How to Cite:
Singh, N., & Talwekar, R. H. (2022). Automatic detection of sleep breathing disorder using Bayesian optimization algorithm from single-lead electrocardiogram. *International Journal of Health Sciences*, *6*(S1), 8331–8343. https://doi.org/10.53730/ijhs.v6nS1.6965

Automatic detection of sleep breathing disorder using Bayesian optimization algorithm from single-lead electrocardiogram

Nivedita Singh
RCET, BHILAI, CG, India
Corresponding author email: nivedita.singhbit@gmail.com

R.H. Talwekar
CG GEC, Raipur, CG, India
Email: ursk.talwekar@gmail.com

***Abstract*---**Background/objective: Deep learning paradigm is very popular for image classification problems and has proven its significance in all domains. The tuning of hyperparameter for deep neural network algorithm is a very tedious task and is performed mostly in the trial-and-error method. We propose a Bayesian optimization algorithm (BOA) to tune hyperparameter in pre-trained GooLeNet architecture to detect sleep breathing disorders using single-lead ECG. We aim to perform automatic detection of sleep apnea using single-lead ECG rather than polysomnography as it is easy to record and implement. Method: The physionet sleep apnea data is used for training and testing of the model proposed. Three different solvers adam, rmsprop, and sgdm are used in pre-trained GoogLeNet architecture for the classification of sleep breathing disorder using single-lead ECG while rest all other hyperparameters are altered too. Result: To detect automatic sleep breathing disorder (SBD) in BOA using pre-trained GoogLeNet and solvers adam, rmsprop, and sgdm the sgdm optimizer is showing the best result as the loss is least in this case but processing times for each are different. Discussion/conclusion: We conclude that the BOA was used to identify the most suitable classifier for the automatic detection of SBD. We also conclude that using the pre-trained GoogLeNet classifier for different solvers namely adam, rmsprop, and sgdm three have shown accuracy, sensitivity, and specificity all are 100%. But all three solvers had different training times the fastest solver is sgdm and the slowest is adam. The proposed method has better performance and has less complexity and time-saving. Limitation/Future Scope: As all the solvers are outperformed using the physionet sleep apnea database hence to validate its performance clinical data would be applied to the proposed system in future work.

International Journal of Health Sciences ISSN 2550-6978 E-ISSN 2550-696X © 2022.
Manuscript submitted: 09 Feb 2022, Manuscript revised: 18 March 2022, Accepted for publication: 27 April 2022

***Keywords*---** Sleep breathing disorder, Bayesian optimization algorithm, electrocardiogram, deep learning, Apnea-Hypopnea Index.

Introduction

Sleep apnea is a sleep breathing disorder that is caused due to cessation of respiration or collapse of the upper airway during sleep. SBD is very common but mostly is undiagnosed [1] and leads to daytime sleepiness, lack of concentration, laziness and cardiac syndrome even heart attack. This SBD is most common in men than women due to interrupted breathing during sleep. Detection of sleep apnea through the Apnea-Hypopnea Index (AHI) is done by polysomnography (PSG) which is efficient and popular.[2] Polysomnography (PSG) is the gold standard for diagnosis of SBD but it requires complete night observation in the sleep lab. PSG is recorded in the sleep lab which includes physiological signals ECG, electroencephalogram, electrooculogram, electromyogram, nasal airflow, blood oxygen saturation, etc. [3], since it is expensive, [4] complex, uncomfortable [5], and needs skilled persons to record the multichannel physiological signals. Single-lead ECG is an important physiological signal which contains information related to cardio and respiration and can easily be obtained using wearable and is accurate too. SBD is classified into 4 categories normal, mild, moderate, and severe according to the value of AHI which is determined as the sum of the total number of apnea and hypopnea every hour during sleep. AHI = (no of apnea + no of hypopnea) / sleep hour.

Case 1. If AHI < 5 then it signifies normal.
Case 2. If 5 < AHI <15 then it signifies mild apnea.
Case 3. If 15 < AHI <30, it signifies moderate apnea.
Case 4. If AHI > 30 then it signifies severe apnea.

In this study [6] it is reported that detection and classification of SBD were better using support vector machines (SVM) rather than neural network algorithm. Detection of SBD before a sleep apnea event for at least 1 to 2 epochs is a more accurate method. In this investigation.[7] In the published work [8] it was shown that it would be the best alternative method to detect sleep apnea than the PSG. Authors [9-10] reported that deep learning-based classifiers are performing better than a machine-learning algorithm to detect sleep apnea using computer-aided diagnosis. To detect sleep apnea using 10 sec ECG segments, the best performance was reported in 1D CNN and GRU. The researchers [11] demonstrated that detection of sleep apnea using short-term 30-segment ECG in CNN shows better performance than long-term ECG signals. According to this work [12], it was proposed that detection of SA does not depend on past ECG segment which is before SA event or during SA rather it depends on time-window ECG signals which gives better performance than traditional non-window ECG signals.

The study [13] showed that the 1D CNN model for sleep apnea detection has performed better than other feature engineering-based approaches and feature selection-based approaches. The data preparation was done per minute per recoding which is more appropriate to be analyzed sleep apnea events. The detailed comparison was shown in the work to signify the approach of their approach and work.

The analysis of the ECG data for detecting SBD using different state of art such as machine learning or traditional methods has some limitations as they require more computation and are time-consuming. The performance of these classifiers is underachieved as compared to the deep learning algorithm-based other approaches.

To overcome these drawbacks, we proposed a novel method of SBD detection using CNN based transfer learning algorithm to perform the classification more efficiently. Different deep learning algorithms such as Recurrent Neural Networks (RNN), Convolutional Neural networks (CNN), and Long-Short Term Memory (LSTM) are implemented to detect SBD. The most suitable algorithm for image classification is CNN.[14] It was observed that designing deep learning approaches performed better than previous studies in terms of detecting SA events, and they could distinguish between apnea and hypopnea events using an ECG signal.[20] This study [21] presents an ECG-based model for the minute-based analysis of sleep apnea. Various classifiers were implemented in this study and it is demonstrated that better performance was achieved when the number of features selected for classification is lesser. In this study [22] it was shown that the hybrid model of CNN and LSTM's best accuracy and sensitivity has been achieved. This work [23] demonstrated that single-lead ECG is used for SBD detection in ResNet CNN which is easy and efficient as it does not require any signal preprocessing, feature selection, and feature engineering.
In our proposed method the state of the art is to detect SBD using single-lead ECG in the Bayesian optimization technique which inhibits selecting the most efficient detection method. In this section, we discuss the block diagram and process flow of the proposed system for automatic detection of SBD using single-lead ECG shown in figure 1.

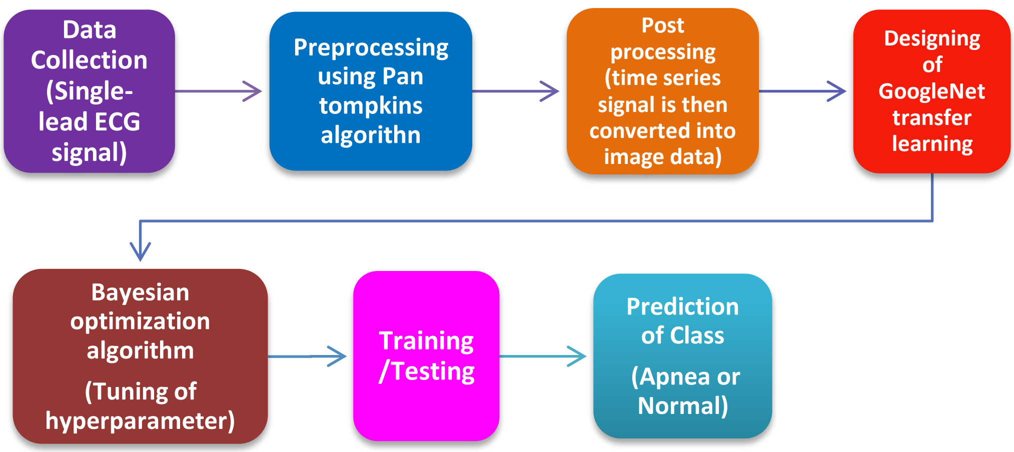


Figure 1. Block diagram and process flow diagram of the proposed system

Figure 1 shows the block diagram of the proposed method. Firstly, the Physionet Apnea-ECG database is preprocessed to remove noise and detect QRS complex.

The next block represents the post-processing block which converts the time-series signal into equivalent images using a continuous wavelet transform of the image size [224 224 3] which is compatible as input for the proposed transfer learning model. Post-processing block followed by designing GoogleNet transfer learning model. The tuning of hyperparameter is the most challenging task in deep learning continuous neural network (CNN). In this experiment, BOA is implemented to ease the work of hyperparameter tuning and achieve the best results which are the next task in the process flow. Finally, the network will be trained and tested to detect automatically SBD using single-lead ECG. The overall performance of the system will be evaluated by accuracy by predicting the class of subject as normal or apnea.

Materials and Methods

Datasets

In this research work, the online dataset is utilized for both the training and testing phases. The main source of our dataset is the PhysioNet Apnea-ECG dataset, provided by Dr. Tomas Penzel of Phillips University.[15] This apnea ECG dataset includes both healthy and normal humans. Both male and female participants of different age groups had agreed to spend a few nights in the sleep laboratory voluntarily. A total number of 70 polysomnography recordings were collected from two groups of participants 35 in each group. From all channels, only single-lead ECG signals with a 100 Hz sampling rate have been taken for this research. There are three classes of recordings depending on the AHI value Class A, Class B, and Class C respectively apnea, borderline and healthy subject. A training dataset was used to estimate the model and a testing set was used to validate the proposed system.

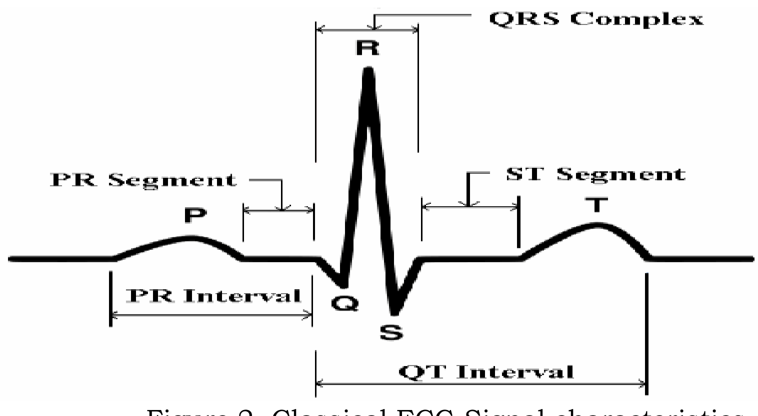


Figure 2. Classical ECG Signal characteristics

Figure 2 depicts an ECG waveform with different segments and waves. The QRS complex and RR interval are the features that are significant for our study. Heart rate variability and ECG are two very popular physiological signals which are used to detect SBD other than EEG and EOG. ECG signals are used to derive heart rate variability (HRV) and ECG-derived respiration (EDR). The time interval between R to R is defined as the RR interval and the variations in it are HRV [16-

17]. Here, our main focus is on the use of single-lead ECG signals alone for the detection of sleep apnea.

Preprocessing

Figure 3. shows an R-R interval plot derived from the single-lead ECG data, which is denoised, and the QRS complex is detected using the most popular and efficient Pan Tompkins algorithm.[24] After denoising using bandpass filter and detection of QRS complex the single-lead ECG signal is segmented and followed by post-processing to convert the data into equivalent images which are then further processed for classification.

Post-processing

The next block represents the post-processing block which converts the time-series signal into equivalent images using a continuous wavelet transform of the image size [224 224 3] which is compatible as input for the proposed transfer learning model. Post-processing block followed by designing GoogleNet transfer learning model. Figure 4 shows images of both normal and affected subjects.

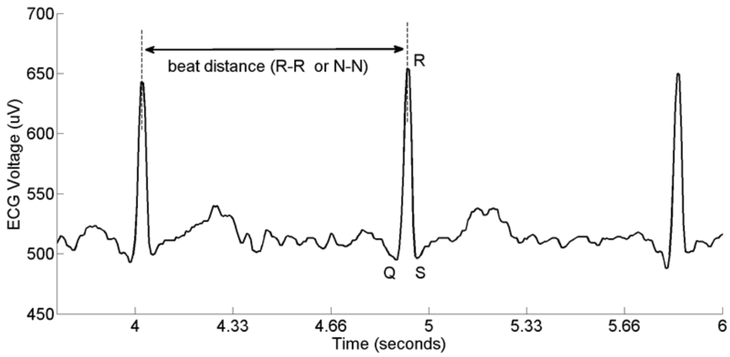
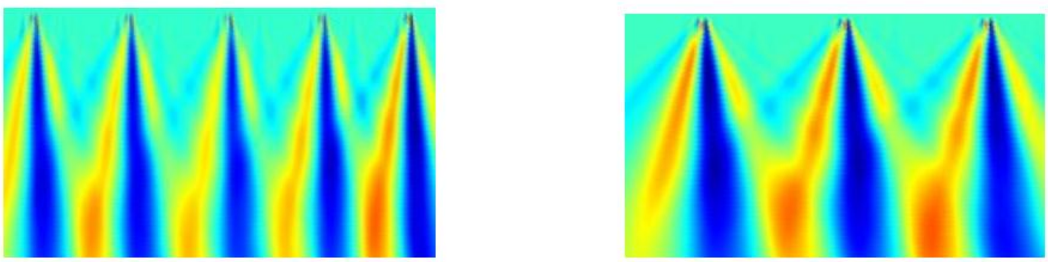


Figure 3. R-R interval



(a) Normal

(b) SBD

Figure 4. (a) Scalogram of normal and (b) Scalogram of SBD subject

Differences between both the scalogram can be seen clearly in figures 4 (a) and (b).

Convolutional Neural Network (CNN) architecture

The proposed pre-trained GoogleNet model is implemented on a Dell laptop having 8 GB RAM, and a Windows 10 processor of 64 bits. The complete MATLAB coding for the experiments and their implementations has been conducted in Matlab 2021b. The dataset of 1000 images from each of the two classes is pre-processed before sending it to the pre-trained GoogleNet model.

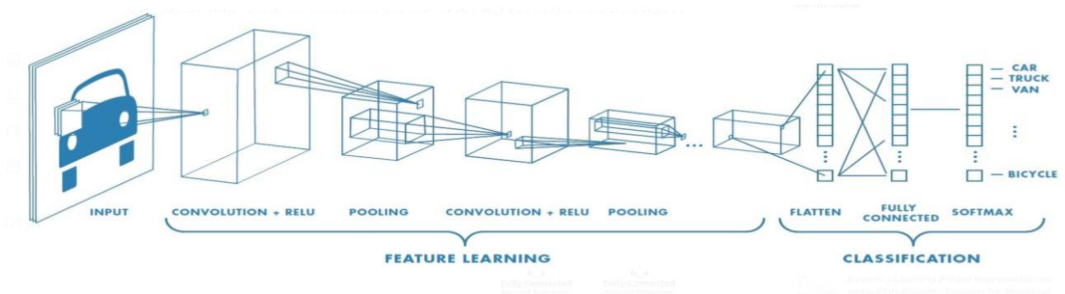


Figure 5. General block diagram of proposed CNN model

Figure 5. represents CNN architecture for image classification for detection of SBD. CNN is composed of three layers namely the convolution layer, pooling layer, and fully connected layers. Convolution layers are hidden layers that include n no. of filters to form a feature map. Pooling layer down-sample the feature map which reduces the dimensionality. The last layer in the CNN is the fully connected layer whose input is output from the final pooling layer and convolution layer, and finally produces an output of the CNN.

GoogLeNet architecture

In the proposed CNN model shown in Table I, a total of 22 layers are combined to construct GoogleNet. As it is shown in table I, the no of epochs is 30 which is required to achieve the best accuracy. The mini-batch size required for training the pre-trained GoogleNet is 128. Different solvers selected as an optimizer during training of the proposed model are adam, rmsprop, and sgdm. The validation approach applied during training is a 10-fold cross for validating the system performance. The performance parameters such as accuracy, sensitivity, and specificity are computed to evaluate the performance parameters.

Table 1
The architecture of GoogLeNet Transfer Learning Classifier

CNN	GoogLeNet
Solver	adam, rmsprop, sgdm
Initial Learn Rate	0.0001
Validation Frequency	50
Max Epochs	30
Mini Batch Size	128
Evolution Environment	Auto
No. layers	22

Activation function	ReLU function
Dropout ratio	0.7

This architecture takes an image of size [224 224 3] with RGB color channels. These convolution layers include rectified linear units (ReLU) as their activation functions. The error rate is significantly decreased as compared to AlexNet architecture as shown in figure 6.

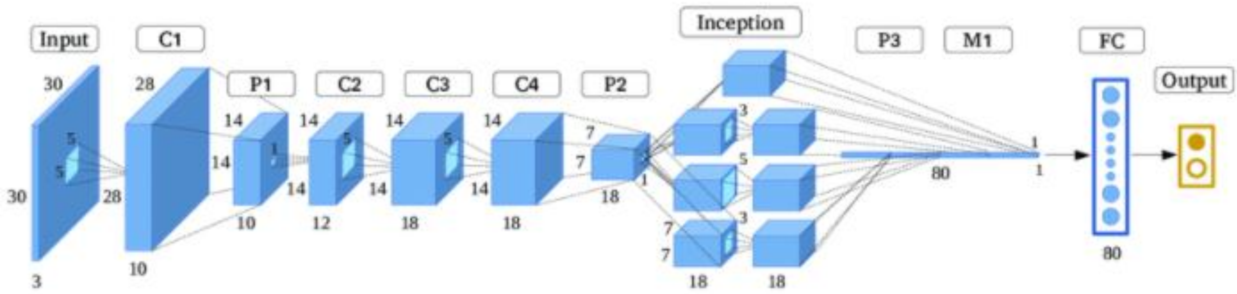


Figure 6. GoogLeNet architecture

GoogLeNet is a kind of CNN architecture that is designed using Inception. The main feature of the Inception module is to choose between multiple convolution filter sizes for each part. Stacks of Inception network include max pooling layer with stride 2 hence the grid resolution remains half. The model consists of a total of 144 layers and needed 30 epochs and a validation frequency of 50 to perform efficiently. The Batch size is set to 128 for training the proposed model. rmsprop is selected as an optimizer during the training of the CNN model.

Bayesian optimization for hyperparameter tuning

In this work, the Bayesian optimization technique was applied to tune the hyperparameter which shows the best suitable accuracy for classification and detection of SBD. This technique is robust and time-saving which is easy to implement. The following approach is implemented to apply the optimization: The flowchart of optimization is shown in figure 7. Firstly, the GoogLeNet architecture is designed according to our experiment and datasets. Secondly, datasets are imported for the training and validation process then the code is run in MATLAB 2021b in deep network designer. Thirdly after the code is exported and saved experiment manager is used to design our own optimizations specification along with solver, learning rate, etc. Finally, the experiment will be conducted and it will tune the hyperparameter and will achieve the best result for classifications along with the tuned hyperparameter.

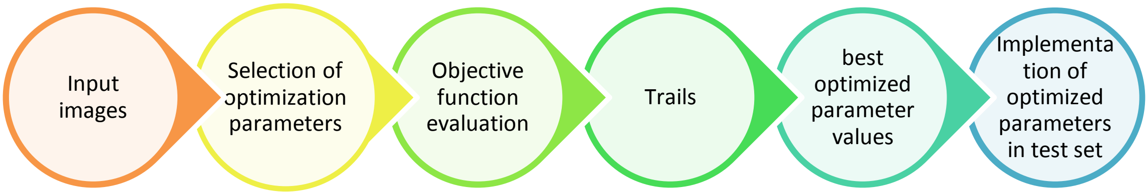


Fig. 7 A flowchart of Bayesian optimization

Results

Performance parameters of the proposed model

The proposed model is used in physionet Apnea ECG data, in which a total of 70 records are available for both training and testing. These datasets are used to evaluate system performance based on different parameters such as sensitivity, specificity, and accuracy.

Sensitivity or TPR = TP / (TP+FN) X 100 % ------- (1)

Specificity or TNR = TN / (TN+FP) X 100 % ------- (2)

Total accuracy or TA = (TP+TN) / (TP+TN+FP+FN) X 100 % ------- (3)

Where TP is true positive, TN is true negative, FP is false positive, FN is false negative.

Confusion matrix

Figure 8 depicts the confusion matrix of both training and validation data in both (a) and (b) parts. The total number of images evaluated for the training process is 1000 and for validation is also 1000 for which the confusion matrix is obtained.

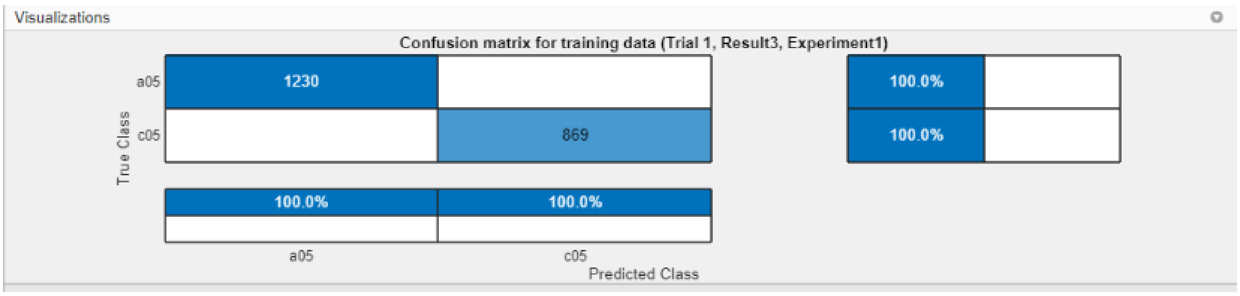


Figure 8 (a) Confusion matrix of training data

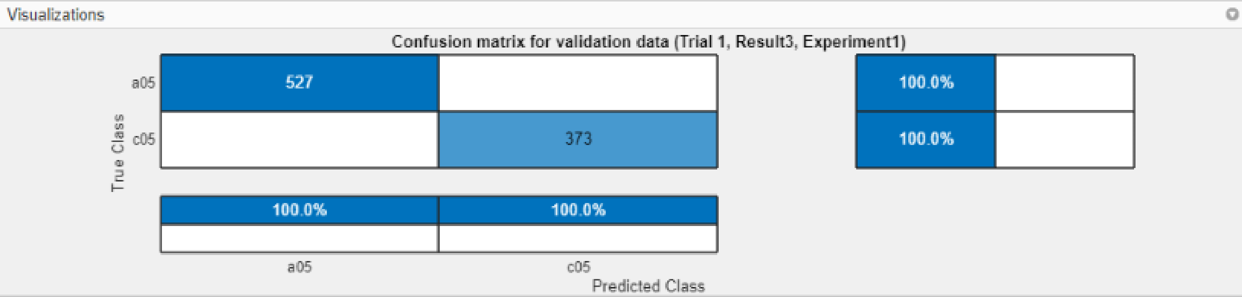


Figure 8 (b) Confusion matrix of validation data

The training process in GoogLeNet

Figure 9. shows a plot of the training process using transfer learning using GoogLeNet. The no of epochs is 30 and the accuracy achieved is 100% and loss is 0 % which is the best out of all other options.

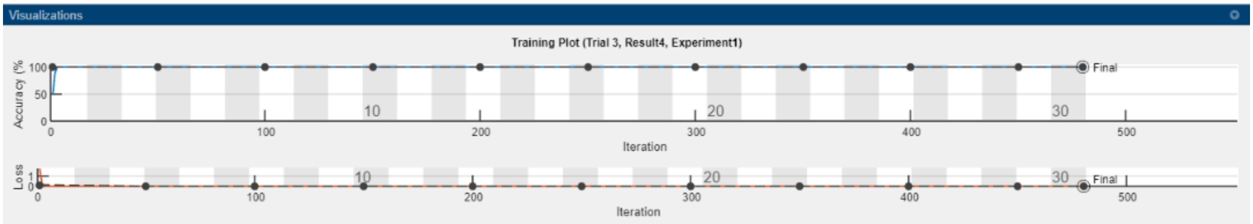


Figure 9. Training process using transfer learning using GoogLeNet

Comparison table for Bayesian optimization technique

Figure 10. is showing all possible parameters for optimizing the classification performance to detect the SBD automatically using a single-lead ECG signal.

Trial	Status	Progress	Elapsed Time	mySolver	myLRR	Training Accu...	Training Loss	Validation Acc...	Validation Loss
1	Complete	100.0%	10 hr 14 min 16 sec	rmsprop	0.0010	100.0000	7.6369e-7	100.0000	4.1564e-7
2	Complete	100.0%	15 hr 7 min 5 sec	rmsprop	0.0006	100.0000	8.2991e-6	100.0000	5.7715e-6
3	Complete	100.0%	21 hr 25 min 15 sec	adam	0.0001	100.0000	1.2387e-7	100.0000	0.0000
4	Complete	100.0%	11 hr 3 min 10 sec	sgdm	0.0003	100.0000	0.0001	100.0000	2.0085e-5

Figure 10. Bayesian Optimization Technique for automatic detection of SBD using pre-trained GoogLeNet model

Discussions

The study verified the automatic detection of SBD using single-lead ECG in the Bayesian optimization technique. The Physionet apnea ECG was used to experiment both for training and validation. The ECG signal is then preprocessed using the Pan Tompkins algorithm and then post-processed to get the image data from the time series ECG signal using CWT, which is then used for the CNN model. Finally, images are fed to the GoogLeNet transfer learning model using Bayesian optimization for three different optimizers viz adam, rmsprop, and sgdm, Using machine learning techniques lot of time and computation are needed which can be reduced while using the deep learning-based model as it is proposed in our model. Several studies proposed different deep learning models for SBD detection using the CNN model which has fixed architecture and could provide only one best solution. But in our proposed model using optimization technique using different optimizers adam, rmsprop, and sgdm for different values is adopted. Table II is depicting a comparison of various CNN-based models for detecting sleep breathing disorders with their methodology and performance.

Paper	Author	Year	Classifier	Result		
				Accuracy	Sensitivity	Specificity
[9]	Aala Sheta et al	2021	computer-aided diagnosis (CAD)	86.25%	NA	NA
[12]	Tao Wang	2021	Mr-ResNet	91.2%,	90.8%	90.5%
[13]	Hung yu chang et al	2020		100%	NA	NA
[14]	Sinam Ajit kumar Singh	2021	CNN, LSTM, GRU, deep hybrid model	80.67%,	75.04%,	84.13%,
[20]	urtnasan erdenebayar et al	2019	DNN, 1D CNN, 2D CNN, RNN, LSTM, GRU	99.0%,	99.0%	NA
[23]	roneel v. sharan et al	2021	1D CNN,	88.23%	NA	NA
[11]	erdenebayar urtnasan et al	2020	CNN	99.0%.	98.0%, (f1-score)	NA
[25]	arlene john et al	2021	1 D CNN	97.79%,	92.23%.	NA
Proposed method		2022	Pre-trained GoogLeNet	100%	100%	100%

The experimental results are shown in Table III, the performance parameters of our model are concluded as sensitivity 100%, specificity 100%, and accuracy 100%. For the sgdm optimizer, the system is showing the best results among all three optimizers.

Table III

The performance evaluation of the CNN model using 10-fold cross-validation.

Sensitivity	100 %
Specificity	100 %
Accuracy	100

Conclusion

This paper proposes a Bayesian optimization algorithm using adam, rmsprop, and sgdm solvers with a GoogLeNet transfer learning algorithm to detect SBD. For testing and training, ECG signals are used. The outstanding performance is shown by all the solvers but sgdm solver has the least processing time using a single CPU. Our proposed GoogLeNet pre-trained model was trained and validated by datasets of the PhysioNet Apnea-ECG database both released and withheld datasets.

The accuracy achieved by our proposed system is outstanding than several previous studies with the accuracy of 100% and specificity of 100% with a corresponding sensitivity of 100% of SBD detection. The proposed system is the most suitable system for the automatic detection of SBD using a single-lead ECG signal.

A Bayesian optimization algorithm is a very significant algorithm and can be easily implemented to tune hyperparameters as the conventional trial and error method takes a lot of time and is a tedious process. BOA also reduces validation errors as the best suitable algorithm is adapted for the detection. This BOA is a very efficient and popular method in transfer learning approaches. SBD is generally undiagnosed and ignored in most cases which may become fatal if it is severe. In the present scenario as most people facing sleep anomalies hence early and automatic detection of SBD is very important. Further improvement can be achieved using several transfer learning algorithms, solvers, and sets of learning rates. This study has several limitations, firstly the experiment had conducted for only two algorithms it could be done for more DL algorithms as well as for hybrid models to design a robust model. Secondly, the dataset for the training and testing is limited and unbalanced which might lead to the outperformance of the system. These limitations could be considered as future challenges and scope.

Future scope

In the present study, we employed transfer learning CNN to detect SBD using single-lead ECG apnea data. In the future, we will detect SBD and also will determine its severity of SBD. We will also deal with the overfitting of the model while validating it using clinical data. We will also apply the more precise method of hyperparameter tuning using the transfer learning approach GoogleNet, AlexNet, and Inception V3 along with different solvers and with a set of learning rates.

Data Availability
The data are publicly available on Physionet.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

Funding
This particular research presented herein received no external/additional funding.

References

[1] M. Kato, T. Adachi, Y. Koshino, and V. K. Somers, “Obstructive Sleep Apnea and Cardiovascular Disease,” p. 8, 2009.

[2] S. Quan, J. C. Gillin, M. R. Littner, and J. W. Shepard, Sleep-related breathing disorders in adults: Recommendations for syndrome definition and measurement techniques in clinical research. Editorials, vol. 22. 1999.

[3] C. A. Kushida et al., “Practice parameters for the indications for polysomnography and related procedures: an update for 2005,” Sleep, vol. 28, no. 4, pp. 499–523, 2005.

[4] W.W. Flemons, N. J. Douglas, S. T. Kuna, D. O. Rodenstein, and J. Wheatley, “Access to Diagnosis and Treatment of Patients with Suspected Sleep Apnea,” American Journal of Respiratory and Critical Care Medicine, vol. 169, no. 6, pp. 668–672, 2004, doi: 10.1164/rccm.200308-1124PP.

[5] A. L. Chesson et al., “Practice parameters for the indications for polysomnography and related procedures,” Sleep, vol. 20, no. 6, pp. 406–422, 1997.

[6] Onur Kocak1, Tuncay Bayrak1, “Automated Detection and Classification of Sleep Apnea Types Using Electrocardiogram (ECG) and Electroencephalogram (EEG) Features”, Advances in Electrocardiograms – Clinical Applications, pp 211-230, 2014.

[7] Laiali Almazaydeh, Khaled Elleithy, “Detection of Obstructive Sleep Apnea Through ECG Signal Features”, conference paper, IEEE International Conference on Electro/Information Technology, 2012.

[8] Hnin Thiri CHAW, Sinchai KAMOLPHIWONG, Krongthong WONGSRITRANG, “SLEEP APNEA DETECTION USING DEEP LEARNING”, TEHNIČKI GLASNIK, vol 13, (4), pp 261-266, 2019.

[9] Sheta, Alaa, Turabieh, Hamza et al., “Diagnosis of obstructive sleep apnea from ECG signals using machine learning and deep learning classifiers”, Applied Sciences, vol 11, pp 6622, 2021.

[10] Erdenebayar, Urtnasan Kim, Yoon Ji et al., “Deep learning approaches for automatic detection of sleep apnea events from an electrocardiogram”, Computer Methods and Programs in Biomedicine, 180, 2019.

[11] Urtnasan, Erdenebayar, “Identification of Sleep Apnea Severity Based on Deep Learning from a Short-term Normal ECG “, Journal of Korean Medical Science, vol 35(47), pp 1-11, 2020.

[12] Tao Wang ,1 Changhua Lu,1,2 and Guohao Shen, “Detection of Sleep Apnea from Single-Lead ECG Signal Using a Time Window Artificial Neural Network”, BioMed Research International**,** 2019, https://doi.org/10.1155/2019/9768072

[13] Hung-Yu Chang 1,2, Cheng-Yu Yeh 3, Chung-Te Lee 3 and Chun-Cheng Lin 3, “A Sleep Apnea Detection System Based on a One Dimensional Deep Convolution Neural Network Model Using Single-Lead Electrocardiogram”, Sensors, vol 20, pp 4157, 2020. doi:10.3390/s20154157.

[14] Sinam Ajit kumar Singh*, and Swanirbhar Majumder, “A Novel Approach OSA Detection Using Single-Lead ECG Scalogram Based on Deep Neural Network”, Journal of Mechanics in Medicine and Biology, vol 19(4), pp 1950026 (18 pages), 2019.

[15] T. Penzel, G.B. Moody, R.G. Mark, A.L. Goldberger, J.H. Peter, “The Apnea-ECG database”, Computers in Cardiology 2000, pp 255–258, 2000.

[16] Phyllis K. Stein a, Yachuan Pu, “Heart rate variability, sleep and sleep disorders”, Sleep Medicine Reviews, vol 16, pp 47-66, 2012.

[17] *T. Sunil Kumar1*, and Vivek Kanhangad,* “Gabor Filter-based 1D-Local Phase Descriptors for Obstructive Sleep Apnea Detection using Single-lead ECG”, IEEE Sensors Letters, vol 2(3), 2017.

[18] Griner, P.F.; Mayewski, R.J.; Mushlin, A.I.; Greenland, P., “Selection and interpretation of diagnostic tests and procedures. Principles and applications.”, Ann. Intern. Med. Vol 94, pp 557–592, 1981.
[19] Metz, C.E., “Basic principles of ROC analysis.”, Seminar on Nuclear Med., vol 8, pp 283–298, 1978.
[20] Erdenebayar Urtnasan1 & Jong-Uk Park1 & Eun-Yeon Joo2 & Kyoung-Joung Lee1, “Automated Detection of Obstructive Sleep Apnea Events from a Single-Lead Electrocardiogram Using a Convolutional Neural Network”, Journal of Medical Systems, vol 42:10, 2018.
[21] Nuno Pombo, Bruno M. C. Silva, André Miguel Pinho and Nuno Garcia, “Classifier Precision Analysis for Sleep Apnea Detection Using ECG Signals”, IEEE access, vol 8, pp 200477-200485, 2020.
[22] Mahsa Bahrami, Mohamad Forouzanfar, “Detection of Sleep Apnea from Single-Lead ECG: Comparison of Deep Learning Algorithms.”, IEEE International Symposium on Medical Measurements, 2021.
[23] Roneel V. Sharan1 Shlomo Berkovsky1 Hao Xiong1 Enrico Coiera1, “End-to-End Sleep Apnea Detection Using Single-Lead ECG Signal and 1-D Residual Neural Networks.”, Journal of Medical and Biological Engineering, vol 41, pp 758–766, 2021. https://doi.org/10.1007/s40846-021- 00646-8.
[24] Jiapu Pan and Willis J. Tompkins, “A real-time QRS detection algorithm”, IEEE transactions on biomedical engineering, vol. BME-32, no. 3, 1985.
[25] ohn, Arlene et al, “A 1D-CNN Based Deep Learning Technique for Sleep Apnea Detection in IoT Sensors”, IEEE International Symposium on Circuits and Systems (ISCAS), 2021.