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EVALUATING HYBRID NEURAL NETWORK ARCHITECTURES FOR PREDICTING SLEEP DISORDERS FROM STRUCTURED DATA

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Abstract

The accurate diagnosis of sleep disorders is crucial for effective treatment and management, yet current methods often rely on subjective assessments and are not always reliable. This research examines the efficacy of various neural network architectures, including dense networks, convolutional neural networks (CNNs), recurrent neural networks (RNNs), and innovative hybrid models, in predicting sleep disorders from structured health data. Our study focuses on comparing the performance of these models using metrics such as accuracy, precision, recall, and F1 score across a dataset comprising 400 individuals with detailed sleep and lifestyle data. Our findings demonstrate that while traditional models like dense networks and CNNs for structured data yield robust results, hybrid models, particularly the CNN-Transformer, significantly outperform others. This model effectively integrates convolutional layers with Transformer's attention mechanisms, excelling in handling complex data interactions and providing superior predictive accuracy with an F1 score and accuracy reaching as high as 0.91. Conversely, RNN models, designed to capture temporal data dependencies, showed less efficacy, underscoring the importance of model selection aligned with data characteristics. This suggests that for datasets not exhibiting strong temporal features, models leveraging spatial relationships or advanced attention mechanisms are more suitable. This study not only advances our understanding of neural network applications in medical diagnostics but also highlights the potential of hybrid models in enhancing diagnostic accuracy. These insights could lead to significant improvements in the early detection and treatment of sleep disorders, thereby enhancing patient outcomes and contributing to the broader field of medical informatics.

Keywords: *Hybrid AI, Neural Networks, Sleep Diagnosis, Machine Learning, CNN-Transformer*

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1. INTRODUCTION

In recent years, the prevalence of sleep disorders has increasingly become a concern, affecting public health significantly [1]–[3]. Disorders such as insomnia and sleep apnea not only degrade individuals' quality of life but are also linked with various chronic diseases, including cardiovascular diseases, diabetes, and obesity [4]–[6]. Traditional methods for monitoring and analyzing sleep patterns typically rely on subjective self-reports and clinical observations, which are often inaccurate and cumbersome [7]–[9]. However, the rise of machine learning (ML) and deep learning (DL) technologies offers a promising avenue for revolutionizing the field of sleep research by enabling more precise and insightful analysis of sleep health data [10]–[12].

Extensive documentation exists in the literature on the exploration of sleep patterns through data-driven approaches. Techniques ranging from Support Vector Machines (SVMs) to Random Forests have been utilized to classify sleep stages from polysomnography data [13]–[15]. More recently, advanced deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) variants [16], have emerged as powerful tools for uncovering complex patterns, and especially in sleep-related data [17]. These models have shown a capacity to significantly enhance accuracy and efficiency over traditional statistical methods, adeptly managing large datasets enriched with multiple input variables [18]. The escalating global incidence of sleep disorders and their severe health repercussions underscore the urgency to advance research in this domain [19].

Accurate diagnosis and effective treatment of sleep disorders are critically dependent on the capability to analyze and predict individual sleep patterns and disturbances accurately [20]. Traditional diagnostic methods, heavily reliant on direct observation and patient self-reporting, demand considerable resources and are prone to inaccuracies [21]. This situation underscores a critical need for more sophisticated, automated analytical tools [22].

The cutting edge of sleep research is defined by hybrid neural network models that combine the capabilities of both CNNs and RNNs, aiming to harness their respective strengths. CNNs excel in extracting spatial hierarchies from data, suitable for processing time-series inputs like those prevalent in sleep data. In contrast, RNNs are particularly effective in capturing temporal dependencies and sequences, essential for understanding patterns over time. Moreover, Transformer models, which utilize self-attention mechanisms, are also gaining popularity for their ability to process sequential data without the limitations inherent to traditional RNNs, offering potentially superior performance in sequence modeling tasks. The principal aim of this research is to develop and assess the effectiveness of hybrid neural network models in predicting sleep disorders based on lifestyle and physiological data. While existing studies have often explored isolated aspects of sleep using either CNNs or RNNs, they rarely combine these approaches in a cohesive model. This research gap highlights an opportunity where the synergistic potential of these models has not been fully explored in a unified framework to analyze sleep health data comprehensively. Additionally, most current models do not sufficiently incorporate lifestyle factors such as physical activity and stress levels, which are crucial for a holistic understanding of sleep patterns and disorders.

This research intends to fill these gaps by implementing and comparing two innovative hybrid models: a CNN-RNN model and a CNN-Transformer model. These models are uniquely designed to capitalize on the spatial feature extraction prowess of CNNs and the sequential modeling strengths of RNNs or Transformers, thereby providing a comprehensive analytical tool for sleep health. This integrative approach, which combines various data dimensions including physiological measurements and lifestyle factors into a coherent predictive framework, is a novel contribution to the field. The remainder of the article will detail the methodology employed, including data preparation, a description of the hybrid models, and the experimental setup for model training and validation. It will then present the experimental results, highlighting model performance metrics such as accuracy, precision, recall, and F1-score. Following this, the discussion will interpret the results, discuss their implications, and compare the performance of our proposed models with traditional models. The article will conclude by summarizing the research contributions and suggesting potential directions for future research in this vibrant area.

2. RESEARCH METHOD

The Sleep Health and Lifestyle Dataset used in this research comprises data from 400 individuals, with each record containing 13 different variables related to demographics, lifestyle, and physiological measurements. Key features include gender, age, occupation, sleep duration, quality of sleep, physical activity level, stress levels, BMI category, blood pressure, heart rate, daily steps, and the presence or absence of sleep disorders like Insomnia and Sleep Apnea. Dataset can be downloaded from [23].

2.1 Data Preprocessing

In this research, data preprocessing forms a critical foundation for building reliable predictive models. The initial step involves a meticulous selection of features from the Sleep Health and Lifestyle Dataset, which contains a diverse array of variables related to personal demographics, lifestyle habits, and physiological measures. The objective here is to refine the dataset to ensure that only relevant variables are fed into the neural networks, thereby enhancing the models' learning efficiency and predictive accuracy.

First, feature selection, in this phase, the dataset was carefully curated to remove columns that do not contribute meaningfully to the predictive modeling process. For instance, 'Person ID' was eliminated as it represents arbitrary identifiers assigned to individuals, offering no intrinsic predictive value regarding sleep disorders. Similarly, 'Age_bin', a derived categorical variable representing age groups, was also excluded. This decision was based on preliminary analyses which suggested that direct age values provide more granular and thus potentially more insightful data for modeling than categorized age groups. The selection process ensures that the models are trained in features that directly impact sleep quality and disorders, such as sleep duration, physical activity levels, and stress. Furthermore, encoding categorial variable, The 'Sleep Disorder' column, which categorizes the type of sleep disorder diagnosed in individuals, was processed using label encoding. This technique converts categorical text data into a numerical format, assigning an integer to each category of disorder. For instance, 'None' may be encoded as 0, 'Insomnia' as 1, and 'Sleep Apnea' as 2. This numeric transformation is crucial as it allows mathematical operations to be performed on the data during model training.

Following label encoding, the numerically represented sleep disorders were further transformed into a one-hot encoded format. One-hot encoding is a process where each numerical value is converted into a binary vector with all zeros except for a single one at the index of the integer label. This is done to accommodate the neural network's output layer, which is designed to predict the probability of each category. This method prevents the model from misinterpreting the ordinal numbers as having some form of hierarchical value, which is not the case with nominal categorical data.

2.2 Model Development

The concept of a "hybrid" in neural network terminology refers to the integration of distinct types of neural networks into a single cohesive model. Each type of network offers unique advantages: CNNs excel in processing data with spatial relationships, making them ideal for analyzing image data or structured datasets where inputs can be treated as images; RNNs are adept at handling sequential data, offering advantages when the order of data points is crucial, such as time-series analysis or speech recognition; Transformers provide significant improvements in handling long-range dependencies within data, surpassing traditional RNNs in tasks that require understanding the context from large input sequences.

By combining these architectures, hybrid models can leverage the specific strengths of each network type, thereby enhancing the model's ability to understand complex, multifaceted data structures. For instance, in sleep disorder diagnostics, patient data often contains both structured data points (like heart rate or blood pressure readings) and sequential data (like changes in sleep quality over time), necessitating a model capable of interpreting these diverse data types effectively. In this study, we have developed three sophisticated hybrid neural network architectures to explore the predictive potential of different combinations of neural network technologies for diagnosing sleep disorders. Each model is tailored to leverage unique aspects of the data, focusing on extracting, and analyzing both spatial and temporal features to robustly predict sleep-related issues.

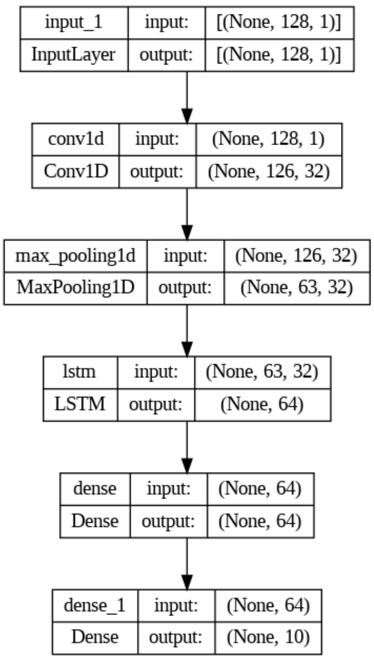

Figure 1. CNN-RNN Hybrid Method

The first of the proposed models as presented in figure 1 is the CNN-RNN Hybrid, which is designed to integrate the strengths of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The CNN layers at the beginning of the model serve to extract spatial features from the dataset. These layers use convolutional filters that effectively identify patterns and characteristics in the input data, which are spatially correlated. Following the CNN layers, MaxPooling is employed to reduce the dimensionality of the data. This reduction not only helps in reducing the computational load but also minimizes the risk of overfitting by abstracting the features and retaining only the most significant ones.

The extracted features are then fed into Long Short-Term Memory (LSTM) units, a type of RNN that is particularly adept at processing sequences of data. LSTMs are designed to remember important information for long periods, which is critical in understanding the temporal dynamics of sleep patterns. This combination allows the model to capture both the immediate (spatial) and historical (temporal) dependencies inherent in the data, making it well-suited for complex pattern recognition tasks like sleep disorder diagnosis.

The second model as presented in the figure 2, the CNN-Transformer Hybrid, begins similarly with CNN layers that process the input data to capture spatial dependencies. These initial layers prepare the data by highlighting essential features before they are processed by the more complex components of the model. The transformative aspect of this model is the incorporation of a Transformer block, which follows the CNN layers. Transformers utilize attention mechanisms that allow the model to weigh and prioritize different parts of the input data based on their relevance to the task at hand.

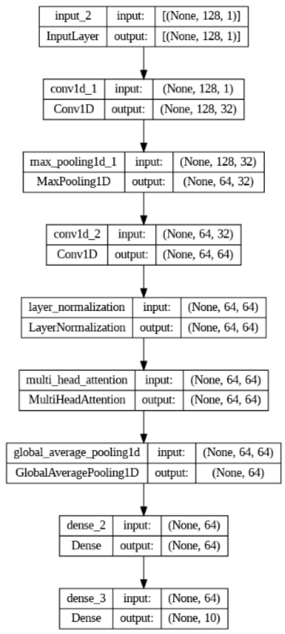

Figure 2. CNN-Transformer Hybrid Method

This mechanism is highly beneficial for modeling long-range interactions in data, as it can assess and connect distant points within the input sequence, thereby providing a more nuanced understanding. The multi-head attention within the Transformer can simultaneously process different subsets of the input data, offering a comprehensive overview that enhances the model's ability to make informed predictions.

To provide a benchmark for evaluating the performance of the hybrid models, a deeper CNN model was also developed. This control model relies solely on multiple layers of CNNs, each designed to delve deeper into the extracted features from the preceding layer. By stacking more convolutional and pooling layers, the model can learn increasingly abstract representations of the input data. The deeper layers can identify complex patterns that simpler models might overlook. This architecture concludes with Flatten and Dense layers, which transform the multidimensional CNN outputs into a format suitable for classification.

These three models collectively encompass a broad spectrum of neural network technologies, from basic CNNs to advanced combinations with RNNs and Transformers. Each model is expected to offer unique insights into the predictive analysis of sleep disorders, providing a robust comparative analysis that will help determine the most effective architectural approach for this type of data. The development of these models represents a significant step forward in applying artificial intelligence to improve diagnostic accuracies in the medical field, particularly in understanding and treating sleep disorders.

In this research, data preprocessing forms a critical foundation for building reliable predictive models. The initial step involves a meticulous selection of features from the Sleep Health and Lifestyle Dataset, which contains a diverse array of variables related to personal demographics, lifestyle habits, and physiological measures. The objective here is to refine the dataset to ensure that only relevant variables are fed into the neural networks, thereby enhancing the models' learning efficiency and predictive accuracy.

2.3 Model Training and Evaluation for Sleep Disorder Prediction

The training and evaluation of our models are pivotal components of this research, designed to rigorously test the robustness and generalizability of each neural network architecture developed for predicting sleep disorders. To achieve this, we adopted a systematic approach involving cross-validation, performance metric assessment, and comprehensive statistical analysis.

The dataset was split into a training set (80%) and a testing set (20%) using stratified sampling to maintain the proportion of categories in both sets. In the field of machine learning, cross-validation is a critical methodology for validating model stability and generalizability. For this study, a 10-fold cross-validation was employed, a technique where the dataset is split into ten separate subsets. Each subset serves as the test set during one iteration of the model evaluation, with the remaining subsets used for training. This method is instrumental in mitigating any biases that might arise from a singular division of data into training and test sets, as each subset is used exactly once as a test set. By rotating through different combinations of training and testing groups, the models are tested under varied conditions, enhancing the reliability of the evaluation results.

After conducting the 10-fold cross-validation, the results from all iterations were aggregated to calculate the mean and standard deviation for each performance metric. These statistics are crucial as they offer a comprehensive view of the model's performance across different data subsets, indicating the effectiveness and stability of each model. Furthermore, a comparative analysis was performed to delineate the performance differences between the hybrid models and the traditional deeper CNN model. This comparison highlights the strengths and potential limitations of each architectural approach, providing valuable insights into their practical applications. The analysis not only underscores the models' predictive capabilities but also their robustness, ensuring that the findings are not merely artefacts of data splits or specificities of the dataset used. Through this meticulous training and evaluation process, the study aims to establish a solid foundation for the deployment of these models in real-world scenarios, contributing to the ongoing efforts to enhance diagnostic accuracies in the healthcare domain, especially in sleep health.

In evaluating the effectiveness of each model comprehensively, a range of performance metrics was employed to gauge their capabilities thoroughly. Accuracy as presented in the equation 1 was utilized to measure the overall correctness of the model, reflecting the proportion of true result: both true positives and true negatives among the total cases examined. This metric serves as a fundamental indicator of the model's performance across the spectrum of test data. Precision as presented in the equation 2 was another critical metric, focusing on the purity of positive identifications. It is defined as the ratio of correctly predicted positive observations to the total predicted positives, thus highlighting the model's effectiveness in producing relevant results without overgeneralizing to incorrect classifications.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions Made}} \tag{1}$$

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2}$$

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

Recall, or sensitivity, as presented in the equation 3 is crucial for understanding the model's ability to identify all relevant instances within the dataset. It is calculated as the ratio of correctly predicted positive observations to all observations in the actual class, offering insight into how well the model captures the necessary cases without neglecting those that are crucial. The F1 Score as presented in the equation 4 integrate both precision and recall into a single measure by representing their harmonic mean. This metric is especially valuable in conditions where the data might be imbalanced, ensuring that the model's efficacy in identifying positive cases is balanced against its precision, thus avoiding a skew towards over-predicting minor classes or under-representing major ones.

These metrics collectively provide a nuanced view of model performance, detailing not only the accuracy but also the models' capabilities in identifying and classifying various classes of sleep disorders correctly. Such comprehensive measurement assists in determining the practical applicability of the models in clinical settings, where accurate diagnosis is paramount.

3. RESULT AND DISCUSSION

This study offers a thorough assessment of various neural network architectures aimed at predicting sleep disorders, providing insights into their performance across multiple metrics: accuracy, precision, recall, and F1 score. The discussion explores the implications of these findings for the future of diagnostic models in sleep health, highlighting the comparative strengths and weaknesses of each tested model.

Table 1. Deep Learning Comparison Results

Model	Avg Accuracy	Avg Precision	Avg Recall	Avg F1 Score
Deeper CNN	0.91	0.92	0.91	0.91
Complex RNN	0.84	0.86	0.84	0.83
CNN-RNN Hybrid	0.87	0.89	0.87	0.87
CNN-Transformer Hybrid	0.91	0.92	0.91	0.91
Dense Network	0.90	0.90	0.90	0.90
CNN	0.90	0.90	0.90	0.90
RNN	0.83	0.84	0.83	0.82

As presented in the table 1, the dense network and CNN for structured data models both exhibited robust performance metrics, with accuracy, precision, recall, and F1 scores hovering around 0.90. This high level of effectiveness suggests that both models adeptly classify sleep disorders when structured data inputs are optimally processed. Interestingly, the similar performance metrics between these two models indicate that the additional convolutional layers in the CNN do not significantly outperform the simpler densely connected layers of the dense network. This could be due to the dataset's lack of complex spatial relationships that convolutional layers are best suited to capture.

In contrast, the RNN model designed for structured data demonstrated lower performance, with accuracy and F1 scores around 0.83. This underperformance may be attributed to the RNN's emphasis on capturing temporal dynamics, which are potentially less relevant for this dataset. This finding suggests that for datasets not characterized by significant time-dependent behaviors, simpler or different architectural focuses may be more effective. The deeper CNN model showed an improvement over its simpler counterpart, achieving average accuracy and F1 scores of about 0.91. This suggests that deeper network architectures, which are capable of capturing more complex data patterns, might be necessary when dealing with intricate datasets. This model's enhanced feature extraction capabilities seem to capture subtle nuances in the data, which simpler models may overlook. The complex RNN model performed similarly to the basic RNN model, with average scores around 0.84 for accuracy and 0.83 for F1. Like its simpler counterpart, the complex RNN is naturally suited to datasets with strong temporal correlations, which might not be dominant in this dataset, hence its comparatively lower performance.

The hybrid models, particularly the CNN-Transformer, achieved impressive results. The CNN-RNN hybrid balanced performance with average scores around 0.87 across metrics, benefiting from the combined spatial and temporal feature extraction capabilities. However, the CNN-Transformer model was particularly effective, matching the highest scores with 0.91 on both accuracy and F1. This model's success indicates that the integration of convolutional layers with the global perspective provided by Transformer's attention mechanisms can be highly beneficial, especially in complex datasets where relationships between features extend beyond simple sequences. The superior performance of the CNN-Transformer hybrid model has significant implications for developing diagnostic tools for sleep disorders. This model's ability to efficiently handle complex patterns suggests that future diagnostic models could become more sophisticated and accurate, capable of interpreting intricate datasets effectively. Moreover, the relative ineffectiveness of the RNN models in this context underscores the importance of matching model architecture with the dataset's nature, particularly concerning the presence or absence of temporal dynamics. For non-sequential datasets, models that focus on spatial relationships or integrate attention mechanisms might be more effective.

4. CONCLUSION

This study embarked on an exploration of various neural network architectures to identify the most effective models for predicting sleep disorders from structured data. Through rigorous evaluation of dense networks, CNNs, RNNs, and innovative hybrid models such as CNN-RNN and CNN-Transformer combinations, we have gained profound insights into the capabilities and performance of these advanced computational tools in the context of sleep health diagnostics. The findings reveal that while traditional dense networks and CNNs for structured data perform robustly, achieving high accuracy and other key performance metrics, the hybrid models, particularly the CNN-Transformer, demonstrate superior effectiveness. This model excels in integrating the strengths of convolutional layers with the advanced processing capabilities of Transformer's attention mechanisms, thereby effectively handling the complexities inherent in medical datasets.

The less-than-optimal performance of RNN models in this study highlights the importance of aligning model architecture with the specific characteristics of the dataset. This observation underscores the critical need for a nuanced approach to model selection, where the temporal or sequential nature of the data must be considered to maximize diagnostic accuracy and efficiency. Looking ahead, the potential of hybrid neural network architectures in transforming diagnostic processes is immense. The ability of these models to accurately predict sleep disorders can significantly aid in early diagnosis and treatment, ultimately improving patient outcomes. Moreover, the insights derived from this research can guide future studies in enhancing model interpretability and in exploring the integration of diverse and complex datasets.

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