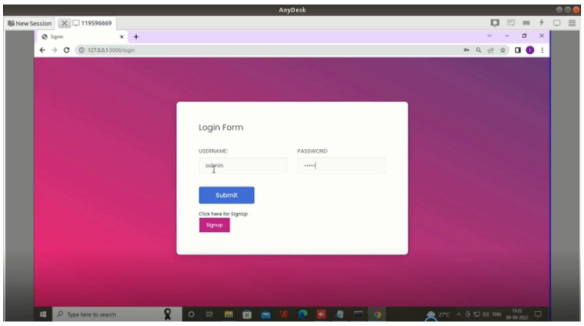

Fig.5: user login

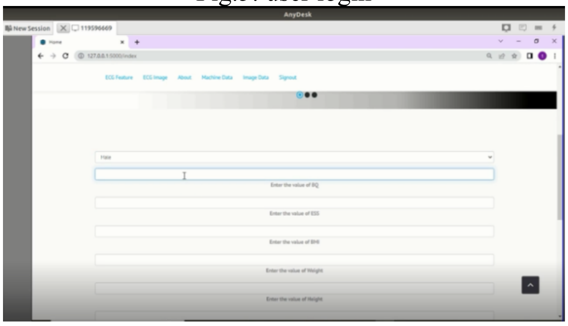

Fig.6: Main screen

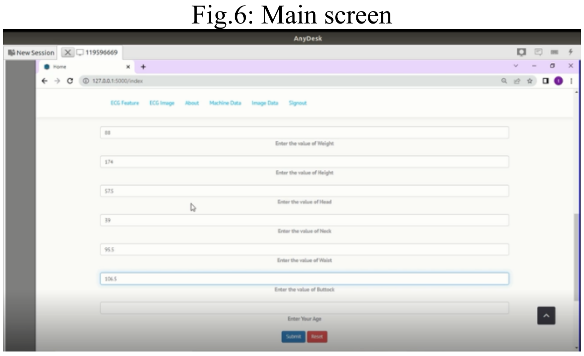

Fig.7: User input

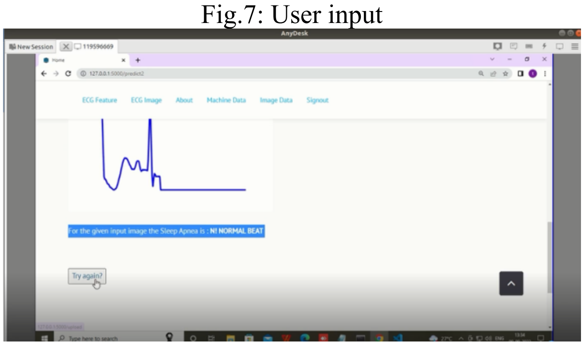

Fig.8: Prediction result

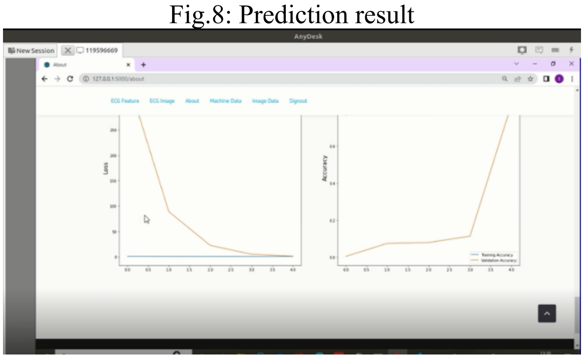

Fig.9: Accuracy graph

VI. CONCLUSION

In this paper a comprehensive comparison between different machine learning and deep learning algorithmsfor the detection of sleep apnea from single-lead ECG analysed.Several machine learning and deep learning classifiers were employed to diagnose the OSA. The performances of the proposed models were validated and tested using the ECG dataset and ECG images. Among the machine learning classifiers, our results indicated that the Voting regressor contributed to the highest performance. Similarly in deep learning inception V3 contributed to the highest performance. This work provides valuable information to sleep apnea researcherson the design and selection of appropriate machine learning anddeep learning algorithms for the detection of sleep apnea.

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