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Obstructive Sleep Apnea Syndrome Identification Using CNN-LSTM Hybrid Model



Abstract: - Obstructive Sleep Apnea (OSA) is a common sleep problem. It causes breathing issues during sleep. This disturbs oxygen intake and sleep patterns. Detecting OSA early and accurately is important for treatment. In our study, we look into using advanced deep learning for OSA detection. We focus on Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and a new combined method. We also check the impact of different functions and methods on OSA detection accuracy. Our tests reveal some interesting facts. The Nadam optimizer gives the best OSA detection at 95.22% accuracy. The combined CNN and LSTM method achieves 95.38% accuracy. Using LSTM with the sigmoid function, we get a 93.80% accuracy. These results stress the importance of choosing suitable models and methods for OSA detection. Our study helps improve diagnostic tools for OSA. These findings can aid in early and improved treatment of OSA, giving people a better quality of life and health.

Keywords: Sleep Apnea, Hypopnea, Hybrid Model, Neural Networks, Lstm, Sleep Disorders, Neurology, Optimizers, Activation.

I. INTRODUCTION

Sleep apnea, a condition that causes difficulty in breathing, is one that is very complicated and dangerous for individuals. Continuous partial or complete blockage of the airway during sleep episodes is a frequent trait of this disease, which has harmful neurological and physiological effects. Although these bouts of suffocation at night seem to be momentary interruptions in respiration, they have the potential to cause various systemic as well as psychiatric disorders far beyond sleeping. One way in which OSA deceives people is by silently entering into their sleep sanctuaries and taking away any chance of using the curative abilities of the nights. While the oblivious and incarcerated prisoners of their dreamscapes, their airways dangerously clog, gasping for life-sustaining breath most people take for granted. There is a brutal disruption of carbon dioxide and oxygen, the body's delicate equilibrium makes the consequences severe. The common hypoxic episodes are a significant danger to the sufferers and the healthcare system they affect, requiring our perpetual vigilance.

Considering the multiple layers on which OSA implications can be examined, one can measure its significant extent of mentality. It is not a mere exhale "gone too soon"; it is a malicious intruder that occupies sleep's sanctity

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and causes a domino effect of dire outcomes. The other common symptom results from the frequent apneic episodes' disruption of the regular sleep architecture, which is very severe. Fragmentation of sleep occurs as one breathes quietly through the struggle and oscillates across the stages of sleep. One is unable to enter the deeper restoring levels of sleep. Hence, this often ends up in a deadly downward spiral of severe exhaustion that is accompanied by nonstop lassitude, mental difficulty, and an unrelenting feeling of unease and tiredness. OSA has a grip on the physiological sphere that, even though it may show itself only through short-term consequences, dictates the course of long-term effects. During long-term central nervous system depression, oxygen levels will drop low, and carbon dioxide will be built up beyond normal, causing extra pressure on your heart and other major organs. Chronic inflammation, endothelial dysfunction, and hypoxia-oxidative stress being incensed by these conditions all together form a terrible storm that is very favourable to the development of cardiovascular disease. The number of tragedies taking place in medical history alone that are associated with untreated OSA and that significantly increase the possibility of hypertension, stroke, coronary artery disease, and congestive heart failure is truly striking.

Sometimes neurologically, slower than imagined, on its path to the inner sanctum it forms a vicious circle of neurons loss. Periodic hypoxia and fragmented sleep impede memory consolidation, cause problems with executive function, and make it harder to focus. Untreated OSA has been linked to emotional disorders, cognitive decline, and an increased risk of neurodegenerative diseases. The widespread effects are comparable to a cascade of cognitive dominoes. The terrifying part of OSA's story may be how pervasive it is, affecting millions of people's lives. People of various ages, colours, and origins are affected by the surprisingly high prevalence of OSA that still exists today. It does; however, seem to favour men, the elderly, and people with certain risk factors, like obesity. Because OSA is so common, it is imperative that a prompt and precise diagnosis be made, and here is where our main effort is focused. Deep learning has come to light as a ray of hope in the never-ending search for early detection and accurate intervention, with the potential to completely transform the field of OSA diagnosis. Our research is focused on the interaction between complex algorithms and physiological inputs. We explore the complexities of Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNN), and a novel hybrid technique that integrates these models. We decipher the maze of diverse optimisation techniques and activation functions to reveal their influence on OSA detection precision.

Not by ourselves, we are accompanied by others who share the same sentiments and aim, seeking knowledge and understanding together. Our progress is based on shared knowledge in discoveries from cutting-edge visionaries. EEG or electroencephalogram uses the brain's electrical activity produced by neurons to interpret, thus uses the generated signals to come up with the zone affected by the OSA. In the other option, depth maps portray the geometric structures had ranging from distance to density of the objects from the eyes, therefore, analysis is expected to discover non-contact diagnosis. At all points of these contributions, therefore, are the mosaic pieces of progress. They are instrumental in achieving the better diagnosis of OSA. Our investigative approach entails the concise integration of differing research works to help us understand OSA and administer an approachable, accurate, and timely diagnostic framework. Current research intend to explore the actuality of physiological signals impinging on the opportunity of applying deep learning for the OSA patients with the hope to be able to improve the chances of the individuals who suffer from this harmful sleep disease and reveal the secret of OSA.

II. RELATED WORKS

The use of technology in the recent years have been the game changers in the way OSA is diagnosed. Researchers are working to improve old means of diagnosis and to make them more straightforward. It talks of the research on the OSA diagnosis that make the test of the OSA be both efficient and fast. They address many problems, that is, making the process of diagnosis easier and helping the doctors do it correctly [10]. Together, their increments are memorable in the sense of early and convenient OSA detection, which is such an important factor since OSA may not only shorten the lives significantly but also many other very bad things can happen to you.

There have been few research already revealed a definite contribution of Machine Learning (ML) in sleep apnea detection. Likewise, in another study by Xie and Minn [1], the combination of several ML algorithms, namely AdaBoost and Bagging, to identify ECG caused by sleep apnea was employed. Feature selection pre-processing

step helped them to achieve the best result of their models. The result that the recognition system managed to show a high accuracy of 82% was impressive.

In the study conducted by Song with others [2], they made the OSA detection more accurate by taking into account the time-associated modifications in physiological signals. The scientists devised an OSA detection system based on the ECG signal, with a Hidden Markov Model (HMM) applied for classification. The system demonstrated high accuracy in per record classification (97.1%) and body segment selection of OSA signal (86.2%) when tested on the Physionet database data. It is an advancement that can overcome existing issues, providing for more precise diagnosis as well as ticking almost all the boxes for disease screening.

The data from study PhysioNet Sleep Data [3] used has been raised in the past as an example of problems like the difficulty of manual Polysomnography (PSG) data analysis, coping with large datasets, and handling data that is not good all the time. The research has not only exhibited how challenging it is to explore the lot of PSG data but has also demonstrated the positive influence of automated detection methods in facilitating this analysis.

In a review study [4], a search found 5,479 articles, with 63 (1.15%) meeting the criteria. Of these, 23 studies focused on diagnostic model development, 26 included internal validation, and 14 used clinical prediction algorithms with independent samples. Logistic regression was used in 35 studies, linear regression in 16 studies, and other methods in fewer studies. The best model had an area under the receiver operating curve of 0.98, achieved using age, waist circumference, Ep-worth Somnolence Scale score, and oxygen saturation as predictors in logistic regression.

In their study, Mietus, Peng, Ivanov, and Goldberger et al. [5] present an auto-mated method for diagnosing obstructive sleep apnea from single-lead electrocardiograms. The method detects periodic oscillations in cardiac inter-beat intervals associated with OSA by utilizing the Hilbert transformation. The algorithm achieved 93.3% accuracy in classifying OSA and normal subjects and 84.5% accuracy in identifying OSA presence or absence in the test data.

In their pursuit of early OSA detection, Jothi et al. [6] recognized the potential to save lives and reduce healthcare costs. Using electrocardiogram and photoplethysmogram readings, they used computer-aided diagnostic approaches, utilising deep learning. To efficiently recognise OSA episodes, they specifically used Densely Connected Long-Short-Term Memory (DC-LSTM) networks and convolutional neural networks with long short-term memory. With an impressive 98.2 percent accuracy, 97.4 percent sensitivity, 97.5 percent specificity, and 0.92 Kappa coefficient, the DC-LSTM network performed admirably. This method not only exhibits exceptional performance, but also has the potential for seamless integration into wearable medical devices, enabling convenient at-home OSA monitoring.

Atri et al. [7] introduced a method for automatically diagnosing OSA using electrocardiogram data. Their approach, which relied solely on ECG recordings during sleep, employed minute-by-minute signal processing. The method involves considering various features derived from “heart rate variability (HRV) and ECG-derived respiratory (EDR) signals”. Notably, they utilized bi-spectral analysis to explore the quadratic phase coupling within HRV and EDR signals, introducing a feature set based on higher-order spectrum analysis. These features were used as inputs for the least-squares support vector machine classifier. Testing their method on Physionet’s, the results demonstrated its effectiveness. Cross-validation achieved an accuracy of 95.57%, with a sensitivity of 98.64% and a specificity of 92.51% in distinguishing normal from apneic recordings. Independent validation using an additional 35 records yielded an accuracy of 94.12%, sensitivity of 93.46%, and specificity of 94.79% for detecting OSA episodes. This method outperformed the existing approaches, highlighting its potential as a reliable tool for automatic OSA identification and improvement in medical services.

Sharma, H et al. [8] have introduced an unconventional way of sleep apnea detection from single-lead ECG data. An inertial sensor extracts characteristics of the QRS complexes using Hermit lower order basis functions. This is then combined with the R-R time series features to distinguish between apnea events and normal events for the guidance approach. The results demonstrate 84% of accuracy in minute-level classification based on LS-SVM and 97.32% accuracy per recording classification with SVM and LS-SVM. Asserting such an approach, accuracy

is the same as many existed ones, but with the decreased computational cost, that does not employ many characteristic features for the classification.

The study by Tsai et al. [9] was a step towards the acceptance of a reliable, user-friendly diagnostic tool in sleep apnea (OSA). When OSA is widely seen, diagnostic approaches that prove to be accurate are of utmost importance. As revealed from the study, the repeatability or precision of such testing techniques as sensitivity and specificity is an essential factor for the proper identification of OSA.

Arguably, Vaquerizo-Villar et al. article [11] contributes significantly towards the diagnosis of childhood OSA. The repeated citations of it stress its importance of the reliable oximetry in the proper way to find out OSA in children. The research brings up limited datasets and model adaptation, the issues of import if the model is to diagnose reliably and accurately.

III. METHODOLOGY

The basis of this approach was the development of deep Neuro-networks, aimed at enhancing OSA-diagnosis precision. The main parts is the Convolutional Neural Networks, Long Short-Term memory networks as well as hybrid model. These algorithms have found the place for the software engineers who make them up. Backbone of the technique and convey a protocol used to determine the existence of complicated cases of OSA.

A. *Data Collection*

Over the course of this study, a dataset called OSASUD (Obstructive Sleep Apnea Stroke Unit Dataset) has been trained. OSASUD stands out as a pioneering effort to compliance to the sizable void in medical care. The project which was initially programmed by the bedside monitor from the Department of Clinical and Experimental Physiology of the University Hospital of Udine resulted in the invention of the method for the diagnosis of obstructive sleep apnic syndrome (OSAS). Unlike many previous studies, OSASUD intentionally includes fewer exclusion criteria, providing a more realistic clinical approach. This approach reflects the challenges faced by healthcare professionals dealing with diverse patient profiles and comorbidities that pose challenges. Each patient sample in the dataset provides rich vital sign information with multi-channel electrocardiography (ECG), photoplethysmography (PPG), and PSG. A detailed note is included in the dataset, showing the time interval of OSAS events.

B. *Data Processing and Alignment*

Because the OSASUD dataset strongly recognizes the importance of data preparation, it includes several important steps to ensure data quality and accuracy. Because the data set combines information from a variety of recording devices, such as the Embletta multi sleep chart and the Mindre monitoring system, careful temporal processing is performed, and the data pre-processing includes consuming overloads on to address and treat values that fall outside of physiological. Averaged PSG values associated with parameters such as abdominal position can provide cleaner and more reliable data for analysis. It should be noted that the data set has been removed to protect patient confidentiality in accordance with the highest ethical standards.

C. *Detailed Data Records*

The OSASUD dataset is formatted as a Pandas Data Frame, with 18 columns and a spread of 961,357 characters. Each line is identified by an anonymous patient code and labelled with a one-second granularity timestamp. Columns in the data set include a broad spectrum of vital sign data, including ECG-derived PPG-derived properties, physician details, PSG signal; and so on. This advanced position enables researchers to examine a wide range of physiological parameters.

D. *Feature Extraction*

Relevant factors were extracted from the data using the ANOVA F-statistic. Analysis of variance (ANOVA) A statistical test called the F-statistic is used to determine whether group means within a data set are significantly different from each other Determine whether group means differences are larger than predicted by accident or

high F-statistics indicate significant group differences, whereas low values indicate group similarity. 'HR(bpm)', 'SpO2(%)', 'PVCs(/min)', 'anomaly', and 'PSG_Snore' were found to be new features after EDA.

E. Model Development

Convolutional neural networks emerged as a key feature, facilitating comprehensive analysis of datasets to diagnose OSA. CNNs, renowned for their proficiency in the sequential processing of images and information, have been judiciously used to dissect complex patterns embedded in multimodal physiological signals, forcing their function as selection of optimal factors strengthens OSA screening protocols. The model includes Conv1D layers with 32 filters and a kernel size of three as shown in Fig. 1, enabling it to convolve over ordinal data, assuming the required model. This convolution function exhibits complex relationships to data, which is very important to disclose subtle signatures of OSA events.

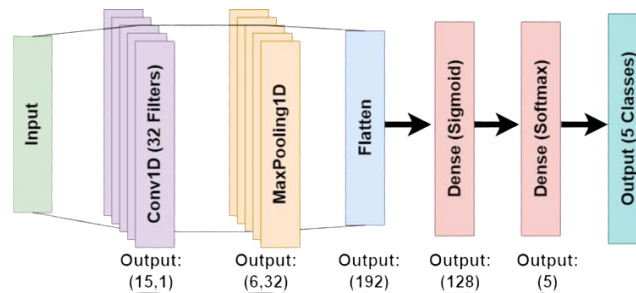


Figure. 1. An architectural schematic of the suggested CNN Model

The next layer, MaxPooling1D, helps to reduce computational complexity by down sampling the data and condensing it to its most essential elements. These layers make sure that the crucial data is saved for further examination by recognising and preserving the important characteristics. Transforming multi-dimensional data into a one-dimensional structure is a critical function of the flatten layer, which makes the move to fully connected layers easier. Dense layers which in our model consist of 128 neurons act as the hubs for making decisions. Activation functions for these layers are selected from a list that includes "relu," "tanh," "sigmoid," and "softmax." The interpretation of the data by the model is the notion of uniqueness, which comes out as result of the activations function of which only some are taken. CNNs are commonly referred to this ability to automatically find a great subset of indispensable information sets itself. This is why automated algorithms to detect sleep apnea are essential for picking up tiny variations in biological signals that can be easily missed by common methods. By classifying these put patterns, our CNN model performs very well in identifying OSA elements, giving the physician a higher chance of clinically diagnostic. Our CNN model which is functioned with hyperbolic tangents have been compared with other activation functions such as rectified linear unit (RELU), sigmoid and tanh activation functions. The decision margins or boundaries of the network model are extensively shaped by the activation functions explored here, which include the RELU, tanh, sigmoid, and softmax functions. With this knowledge, we can better understand the intricate details involved with each approach and how they affect the accuracy of alveolar sleep apnea.

Furthermore, our neural network model has been trained with "sigmoid" activation functions and tested against different optimizers by means of A/B testing (i.e., "Adam," "SGD," "RMSprop," "Adagrad," and "Adadelta" optimizers). The learning rate and convergence behaviour of the model are conditioned by the optimizers' selection and here our studies give us ground to what degree.

Nevertheless, the most important is LSTM, as shown in Fig. 2. The LSTM impresses the most with its extraordinary capacities to build a network of connections and patterns of sequences. Our approach of employing LSTM among other advanced learning algorithms working under the hood of OSA structure is far more accurate, because LSTM, a certain type of recurrent neural network (RNN), deals with difficult temporal patterns present in physiological information. Our model LSTM is the center of everything, and its architecture is very distinguishable in its sequential operations. It has 2 LSTM layers, each with 64 cells in both layers. A reference to sequential information is made through these layer mechanisms, where data from multiple model units is not considered in isolation but spoken hierarchy instead is seen.

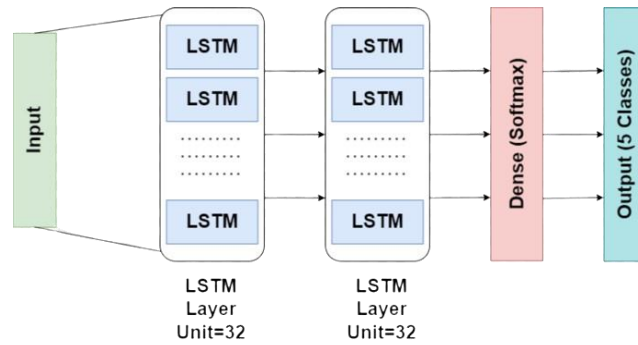


Figure. 2. An architectural schematic of the suggested LSTM Model

Coordinating architectural with this goal will make it possible to analyze the physiological data with confidence thereby to pinpoint the exact times OSA was taking place. The ability to understand and extrapolate the temporal linkage is what differentiate LSTM and makes it a good option for data processing situations where the data sequences heretoforeial may be vital. An LSTM's capacity to not only portray but also hold on to these complex temporal patterns, matters most when it comes to diagnosing OSA which has a dynamic physiological composition over time.

Through a thorough trial of the activation function of the LSTM model, we compare its impact on the performance of the LSTM model accordingly. The LSTM cells' activity and input processing are influenced by activation functions such as "softmax," "sigmoid," "tanh" and "ReLU". In case we examine these functions thoroughly, we can have a better understanding of the role they play on the prediction accuracy of our model in creating OSA episodes. We chose Adam, the optimizer, as our helper during the training sessions so that they are able to make the process of fine-tuning the model a matter of tuning a learning rate with pinpoint accuracy. In this compliance with the LSTM structure and this optimizer of a loss function, the model is ready for OSA event detection.

Our LSTM-based diagnosis approach tries to be thorough and data-driven as it is built on a lot of trials, training sessions, and evaluation stages. Our ambition is to ensure the efficacy and dependability of OSA recognition by using this technology to optimise the capability for identifying this sleep disease. A mixture of the hybrid model, as shown in Fig. 3, was implemented in the research of a precise and trustworthy OSA detection system. While this method integrates the benefits of the LSTM as well as CNN it ignores other alternatives such as wind farms. The exclusive benefits that these two models propound are the very factors that make this combination attractive.

The hybrid model is evident in the Scheme 3 that was used in the search for a highly accurate and reliable OSA detection system for efficiency. This model is strengthened by the LSTM and CNN methods in which both of these approaches are highly advantageous in terms of information processing capability. On the other hand, the unusual functionalities of these two designs that affect their combined production are what motivates this combination.

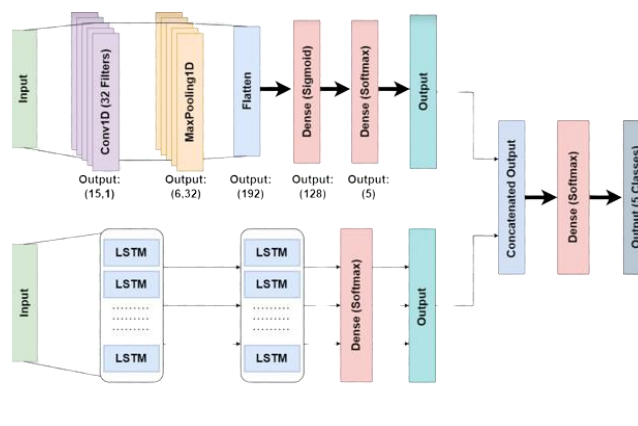


Figure. 3. The CNN-LSTM Hybrid Model's proposed architecture diagram

IV. RESULTS AND DISCUSSIONS

F. Results and Summary on Different Activation Functions

The accuracy for CNN and LSTM models were calculated using Adam as the optimizer and different activation functions as shown Table 1. Sigmoid was found to be the best activation function out of all.

Table 1. Accuracy values for different activation functions used on CNN and LSTM models using Adam optimizer.

Optimizer	Activation Function	Accuracy	
		CNN	LSTM
Adam	RELU	94.87	92.79
	Tanh	93.90	93.69
	Sigmoid	95.12	93.80
	Softmax	94.38	92.63

G. Results Summary on Optimizers

Table 2. Accuracy values for different optimizers used on CNN and LSTM models using Sigmoid optimizer.

Activation Function	Optimizer	Accuracy	
		CNN	LSTM
Sigmoid	Adam	94.91	93.81
	SGD	92.96	83.99
	RMSprop	94.22	93.83
	Adagrad	93.25	92.48
	Adadelta	94.55	84.03
	Nadam	95.22	94.75

By using sigmoid activation function, the accuracies of CNN and LSTM models were calculated for different optimizers as shown Table 2. Nadam optimizer was found to be the best out of all.

H. Results Summary on Taking Different Variables

Table 3. Accuracy values for different optimizers used on CNN and LSTM models using Sigmoid optimizer.

Features	Accuracy		
	CN N	LST M	CNN-LSTM Hybrid
All Features	93.7 1	94.08	95.26
Top 5 (Identified using ANOVA)	92.9 2	93.23	93.63
ECG Signals (ECG i, ECG ii, ECG iii)	84.1 2	84.75	83.85

The accuracy for all the models were calculated for all features, top 5 features and all ECG values. The hybrid model was found to be the best model on both the packs of features as shown in Table 3.

V. CONCLUSION

The identification of OSA is a crucial medical issue that appears to be amenable to resolution using sophisticated machine learning methods like LSTM, CNN, and a combination of these models. In conclusion, these models' combined efforts provide several insights and possible advantages: In the realm of OSA detection, combining CNN and LSTM models effectively is a crucial tactic. While CNN models are skilled at finding spatial patterns in the data, which might be useful for detecting OSA signs, LSTM models excel at processing sequential

physiological time series data, capturing temporal relationships. Together, these models provide improved accuracy and lower the possibility of false positives and false negatives in Hybrid methods. The Hybrid model's overall prediction power is strengthened by the combination of multimodal data, such as heart rate, oxygen saturation, and breathing rate. This is crucial assistance for clinical decision-making in the diagnosis and treatment of OSA. Even though deep learning approaches hold out hope for ongoing study and progress in OSA detection, issues like inconsistent data and interpretability of models continue to be obstacles. Expanding training datasets, improving model hyper parameters, and investigating explainable AI techniques should be the main areas of future research to encourage broader clinical application of these potent instruments.

There is great potential for identifying OSA with the use of sophisticated deep learning methods like CNN, Hybrid models, and LSTM. This field of study and application has a broad future reach and presents some chances for advancement and innovation, including more research and development is needed to optimize current models and produce more accurate algorithms, which will help to improve OSA detection performance by lowering the number of false positives and false negatives in the detection process. To do this, it is necessary to work with healthcare institutions and organizations to obtain large, diverse datasets, which are critical to the models' accuracy. Furthermore, wearable technologies and sensors can help to develop real-time OSA monitoring systems, which can assist early identification and continuous monitoring in addition to providing prompt feedback.

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