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Research article

Comparison of ALEXNET and GOOGLENET convolutional neural network models to detect obstructive sleep apnea using single-channel electrocardiogram

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ABSTRACT

Obstructive Sleep apnea (OSA) is a type of sleep disorder caused due to respiratory collapse during sleep. This sleep disorder generally goes undiagnosed and neglected. Severe OSA may cause arrhythmia, sudden death, high blood pressure, and other cardiac anomalies. Polysomnography (PSG) is the most popular gold standard used by many researchers to detect OSA. PSG required a well-equipped sleep laboratory and skilled persons to record multi- channel signals to detect OSA. PSG is a complex and expensive method and hence motivated to conduct the research using single-channel electrocardiogram (ECG). An automatic detection method of OSA using single-channel ECG in Convolutional Neural Network (CNN) takes less computing time as feature engineering does not require. This paper focuses on the automatic detection of OSA using ECG with two different deep CNN architectures AlexNet and GoogLeNet transfer learning. The apnea ECG datasheet is used for assessing the method proposed. The state of art using deep learning models are applied to single-channel ECG data. The GoogLeNet architecture is more complex and achieves 100 % accuracy whereas AlexNet architecture shows 99.7 % accuracy to detect OSA. The proposed work is applied to physionet apnea ECG online data which leads to an overfitting problem that can be resolved using clinical data to further enhance the robustness of the model.

Keywords: Convolution neural network, Deep learning architecture, Electrocardiogram, Polysomnography, AlexNet, GoogLeNet.

INTRODUCTION

Humans engage about 1/3rd of their whole lifespan in sleeping, during sleep our body repairs. Sleeping is a very significant part of human life that is ignorantly neglected by all of us. Without sleeping, we could not perform our day-to-day functions effectively since sleep rejuvenates various life processes of humans in general or specific.

Do you know that a normal adult human must take sound sleep of 6 to 8 hours? But due to pandemics and dependency on technology and social media, the circadian cycle gets disturbed. Most young people are compelled to use gadgets extensively and as a result, their sleep hours are reduced by 4 to 5 hours and causing various types of sleep disorders.

Sleep disorders are caused by various conditions mainly lack of sufficient and sound sleep. Sometimes it is caused by other comorbid or physiological reasons. Dyssomnias and parasomnias are two important classes of sleep disorders. Sleep Apnea (SA) lies under dyssomnia, it is also categorized as a sleep-breathing disorder. SA occurred due to hypopnea and apnea; apnea is defined as a total collapse of the respiratory tract, whereas hypopnea is defined as the reduction of air passage for more than, and equal to 10 sec. Severe sleep apnea may cause arrhythmia, heart failure, sudden death, and other cardiac anomalies [1].

Figure 2: Categories of Sleep Disorder

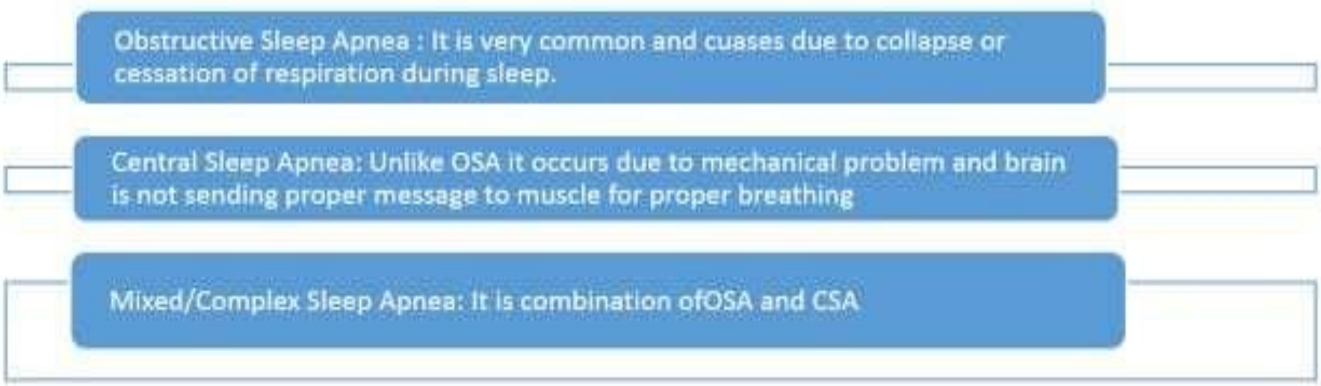
The most important feature to detect obstructive sleep apnea (OSA) is an apnea-hypopnea index (AHI) [2]. Many researchers investigated that OSA is seen in men significantly higher ratio than in women because of the wider upper airways present biologically.

Categories of Sleep Apnea

Figure 1. Represents types of sleep apnea, amongst them, OSA is a very common type and mostly undiagnosed and finally results in various other types of health issues.

But when the experiment was performed on various age groups of men and women it was discovered that women suffer from OSA more than men in their late 50s. Nowadays OSA could be seen in the teen-aged and adults [3-5]. Daytime sleepiness is another concern that may lead to road accidents [6]. AHI score is one of the most significant features to detect OSA and classify it as well using electrocardiogram (ECG) signals. Figure 2 depicts different types of sleep disorders that occur during different stages of sleep during full night sleep or daytime.

Figure 1: Types of Sleep Apnea



Related work

According to M Cheng et al, SA detection using ECG in recurrent neural networks (RNN) performed better than a conventional neural network (CNN). The RNN model performed better when the epochs increased from 20 to 50 [7]. Whereas a study proposed that OSA detection and classification performed better in the CNN model as compared to the RNN long short-term memory (LSTM) and machine learning (ML) classifiers [8]. When the epoch is set to 15, setting the epoch is a tedious task and one should be very cautious while setting it to avoid overfitting or underfitting.

A study reported that the single-channel ECG signal was divided into per segment and recording and then preprocessed to detect RR interval which was fed into 1D CNN [9]. The accuracy obtained was 87.9% and 97.1% respectively. This shows that per-recording data has performed better than per-segment data. A study investigated different RNN, CNN, and deep hybrid models [10]. The results showed that the for-hybrid model and LSTM system performance were better than other models. The research published demonstrates SA detection using CNN for SpO_2 signal is an alternative to full-channel polysomnography (PSG) and it is a cost-effective as well as portable method [11]. The study reported that classification based on the severity of SA using only instantaneous heart rate or only SpO_2 signal in the LSTM-RNN method was performed satisfactorily [12].

Deep learning has attracted the focus of many researchers in the thematic area of research. A CNN architecture is very common in image classification [13]. Urtnasan et al showed that the CNN having 6 layers for the detection of OSA using ECG has better accuracy [14]. Jiang et al proposed a model to detect SA using EEG signals in multi-scale parallel CNN [15]. Haidar et al showed that to detect OSA the modern and advanced classifier using CNN outperforms the traditional machine learning classifier [16]. Van Steenkiste et al investigated the detection of sleep using chest and abdominal data in RNN LSTM performs better than other conventional classifiers [17-18]. Some researchers identified OSA detection using RNN architecture performs with average accuracy as compared to the machine learning classifier [13-19]. Many researchers reported the classification of only apnea while neglecting hypopnea but identification of hypopnea is equally important as apnea and its treatment [20-24].

Motivation

The most popular gold standard of SA detection PSG is widely accepted. But mere dependency on PSG is not a wise choice as it requires a well-equipped sleep laboratory and a skilled person to record data, this process is a complex and expensive tool. PSG is inconvenient, time-consuming, and expensive. PSG has a complex and uncomfortable process to record physiological signals and needs a skilled physician to acquire them. These limitations of PSG have motivated to use and analyze ECG for the detection of OSA. OSA detection can be automated and easily implemented using a single-channel ECG signal. Many works had been reported on SA detection in ML in the last decade. Deep learning (DL) methods for the classification and detection of OSA have become popular because automatic feature extraction is performed by convolution layers and becomes easy and quick.

Although PSG is known as the gold standard to diagnose OSA which includes various physiological signals. Then also ECG signals are implemented for study since this signal is the reflection of cardiac behavior which may be affected by another physiological signal such as respiratory signals. OSA is another class of respiratory and sleep disorders and hence single channel ECG succeeds as the most appropriate signal for OSA detection [23]. The comparison architecture proposed for the automatic detection of OSA.

In this article, we propose to perform the detection of OSA using two CNN architectures AlexNet and GoogLeNet.

- Data preprocessing is done using Pan-Tompkin's algorithms [33].
- ECG signals will then be converted into an image of size [224 224 3] and size [227 227 3] according to the selected architecture.
- Designing the architecture of AlexNet and GoogLeNet will be done according to the dataset.
- This proposed method is simple and easy to detect sleep apnea efficiently without any complexity. Tuning of the hyperparameters to get the best performance.
- Finally, performance validation of the result has been conducted through the hold-out method.

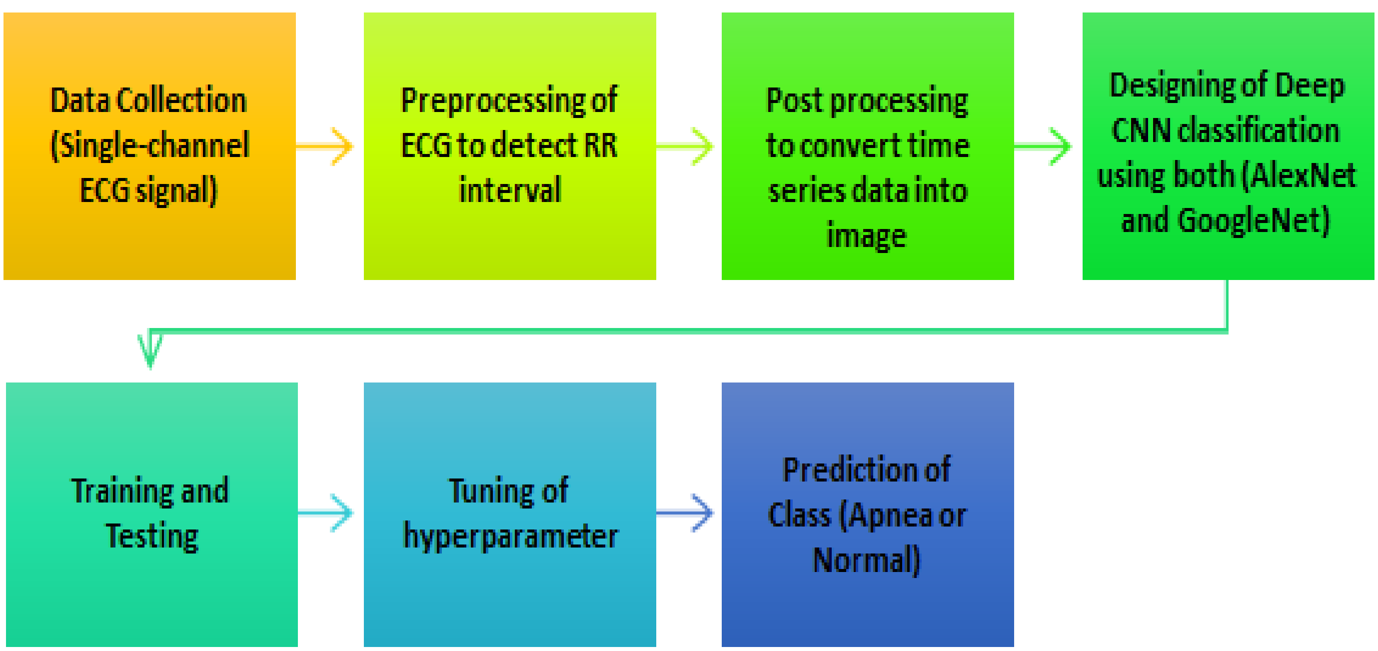
MATERIAL AND METHODS

The study proposes performance comparisons of two methods for OSA detection. The proposed methods are AlexNet and GoogLeNet CNN architectures. A process flow diagram of the study is shown in Figure 3. Which is further dealt with in sub-sections.

Datasets

The experiment was performed on the Physionet Apnea-ECG database. This database has a total of 70 recorded data from 57 men and 13 women divided into 35 training data and 35 testing data. The sampling frequency of the single-channel ECG is 100 Hz. The total duration of sleep recording is 7-8 hours approximately. According to the AHI label, the dataset consists of three classes A(apnea), B(borderline), and C(control). To record the ECG the electrode position was connected at (modified lead V2) in the standard sleep laboratory [25].

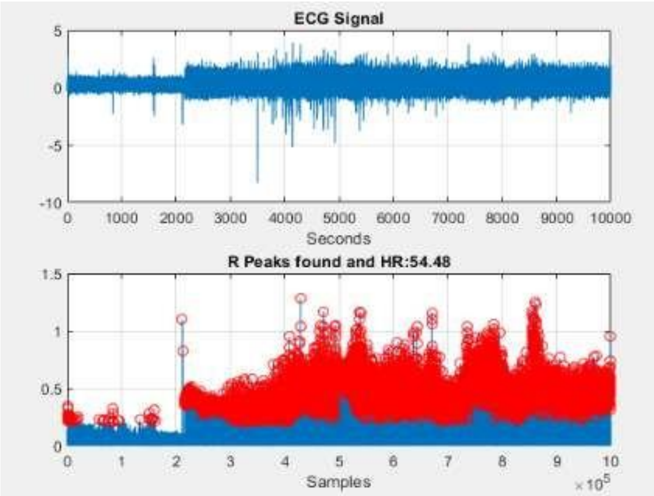
Figure 3: General flow diagram of the proposed study



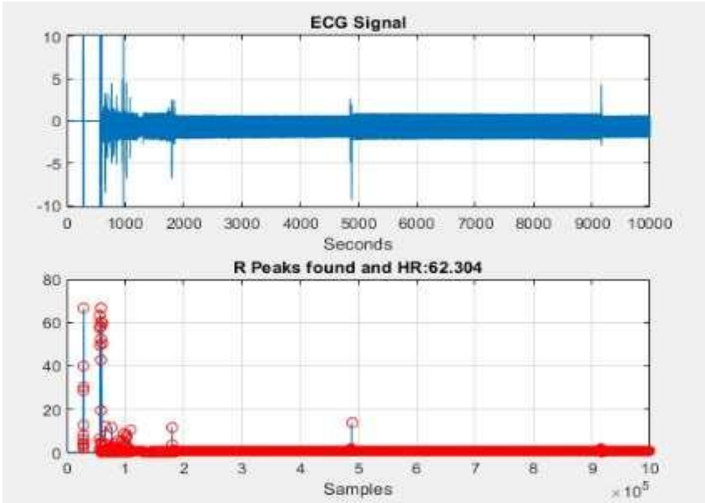
Data preprocessing

The online single-channel ECG signal was preprocessed by the Pan Tompkins algorithm to remove noise and detect QRS complex for both apnea and normal records which are depicted in Figure 4.

Figure 4: Original ECG signal and preprocessed ECG signals for (a) Apnea (b) Normal



(a)



(b)

Raw ECG data for the complete night is preprocessed by the Pan Tompkins algorithm to detect QRS complex. Single-channel ECG is preprocessed using a sequence of the bandpass filter, and derivative filter which is followed by squaring and moving window integration [33]. The data is segmented in 1 minute from each hour of data per record. It is seen that the heart rate of apnea is 54.48 while the normal subject has a 62.30 heart rate.

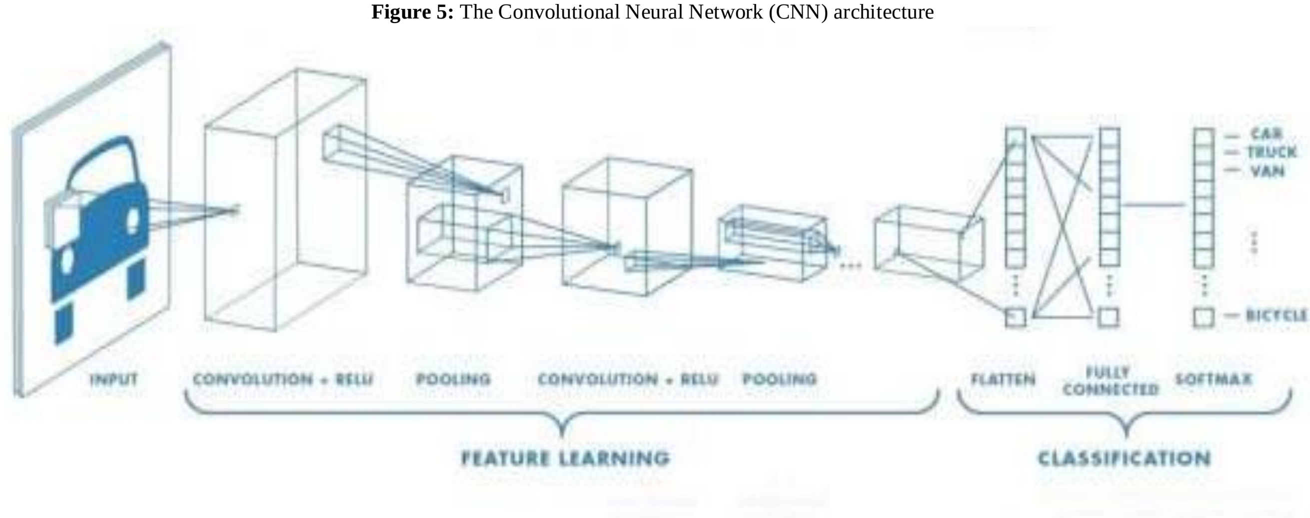
RESULTS AND DISCUSSION

The proposed CNN transfer learning models are simulated on a Dell Single central processing unit (CPU) laptop with inbuilt 8 GB RAM and an Intel i3 processor 64 bits. Data pre-processing and post-processing for training the model and testing are implemented in MATLAB 2021b. The dataset of ECG signal is pre-processed and then converted to the image size of [227 227 3] and [224 224 3] before being fed to both AlexNet and GoogLeNet models respectively.

Convolutional Neural Network (CNN)

Figure 5 shows the complete structure of the CNN model. To detect and classify the OSA while converting the ECG time series signals are to be transformed into equivalent images of desired size before being fed to the CNN. The common layers designed in CNN are input and output layers which are enclosing another number of hidden layers. The first layer which is followed input is the convolution layer, which is the feature extraction layer next is the Relu layer, and then the normalization layer. Once the features are normalized it is sent to the pooling layer. Then the same set of layers is cascaded 5 times to derive the final feature map. The reduction of features is then performed using the Pooling layer. As an output layer three consecutive layers are connected respectively the fully connected (FC) layer, classification, and softmax layer which produces an output of the CNN as shown below in Figure 5.

Figure 5: The Convolutional Neural Network (CNN) architecture

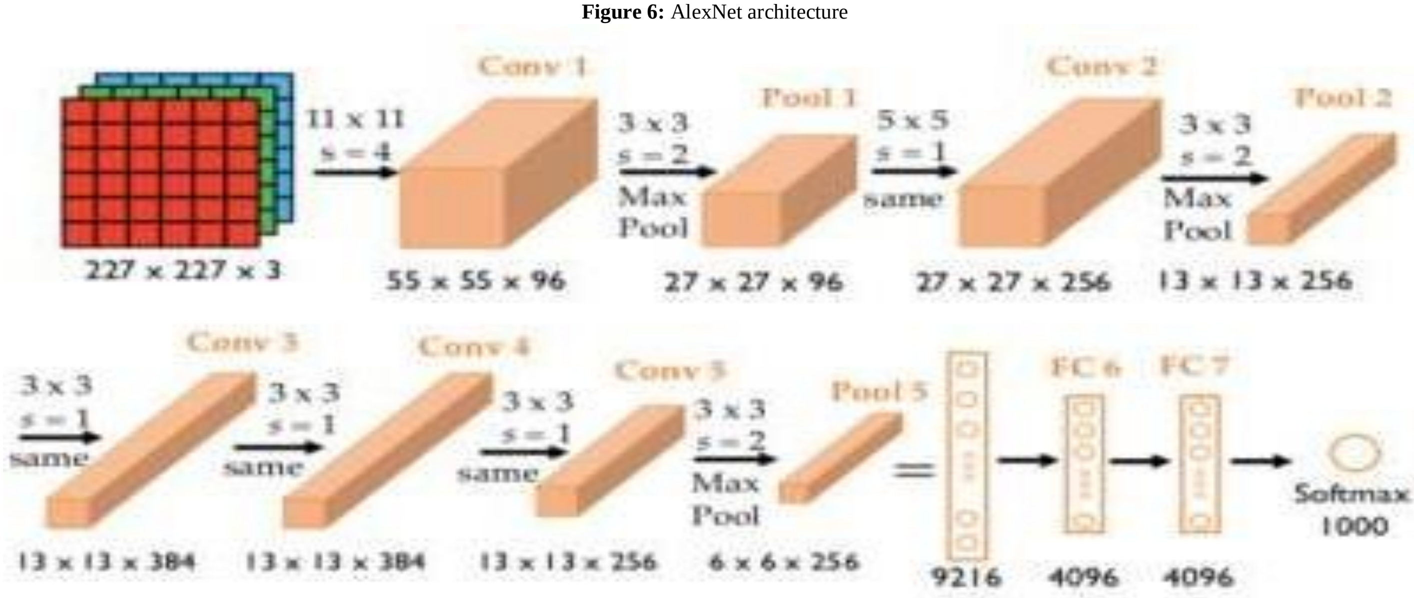


AlexNet architecture

This architecture is one of the leading CNN architectures as shown in Figure 6. AlexNet architecture consists of a total of 25 layers amongst them 5 convolutional layers and 3 FC layers (FC) are learnable, 7 ReLu layers, 2 normalization layers, 3 max-pooling layers (pool), 2 dropout layers (drop), 1 softmax layer (prob), input and output unit.

The input to this model is the images of size 227X227X3. There are two classes defined in this experiment i.e., apnea and control, and the total no of images are 1000 for each class, out of which 700 image data are used for training and 300 images are used for validation. The total learnable parameter obtained using this architecture is 16 million. The original architecture is having 62.3 million learnable parameters where a total of 10000 classes are defined as FC layer, softmax layer, and classification layer to generate the output.

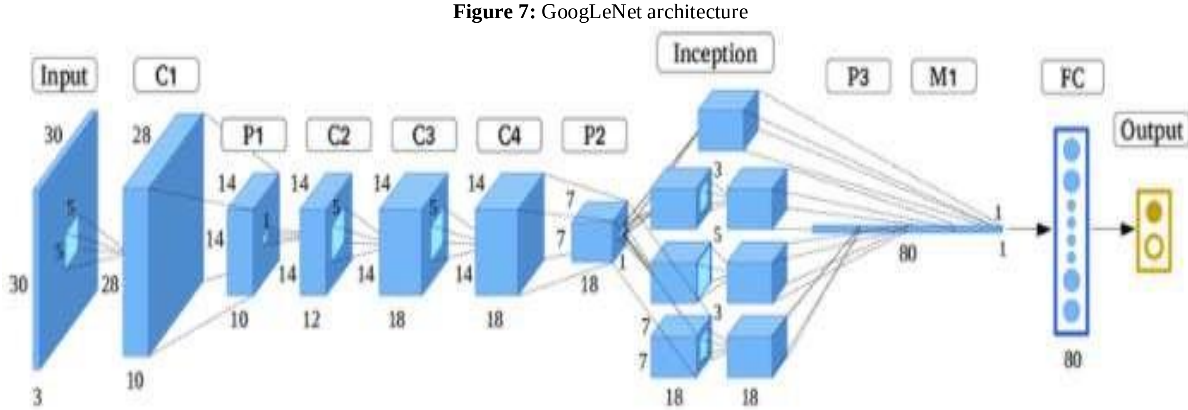
Figure 6: AlexNet architecture



GoogLeNet architecture

GoogLeNet architecture processes RGB images of size [224 224 3]. The sequence of layers followed in this architecture enables a reduction in error rate as compared to the earlier model AlexNet. The architecture designed has similar initial layers but with the addition of unique inception layers. The activation function is the Relu layer as shown in Figure 7.

Figure 7: GoogLeNet architecture



The main difference between AlexNet and GoogLeNet is identified by Inception which is the most promising feature of this CNN architecture. The dominant role of the inception block is to take multiple filter sizes for each section.

This GoogLeNet architecture has a total of 144 layers with 30 epochs and a validation frequency of 50. The proposed model has a 128-batch size for training. The optimizer which is designated for the CNN model is sgdm. Table I shows the transfer learning architecture of AlexNet and GoogLeNet. Both the architecture proposed for the detection of OSA have common parameters.

Figure 8 and Figure 9 are depicting the confusion matrix for training data as well as testing data which was investigated on the Physionet Apnea-ECG database. The training accuracy obtained by both methods is 100% for the training stage and 99.7% for the validation stage in the case of AlexNet, unlike GoogLeNet.

Table 1: Architecture of AlexNet and GoogLeNet

Type of CNN	AlexNet	GoogLeNet
Optimizer	sgdm	sgdm
InitialLearnRate	0.0001	0.0001
Frequency of validation	50	50
Maximum no of epochs	30	30
Minimum batch size	128	128
Evolution Environment	auto	Auto

Figure 8 is showing a confusion matrix for training data, a total of 2000 data were implemented and 70 % of data were used for training and 30 % of data were used for validation. The accuracy of training data is derived 100% hence no data is misqualified or disqualified incorrectly. Figure 9 depicts the confusion matrix for 600 validation data with 99.7 % accuracy in the AlexNet testing.

Figure 8: Confusion matrix for training data

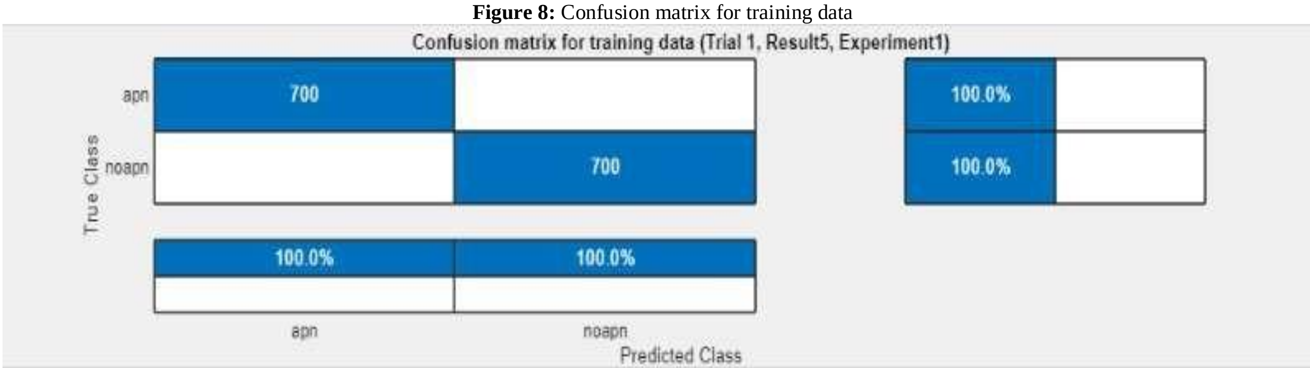


Figure 9: Confusion matrix for validation data

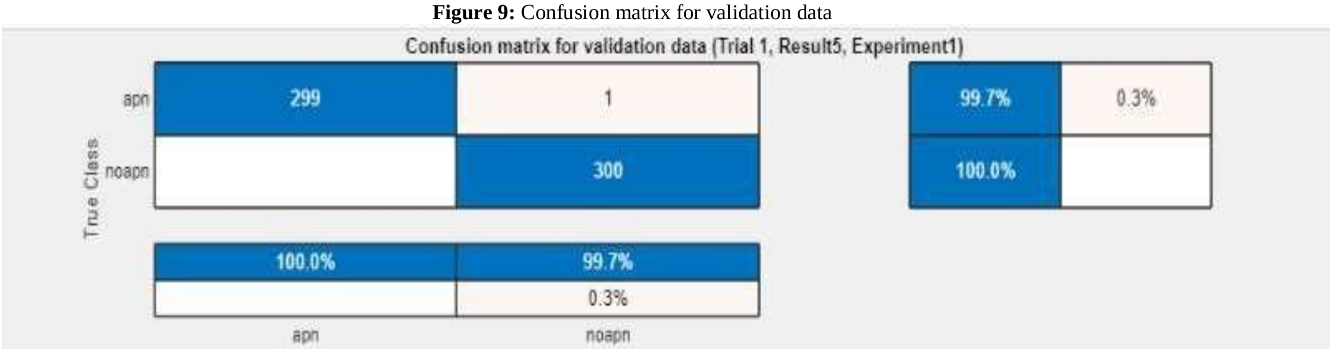


Figure 10 and Figure 11 shows the performance of the GoogLeNet model through the confusion matrix both for the training and validation stages. The accuracy achieved is 100% for both stages.

Figure 10: Confusion matrix for training data

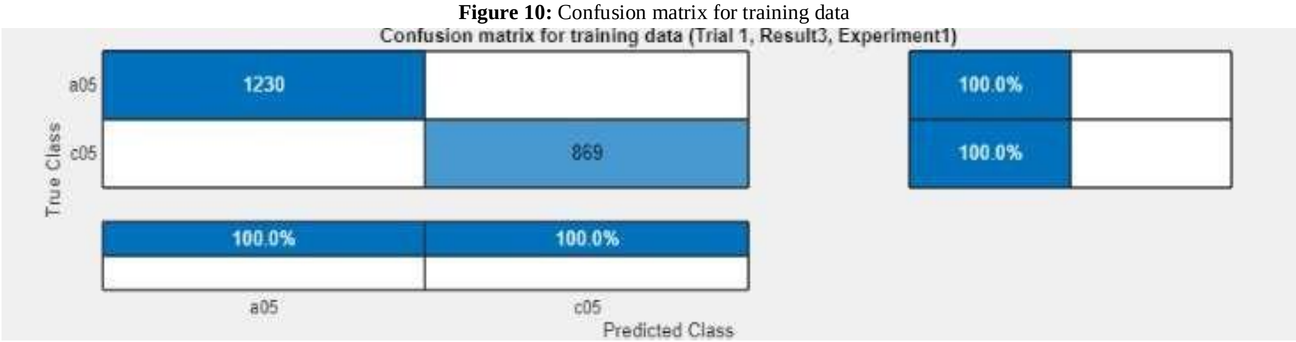


Figure 11: Confusion matrix for validation data

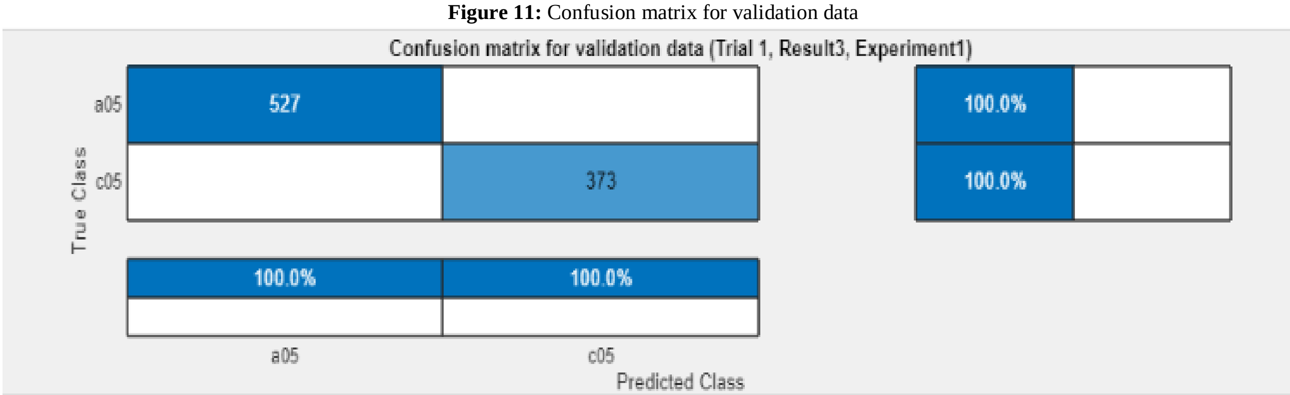


Table 2: Comparison table of both models

Model	Training data	Validation data	Training accuracy	Validation accuracy
AlexNet	1400	600	100%	99.7%
GoogLeNet	1400	600	100 %	100 %

To compare the performances of both models table II demonstrates the accuracy achieved by both models. The validation accuracy for the GoogLeNet model is 100%.

In table III the performance achieved from the given methods is analyzed with reported literature mentioned in the same specific research area using single channel ECG signal.

Table 3: Comparison of various classifiers, and their performance with limitations

Paper	Classifier	Signal	Result (in %)		
			Accuracy	Sensitivity	Specificity
[24]	DNN, 1D CNN, 2D CNN, RNN, LSTM, and GRU	ECG	99.0	99.0	NA
[26]	CNN	ECG	99.0	98.0 (f1-score)	NA
[28]	1 D CNN	ECG	97.79	92.23	NA
[29]	RNN, CNN, LSTM, and CNN LSTM	ECG	86.25	NA	NA
[31]	LSTM-RNN GRU, deep hybrid model	ECG	80.67	75.04	84.13
[32]	LSTM-RNN	Instantaneous heart rate (IHR)	85	NA	NA
Proposed Method	**AlexNet** **GoogLeNet**	**ECG** **ECG**	**99.7** **100**	**NA**	**NA**

The key findings of the proposed method: (1) Comparison of the two transfer learning architectures AlexNet and GoogLeNet to detect OSA. (2) Analysis of the performance of both the models was evaluated using only single-channel ECG signals, with an accuracy of 99.7%, and 100%. (3) The performance is better than the existing approach for OSA detection using ECG signal in AlexNet and GoogLeNet transfer learning models. Both methods performed better than the traditional method and require less computing time which leads to the usefulness of the proposed method.

CONCLUSION

This work concludes that the deep learning library (DLL) approach for OSA detection is most suitable as the image classification is performed efficiently using CNN architecture. A comparison of transfer learning CNN for the detection of OSA is conducted for AlexNet and GoogLeNet achieving an accuracy of 99.7% and 100% respectively which outperforms and is better than other conventional ML methods. The most suitable method for classification is a hybrid model of CNN and RNN model which is one of the limitations of the proposed work.

Future Scope

In future work, the classification of OSA and the characterization of the severity of OSA as normal, borderline, mild, and severe OSA will be done. Further research will be conducted to resolve over fitting with an increased population size of both training and testing using clinical data.

Conflicts of interest

We both authors do not have any conflict of interest. This research is not receiving any grant from any organization.

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