Sleep Disorder Prediction Using CNN and Bidirectional LSTM

P.Shanmugapriya[1]
[1]Department of Computer Science and Engineering
PSG Institute of Technology and Applied Research
Coimbatore, India
priyasenthilraja@gmail.com

Dr D. Senthil Raja[2]
[2]Department of Mathematics,
Sri Krishna College of Engineering and Technology,
Coimbatore, India
dsr.senthil@gmail.com

V.Karun Rozariyo[3]
[3]Department of Computer Technology
Kongu Engineering College
Erode, India
karunrozariyov.21msc@kongu.edu

Dr M.N. Kavitha[4]
[4]Department of Computer Science and Engineering
PSG Institute of Technology and Applied Research
Coimbatore, India
kavithafeb1@gmail.com

T.E.Ramya[5]
[5]Department of Computer Science and Engineering
Kongu Engineering College
Perundurai, India
ramyaerusan@gmail.com

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***Abstract*— Sleep disorders pose a serious health hazard, and hence, accurate classification is required for effective intervention at the right time. This study proposes an optimized architecture for deep learning from Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) to enhance the classification of sleep disorders. Now that the Sleep Health and Lifestyle Dataset has been made available publicly, the model uses advanced feature engineering, SMOTETomek class balancing, and hyperparameter tuning to reach the optimum performance level. The proposed architecture captures spatial and temporal patterns with convolutional and bidirectional LSTM layers, and dense layers with dropout regularization for preventing overfitting. Experimental results are significantly better compared to conventional methods with a classification accuracy of 95%, outperforming existing state-of-the-art methods. This paper demonstrates the potential of deep learning for automating sleep disorder diagnosis and improving clinical decision-making. Future studies will attempt to combine multi-modal data fusion with real-time application for improved diagnostic precision.**

Keywords – ***Sleep disorder classification, CNN-BiLSTM, deep learning, machine learning, SMOTETomek, feature engineering, hyperparameter tuning.***

I. INTRODUCTION

Sleep ranks among the simplest biological processes which are crucial in the maintenance of physical and mental well-being. Any disruption in the sleep-wake cycles will lead to medical issues such as cardiovascular system conditions, overweight, and neurologic system-related or endocrine system-related diseases. Several sleep disorders that affect a significant percentage of the population, from insomnia to sleep apnea, negatively affect individual and professional efficiency and deal a severe blow to the level of quality of life an individual has. Conventional diagnostic methods are laboratory-based overnight polysomnography (PSG) by direct observation, expensive specialized equipment, and expert analysis, which are comparatively restrictive and inefficient for screening large populations. Increased demand for effective and automated sleep disorder classification method has encouraged research and development in deep learning and machine learning methods. Machine learning and deep learning have been highly successful in healthcare applications, particularly in medical condition diagnosis based on data analysis by machines.

The classical machine learning algorithms such as Support Vector Machines (SVM), Decision Trees (DT), and Random Forests (RF) have been employed to differentiate between sleep disorders. These models, however, tend to rely on hand-crafted feature extraction, which may not always accurately represent the complexity of sleep data. Deep learning algorithms, Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have been found to excel in outperforming by automatically identifying intricate patterns in data. Joining CNN to Bidirectional LSTM (BiLSTM) leverages spatial and temporal extraction of features improving classification of sleep disorders. CNN extracts important spatial features from sleep-related attributes, as BiLSTM extracts sequential dependencies, thereby resulting in improved classification accuracy. Other methods improve the model's performance. Feature engineering, SMOTETomek for class balance, and hyperparameter tuning are these methods. When you are handling data imbalance and when you are tuning the model's parameter, it helps to make more generalized predictions. The Sleep Health and Lifestyle Dataset enables evaluation for all. It features sleeping hours, sleep quality, stress level, heart rate, along with daily activity levels. Giant experimentation average F1-score of 0.95 supports that the overall performance is sound even when imbalances in classes are taken into consideration. These findings validate the excellence of the CNN-BiLSTM architecture in handling both spatial and temporal relationships in sleep data, warranting precise and scalable sleep disorder classification.

Class Label	Class Name	Precision	Recall	F1-Score	Support
0	Normal	0.97	0.89	0.93	38
1	Insomnia	0.92	0.95	0.94	38
2	Sleep Apnea	0.95	0.98	0.96	55
Macro Average	-	0.95	0.94	0.94	131
Weighted Average	-	0.95	0.95	0.95	131
Overall Accuracy				**0.95**	**131**

Figure 5. Classification Report

V. CONCLUSION

The proposed CNN-BiLSTM model demonstrates high potential for sleep disorder classification based on spatial as well as temporal feature extraction. With reported classification accuracy of 94.66%, with further backing by precision, recall, and F1-score, the model is demonstrated to be capable of robust detection of diverse states of sleep. Performance is enhanced by techniques such as SMOTETomek balancing, feature engineering, and optimization. Divergence of training and validation metrics observed during experimentation, however, indicates signs of overfitting, showing a limitation in the model's generalizability to new data. To counter this, techniques such as dropout regularization, L2 penalties, early stopping, and learning rate decay were employed to enhance stability. These results demonstrate promise of deep learning in sleep disorder diagnosis in terms of increased generalization through further optimization. Future real-time use and clinical validation—particularly through wearable technology—may further enhance its practicality and scope.

VI. FUTURE WORK

Future studies will aim to improve generalizability and scalability of the model to real-world environments. To prevent overfitting and improve robustness, we intend to investigate model reduction, more aggressive regularization, and data augmentation of time-series signals. Addition of multi-modal physiological signals, e.g., EEG, ECG, and heart rate variability, and respiratory patterns can further provide richer context for better classification accuracy. Addition of attention mechanisms to the CNN-BiLSTM architecture will be expected to improve interpretability and feature saliency. Real-time validation in the clinic and home will be a high priority to ascertain real-world utility. Addition of more heterogeneous sleep disorders (e.g., narcolepsy, restless leg syndrome) and demographics to the dataset will improve generalizability. Experiments with ensemble learning and self-supervised strategies may also further improve diagnostic performance and flexibility in different healthcare environments.

VII. REFERENCES

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