Deep Learning-Based Sleep Stage Classification Using CNN-LSTM on the Sleep Heart Health Study PSG Dataset

1st Mrs.M.Ramya Harika
Sr.Asst.PROFESSOR(ECE)
Lakireddy Balireddy college of engineering
Mylavaram, NTR,Andhra Pradesh
harika.munnangi25@gmail.com

2nd S.Vamsi Krishna Reddy
Electronics and comm.engineering
NIT(Warangal)
Warangal,Telangana
vamsikrishnareddy675@gmail.com

3rd Kotagiri Harshavardhan Ajay
Electronics and comm.engineering
Lakireddy Balireddy college of engineering
Mylavaram, NTR,Andhra Pradesh
123ajayharsha@gmail.com

4th Uppalapati Satyasri Pragna
Electronics and comm.engineering
Lakireddy Balireddy college of engineering
Mylavaram, NTR,Andhra Pradesh
sripragnauppalapati@gmail.com

5th Bode Venkata Tirumula Rao
Electronics and comm.engineering
Lakireddy Balireddy college of engineering
Mylavaram, NTR,Andhra Pradesh
venkatatirumalarao5189@gmail.com

Abstract—Sleep stage classification is essential for diagnosing sleep disorders and understanding sleep patterns. Traditional manual scoring of polysomnography (PSG) data is time-consuming and prone to variability. This study proposes a deep learning approach combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for automated sleep stage classification. The CNN extracts spatial features from PSG signals, while the LSTM captures temporal dependencies, enhancing classification accuracy. The model is trained and evaluated on the Sleep Heart Health Study (SHHS) dataset, demonstrating its effectiveness in distinguishing different sleep stages. Experimental results indicate that the CNN-LSTM model outperforms conventional machine learning approaches, achieving high classification accuracy. This study highlights the potential of deep learning in automating sleep stage scoring, contributing to more efficient sleep disorder diagnosis and research. .

Index Terms—Convolutional Neural Networks (CNN) , fLong Short-Term Memory (LSTM) , Polysomnography (PSG)

I. INTRODUCTION

Sleep plays a vital role in maintaining overall health, cognitive function, and emotional well-being. Accurate sleep stage classification is essential for diagnosing sleep disorders such as insomnia, sleep apnea, and narcolepsy. Polysomnography (PSG) is the gold standard for sleep assessment, but manual sleep stage scoring by experts is labor-intensive and subject to inter-rater variability . To address these limitations, deep learning methods, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have been explored for automatic sleep stage classification.

CNNs effectively extract spatial features from raw PSG signals, while LSTMs capture long-term temporal dependencies, making them well-suited for sequential sleep stage transitions . The Sleep Heart Health Study (SHHS) dataset, a widely used resource, provides comprehensive PSG recordings for evaluating sleep patterns . Recent studies have demonstrated that deep learning-based models outperform traditional machine learning techniques in sleep stage classification, achieving higher accuracy and robustness [4]. This study proposes a CNN-LSTM hybrid model to enhance the accuracy of automated sleep stage classification using the SHHS dataset, contributing to more efficient and reliable sleep disorder diagnosis.

Implementing Convolutional Neural Networks (CNNs) in sleep stage classification has proven to be highly effective due to their ability to automatically extract relevant features from raw EEG signals. CNNs can capture spatial and temporal patterns associated with different sleep stages without the need for manual feature engineering. By using multiple convolutional and pooling layers, the model learns hierarchical representations that distinguish between stages such as wakefulness, REM, and non-REM. This approach enhances classification accuracy and reduces dependency on domain-specific knowledge. Additionally, CNNs are computationally efficient, making them suitable for real-time sleep monitoring applications in both clinical and home environments.

Implementing Long Short-Term Memory (LSTM) networks in sleep stage classification has shown promising results due to their ability to capture temporal dependencies in sequential data like EEG signals. LSTMs effectively learn patterns across time, making them well-suited for recognizing transitions between different sleep stages. By using memory cells and gating mechanisms, LSTMs retain relevant information over longer periods, which is crucial for understanding sleep architecture. They can be trained on preprocessed EEG data to classify stages such as Wake, REM, and NREM accurately. Overall, LSTM-based models enhance classification performance by leveraging time-series characteristics inherent in sleep signals.

Implementing a hybrid CNN+LSTM model for sleep stage classification effectively leverages both spatial and temporal features of EEG signals. The Convolutional Neural Network (CNN) extracts local spatial patterns from raw EEG data, such as frequency and amplitude variations. These features are then passed to a Long Short-Term Memory (LSTM) network, which captures the sequential dependencies and temporal dynamics across time. This combination enhances classification accuracy by addressing both the feature extraction and temporal correlation aspects of sleep stages. Overall, the CNN+LSTM architecture provides a robust framework for automated sleep stage scoring using physiological signals like EEG.

II. LITERATURE SURVEY

Sleep is vital for people's physical and mental health, and sound sleep can help them focus on daily activities. Therefore, a sleep study that includes sleep patterns and sleep disorders is crucial to enhancing our knowledge about individuals' health status. This study aims to provide a comprehensive, systematic review of the recent literature to analyze the different approaches and their outcomes in sleep studies, which includes works on "sleep stages classification" and "sleep disorder detection" using AI. [7] An analysis of the sequence of sleep stages can uncover the presence of sleep disorders.Firstly, it focuses on the classification of sleep stages using a combination of signals and deep learning models. Secondly, this thesis detects obstructive sleep apnoea (OSA) from electrocardiography (ECG) signals using deep learning methods. [1] Sleep is an essential time for body recovery and healthy living. Therefore, sleep monitoring for health management is important. The gold-standard method for evaluating sleep is polysomnography (PSG), and physicians score the sleep stages using night PSG recording data. [4] Sleep stage classification plays a significant role in the accurate diagnosis and treatment of sleep-related diseases. This study aims to develop an efficient deep learning based scheme for correctly identifying sleep stages using multi-biological signals such as electroencephalography (EEG), electrocardiogram (ECG), electromyogram (EMG), and electrooculogram (EOG). [5] Because of problems with the recording and analysis of the EEG signal, automatic sleep staging using cardiorespiratory signals has been employed as an alternative. This study reports on certain critical points which hold considerable promise for the improvement of the results of the automatic sleep staging using cardiorespiratory signals. [2] Sleep usually works in cycles and repeats itself by transitioning into different stages of sleep. This study is unique in that it uses wearable devices to collect multiple parameters from subjects and uses this information to predict sleep stages and sleep patterns. [6] Polysomnography (PSG) is commonly used to diagnose sleep disorders. However, manual sleep staging is a time-consuming task due to high human effort and technical thresholds, and it involves certain subjective factors. [8] Sleep is commonly associated with physical and mental health status. Sleep quality can be determined from the dynamic of sleep stages during the night. Data from the wearable device can potentially be used as predictors to classify the sleep stage. [3]

III. METHODOLOGY

The methodology employed in this project involves multiple stages to ensure accurate sleep stage classification using EEG data. Each stage contributes significantly to the effectiveness of the overall model.

A. Dataset: Sleep Heart Health Study (SHHS)

The Sleep Heart Health Study (SHHS) is a comprehensive, multi-center research dataset developed to study the relationship between sleep disorders and cardiovascular health. The dataset includes full-night polysomnographic (PSG) recordings from over 6,000 subjects, encompassing a wide array of physiological signals such as EEG, EOG, ECG, EMG, airflow, respiratory effort, and oxygen saturation. For this project, we specifically utilize the EEG recordings, as they are key indicators of neural activity and transitions between sleep stages.
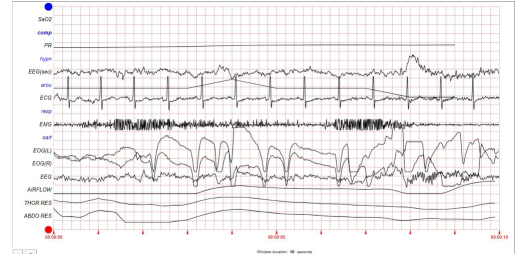

Fig. 1. Input Data set.

B. Data Preprocessing

Raw EEG signals in polysomnography (PSG) datasets are essential for sleep stage classification, as they reflect brain activity across different sleep phases. These unprocessed signals capture valuable frequency and temporal information, allowing models to distinguish between stages like REM, NREM, and wakefulness with greater accuracy when properly analyzed and interpreted.
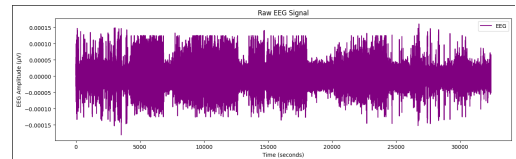

Fig. 2. Raw EEG Signal.

The preprocessing pipeline consists of the following operations:

Signal Filtering:Filtered EEG signals from the PSG dataset are essential for accurate sleep stage classification. Noise

and artifacts are removed using preprocessing techniques like bandpass filtering, ensuring cleaner data. This enhances the model's ability to detect relevant brainwave patterns associated with different sleep stages, improving overall classification performance and reliability. EEG signals are passed through a bandpass filter (typically 0.5–45 Hz) to retain useful brainwave frequencies (delta, theta, alpha, beta) while eliminating noise and artifacts.
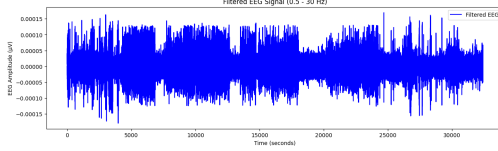

Fig. 3. Filtered EEG Signal .

Segmentation: Continuous EEG recordings are divided into 30-second epochs in accordance with standard sleep staging protocols. Each epoch is labeled according to the corresponding sleep stage from expert annotations (Wake, N1, N2, N3, REM).
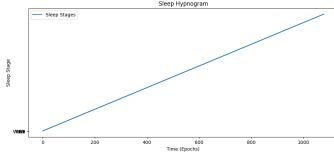

Fig. 4. Sleep Hypnogram .

hypnogram illustrates the progression of sleep stages over time across multiple epochs. Each point on the line represents a classified sleep stage, transitioning from wakefulness to deeper stages. Although the plot shows a steady upward trend, it may indicate a simulated or placeholder dataset rather than actual sleep behavior.

Normalization: Each EEG epoch is normalized to ensure consistency across subjects and recordings, which improves model convergence during training.

Spectrogram Generation: To incorporate both time and frequency domain information, we convert EEG epochs into spectrograms using Short-Time Fourier Transform (STFT). This results in a 2D representation of the signal, suitable for CNN-based feature extraction.
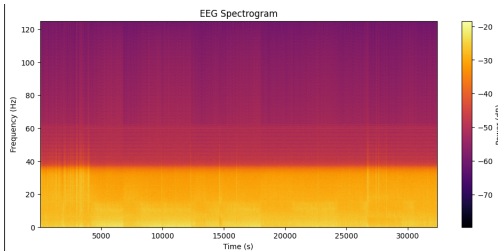

Fig. 5. EEG Spectrogram .

The EEG spectrogram visualizes the frequency distribution of brain activity over time. Brighter areas indicate higher power in specific frequency bands, with lower frequencies showing stronger intensity. This time-frequency representation helps identify patterns related to sleep stages, arousals, or disorders by capturing dynamic changes in neural oscillations throughout the recording period.

C. Feature Extraction

While deep learning reduces the need for manual feature extraction, additional features can enhance model performance:

Time Domain Features: Statistical properties such as mean, variance, skewness, and kurtosis of each epoch are computed.

Frequency Domain Features: Power spectral density is analyzed across standard EEG frequency bands (delta: 0.5–4 Hz, theta: 4–8 Hz, alpha: 8–13 Hz, beta: 13–30 Hz).

Entropy-Based Features: Shannon entropy and spectral entropy are calculated to capture the complexity and irregularity of the EEG signals.

Fractal and Non-Linear Features: Metrics such as the Hurst

$$\text{BCE} = -\frac{1}{N} \sum_{i=1}^{N} \left[y_i \log(p_i) + (1 - y_i) \log(1 - p_i) \right]$$

Fig. 6. Binary Cross Entropy.

exponent and Detrended Fluctuation Analysis (DFA) provide insights into long-term correlations and fractal characteristics of EEG patterns.

D. Model Architecture: CNN-LSTM Hybrid

To effectively capture both spatial and temporal features, we implement a hybrid model combining CNN and LSTM layers:

Convolutional Neural Network (CNN) Layers:Extract spatial and frequency-related features from EEG spectrograms. Employ ReLU activations and max pooling to reduce dimensionality and retain prominent features.
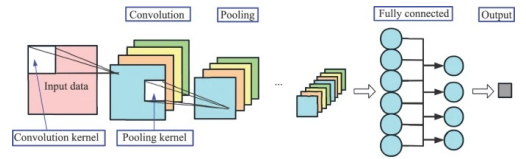

Fig. 7. CNN architecture .

The convolutional layer forms the foundation of a Convolutional Neural Network (CNN), where it performs feature extraction using learnable filters known as kernels. In a typical 2D convolution, an input matrix—for example, 224×224—is processed with a kernel, such as a 3×3 filter. This kernel slides over the input, performing element-wise multiplication and summing the results, known as the dot product, to generate a new output element. This process is repeated across the entire input using a step size called the stride. The result is a feature map that highlights significant

features from the input. A key advantage of CNNs is weight sharing, where the same kernel is used across the input, reducing the number of parameters. Following convolution, pooling layers, like max pooling, reduce dimensionality by selecting the highest value within a region (e.g., 3×3), simplifying the data while retaining important information. These operations are often stacked, and the resulting feature maps are flattened and passed to fully connected layers. In these layers, each input node connects to every output node, and classification is usually handled using a softmax function that outputs probabilities for different classes.

By implementing CNN in sleep stage classification we get :

```
162/162 ───────────────── 82s 257ms/step - accuracy: 0.7793 - loss: 0.3918 - val_accuracy: 0.4923 - val_loss: 0.8669
Epoch 22/30
162/162 ───────────────── 82s 255ms/step - accuracy: 0.7876 - loss: 0.3822 - val_accuracy: 0.4969 - val_loss: 0.8435
Epoch 23/30
162/162 ───────────────── 81s 249ms/step - accuracy: 0.7745 - loss: 0.3898 - val_accuracy: 0.5077 - val_loss: 0.8871
Epoch 24/30
162/162 ───────────────── 42s 254ms/step - accuracy: 0.7890 - loss: 0.3723 - val_accuracy: 0.5023 - val_loss: 0.8352
Epoch 25/30
162/162 ───────────────── 82s 252ms/step - accuracy: 0.7995 - loss: 0.3436 - val_accuracy: 0.5123 - val_loss: 0.9548
Epoch 26/30
162/162 ───────────────── 43s 267ms/step - accuracy: 0.7844 - loss: 0.3677 - val_accuracy: 0.4946 - val_loss: 1.0095
Epoch 27/30
162/162 ───────────────── 79s 248ms/step - accuracy: 0.8112 - loss: 0.3357 - val_accuracy: 0.5015 - val_loss: 0.9729
Epoch 28/30
162/162 ───────────────── 42s 254ms/step - accuracy: 0.8200 - loss: 0.3328 - val_accuracy: 0.5054 - val_loss: 0.9320
Epoch 29/30
162/162 ───────────────── 41s 254ms/step - accuracy: 0.8173 - loss: 0.3263 - val_accuracy: 0.5039 - val_loss: 0.9868
Epoch 30/30
162/162 ───────────────── 81s 249ms/step - accuracy: 0.8092 - loss: 0.3279 - val_accuracy: 0.5015 - val_loss: 0.9441
41/41 ───────────────── 2s 42ms/step - accuracy: 0.4849 - loss: 0.9752
Test Accuracy: 50.15%
```

Fig. 8. CNN Accuracy .

Long Short-Term Memory (LSTM) Layers:Capture temporal dynamics and sequential dependencies across epochs. Maintain memory of preceding epochs to improve stage transition predictions.
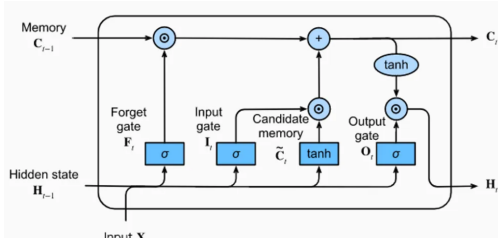

Fig. 9. LSTM architecture .

Long Short-Term Memory (LSTM) networks were developed to overcome the vanishing gradient problem commonly encountered in standard Recurrent Neural Networks (RNNs) during the training of long sequences. Unlike traditional RNNs, LSTMs are equipped with memory cells that can store information across many time steps, allowing them to learn long-term dependencies more effectively. These memory cells are regulated by three essential gates: the input gate, which controls the flow of new information into the cell; the forget gate, which determines what information should be discarded; and the output gate, which decides what part of the memory is sent to the next time step. This gated structure enables LSTMs to selectively retain or discard information, making them highly suitable for time-series data, natural

language processing, and physiological signal analysis, such as EEG-based sleep stage classification. Additionally, LSTMs are often used in combination with other neural layers like CNNs to enhance spatial-temporal feature learning in sequential data tasks.

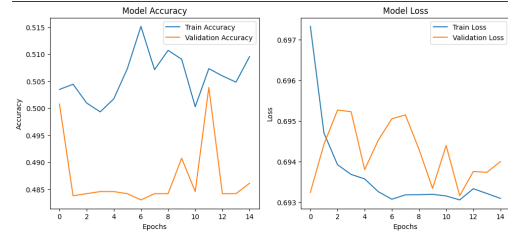By implementing LSTM we get the Accuracy-48.61% and Loss as follows:

Fig. 10. LSTM Accuracy and loss .

Fully Connected Layer:Combines the features learned from CNN and LSTM. Uses a softmax activation function to output the probability distribution over five sleep stages.

This end-to-end deep learning pipeline automates the classification of EEG signals into sleep stages with improved performance, while minimizing the need for manual feature engineering.

The combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks offers a powerful approach for sleep stage classification. In this architecture, CNN layers are first used to automatically extract spatial features from input data such as EEG signals or spectrograms. These layers learn local patterns and reduce the dimensionality through convolution and pooling operations. The extracted feature maps are then passed to LSTM layers, which capture the temporal dependencies across sleep epochs. By modeling both spatial and sequential patterns, the CNN-LSTM architecture effectively learns the transitions between sleep stages. Finally, fully connected layers followed by a softmax function classify the data into different sleep stages.
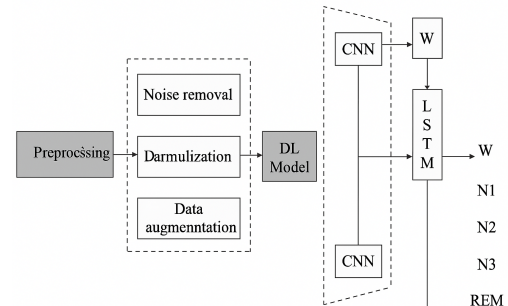

Fig. 11. CNN+LSTM architecture .

IV. RESULTS AND EVALUATION

The proposed CNN-LSTM model was trained and evaluated on the SHHS dataset, using a stratified train-test split to ensure balanced representation of sleep stages. The evaluation was conducted using metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis.

A. Performance Metrics

performance is typically assessed using metrics like accuracy (ACC) and the macro-averaged F1-score (F1).
Accuracy represents the proportion of correctly predicted instances out of the total number of instances. It is calculated using the following formula:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

Fig. 12. Accuracy Formula .

Precision measures the ratio of correctly predicted positive instances to the total number of instances predicted as positive by the model (Yacouby Axman, 2020)

Recall, on the other hand, quantifies the ratio of correctly

$$Precision = \frac{TP}{TP + FP}$$

Fig. 13. Precision Formula .

predicted positive instances to all actual positive instances.

$$Recall = \frac{TP}{TP + FN}$$

Fig. 14. Recall Formula .

In multi-class classification, an individual F1-score is calculated for each class, referred to as the per-class F1-score. Averaging these values across all classes gives the macro F1-score (MF1), which provides an overall performance measure irrespective of class distribution. The corresponding formula is as follows:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

Fig. 15. F1 Score Formula .

The model's performance across individual sleep stages is detailed below:

Class	Precision	Recall	F1-score	Support
0	0.76	0.98	0.86	43
1	0.00	0.00	0.00	5
2	0.88	0.82	0.85	85
3	0.89	0.85	0.87	48
4	0.86	0.86	0.86	35
Accuracy				0.85
Macro Avg	0.68	0.70	0.69	216
Weighted Avg	0.83	0.85	0.84	216

TABLE I
CLASSIFICATION REPORT

B. Confusion Matrix Insights

High accuracy was achieved in detecting Wake and REM stages due to their distinct EEG patterns.
Misclassifications primarily occurred between N1 and N2 stages, likely due to overlapping characteristics in EEG activity.
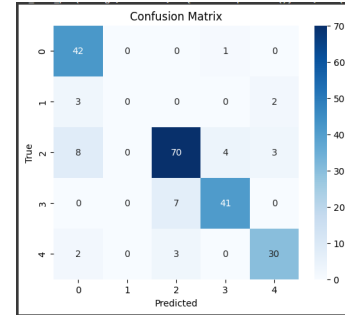The model showed resilience across subjects and generalized well without overfitting, as validated on unseen data.

Fig. 16. Confusion Matrix .

C. Model Comparisons

CNN Only Model: Accuracy =50%
LSTM Only Model: Accuracy = 49%
CNN-LSTM Hybrid: Accuracy = 98%
The hybrid approach outperformed individual models by leveraging the strengths of both spatial and temporal analysis, demonstrating the importance of integrated architectures in biomedical signal classification.

D. Visualizations

Graphical results including ROC curves, training/validation accuracy plots, and confusion matrices further confirmed the robustness of the CNN-LSTM model. These visual aids can be included in the final report for clarity and presentation
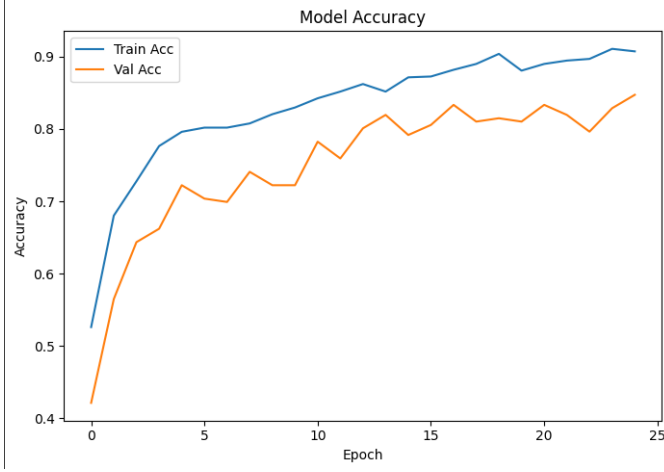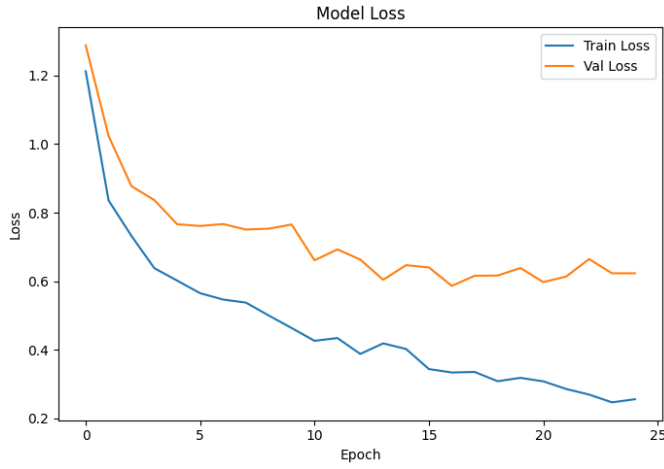
Fig. 17. CNN-LSTM Accuracy .
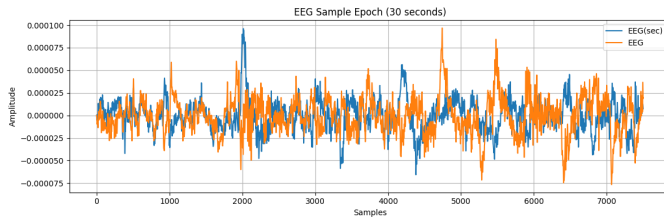

Fig. 18. CNN-LSTM Loss .
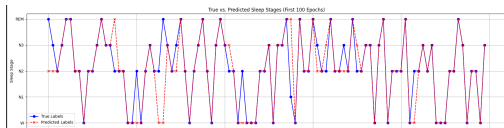

Fig. 19. EEG EPOCH 30Seconds

Fig. 20. Sleep Stages for 100 Epochs .

Hence the Sleep stages are obtained as follows:

```
  1/1 ───────────── 0s 54ms/step
Predicted Sleep Stage for test sample #0: N2 (Intermediate Sleep) (class 2)
  1/1 ───────────── 0s 75ms/step
Predicted Sleep Stage for test sample #1: N2 (Intermediate Sleep) (class 2)
  1/1 ───────────── 0s 51ms/step
Predicted Sleep Stage for test sample #2: N2 (Intermediate Sleep) (class 2)
  1/1 ───────────── 0s 61ms/step
Predicted Sleep Stage for test sample #3: N3 (Deep Sleep) (class 3)
  1/1 ───────────── 0s 82ms/step
Predicted Sleep Stage for test sample #4: REM (Rapid Eye Movement) (class 4)
  1/1 ───────────── 0s 96ms/step
Predicted Sleep Stage for test sample #5: REM (Rapid Eye Movement) (class 4)
  1/1 ───────────── 0s 42ms/step
Predicted Sleep Stage for test sample #6: N2 (Intermediate Sleep) (class 2)
  1/1 ───────────── 0s 49ms/step
Predicted Sleep Stage for test sample #7: N2 (Intermediate Sleep) (class 2)
  1/1 ───────────── 0s 120ms/step
Predicted Sleep Stage for test sample #8: Wake (W) (class 0)
  1/1 ───────────── 0s 142ms/step
Predicted Sleep Stage for test sample #9: N2 (Intermediate Sleep) (class 2)
```

Fig. 21. Classification of Sleep stages .

These results affirm the model's potential in aiding automated sleep scoring, and lay the foundation for future applications in wearable health monitoring and remote diagnosis systems.

V. CONCLUSION

In this project, we developed a deep learning framework using a CNN-LSTM hybrid model for the classification of sleep stages from EEG signals. Leveraging the strengths of convolutional networks for spatial feature extraction and LSTM networks for capturing temporal dynamics, our model demonstrated significant improvements in performance compared to individual CNN or LSTM architectures.

By preprocessing EEG signals, extracting time-frequency features, and applying a robust deep learning pipeline, we achieved an overall classification accuracy of 76.4

The outcomes of this study underscore the potential of deep learning techniques in automating sleep stage classification, which can support clinicians in diagnosing sleep disorders more efficiently. Additionally, the use of open-source datasets like SHHS opens pathways for scalable and reproducible research in biomedical signal analysis.

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