Good afternoon, colleagues, mentors, and fellow researchers. My name is Om, and I am currently a final-year undergraduate student at Pandit Deendayal Energy University. Today, I am honored to present my review paper, titled *Automated Sleep Stage Classification using Machine Intelligence Techniques: Physiological Signals, Sleep Data Presentation, and Models,* which has been accepted at this prestigious ADCIS 2024 conference. Over the next 6 to 7 minutes, I will walk you through the essence of my work, emphasizing the dynamic nature of sleep, the challenges in sleep stage classification, and the models employed to address these challenges.

Slide 2: Outline

I'll begin with introduction to the relevance of sleep research, move on to related works and derive key inferences from the literature, then discuss a framework for a sleep staging system, and conclude by suggesting future scope and research directions.

Slide 3: Introduction

What comes to our mind when we think of sleep?
Until few years sleep was considered to be steady state of unconsciousness, but the actual truth backed by multiple research reveals that it is a highly active and dynamic process where the brain remains functional.
As we know Adequate sleep is must for various physiological functions, including cardiac health, mental restoration, cognitive performance, and overall well-being.
Being sleep deprived can have worse longterm and short term effects on our body, such as reduced oncentration, mental and physical impairments, disrupting our immune system and many other heaalth issues.
In fact, about one-third of human life is spent sleeping, thus to make the rest ⅔ rd productive, analyzing and studying them is must..

Slide 4: Sleep Cycle Dynamics

As i mentioned from research findings Sleep is a continuous, cyclic process involving two main stages: Rapid Eye Movement (REM) and Non-Rapid Eye Movement (NREM) sleep.
These stages occur approximately every 45 to 60 minutes in cyclic manner.
To analyse and classify sleeg stages like NREM have been divided further based on two major frameworks
1st the Rechtschaffen and Kales (R&K) standard: Which classified NREM into 4 stages, s1,s2,s3,s4 from drowsiness to deep sleep.
2nd American Academy of Sleep Medicine (AASM) guidelines classify NREM into 3 stages , N1 and N2
This further classification helps us to understand diagnosing various sleep disorders.

Slide 5: Polysomnography (PSG) and Sleep Staging

Polysomnography (PSG) is the gold standard for monitoring sleep stage as they include most of the electrophsiological signals such as electroencephalograms (EEG), electrooculograms (EOG), and electromyograms (EMG), provide comprehensive data for sleep assessment.
During sleep staging process, a sleep specialist must be there following either R&K or AASM guidelines.
Sleep recordings are typically divided into 30-second epochs which helps to represent certain sleep stages, while hypnograms provide visualization of sleep stages across the night. This data is instrumental in understanding sleep quality and diagnosing sleep abnormalities.

Slide 6: Sleep Stage Characteristics

Here the sleep stage characteristics are being showcased
Where Stage 0 represents wakefulness, followed by NREM stages (N1 to N3) and REM sleep stage R.
These stages are characterized by specific brain waves and physiological events.
For instance, Stage N3—deep sleep—is dominated by slow-wave activity on EEG (shown by theta,delta waaves) ,
While in Stage R', brainwave patterns are similar to wakefulness and associated with vivid dreaming.
While in Stage 2 is the main body of light sleep, where memory consolidation, cell repairing and other functions are carried out by brain.
These Accurate classification of these stages is key for sleep researchers and clinicians.

Slide 7: Related Works

Now, let's go through few Related works

1. Yan et al. (2019)
In this study, **Yan et al.** applied **multivariate pattern analysis** to combine different polysomnography (PSG) to improve classification accuracy. They successfully extracted useful multimodal features;
But, one major drawback was the misclassification of **Stage S1** as wakefulness or REM sleep due to the similar EEG patterns during these stages.
This shows a common challenge in sleep classification models. Which highlights the complexity of distinguishing lighter sleep stages from wakefulness using standard models.

3. Shen et al. (2020)
Shen et al. proposed a dual-state space model that incorporated improved **model-based essence features** to better understand sleep dynamics. Their model employed a grid search strategy for hyperparameter tuning, significantly improving classification accuracy across multiple sleep stages. However, they faced the same challenge as yen in **Stage S2** classification, where accuracy remained lower compared to other stages.

2. Zhou et al. (2020)
Zhou along with his colleagues developed a **two-layer stacked ensemble model** using single-channel EEG data. Their model employed **Random Forest** and **LightGBM** to reduce bias and variance, to get higher classification performance. Their ensemble approach improved accuracy, especially for deep sleep stages (N3)
But bias could be seen ad data was tested on healthy subjects, leaving out data from patients with sleep disorders.

4. Huang et al. (2019)
Also in 2019 Huang et al. explored multichannel data fusion, aiming to enhance sleep staging accuracy by combining EEG, EOG, and EMG signals. Where the model used **convolutional neural networks (CNNs)** for feature extraction, taking advantage of the temporal and spatial information present in PSG signals.
Despite this, the approach struggled with **signal heterogeneity** and variability in PSG data from different subjects, making it difficult to achieve consistently high accuracy across all sleep stages.
The study underscores the need for more robust preprocessing and normalization techniques when working with multichannel data.

6. Supratak et al. (2017)
In 2017 Supratak and colleagues developed **DeepSleepNet**, a deep learning architecture based on **CNN** and **bi-directional LSTM** to classify sleep stages. DeepSleepNet used to handle large-scale EEG data by extracting both short- and long-term dependencies. The model achieved best performance on several datasets, but as with other deep models, it required extensive computational resources and was challenging to implement in real-time clinical settings. Additionally, this model also encountered difficulties in generalizing across different subject populations, particularly those with sleep disorders

5. Biswal et al. (2018)
Biswal et al. employed a **deep learning-based CNN-LSTM model** that combined CNN for feature extraction and LSTM for capturing long-term dependencies in PSG signals. They were succesfully leveraging the temporal nature of sleep data.
However, due to the large amount of data required to train deep learning models, they faced overfitting issues with smaller datasets.
Moreover, the model performed better on deeper sleep stages but still struggled with classifying **transitional stages (N1 and N2)** due to the subtle differences in physiological signals.

.**7. Phan et al. (2018)**
In 2018 phan used multiscale CNN-based approach, getting improved accuracy across sleep stages, but faced same Stage N1 classification problem due to its low prevalence in sleep datasets, leading to class imbalance issues.

8. Chambon et al. (2018)
In Chambon et al. proposed a model based on **time-frequency domain analysis** using **short-time Fourier transforms (STFT)** combined with CNNs to improve sleep staging

accuracy. Their approach capitalized on the fact that different sleep stages are characterized by distinct frequency bands in EEG signals. While this method yielded high performance for REM and NREM stages,
Its reliance on handcrafted features meant that it lacked the flexibility of more generalized deep learning approaches. Furthermore, it struggled with the **variability in EEG patterns** across individuals, which impacted its real-world applicability.

Slide 8: Inferences from Literature

1. **Class Imbalance**: Light sleep stages like N1 and N2 are often misclassified because they are very similar to being awake or in REM sleep. These stages appear less frequently in the data, causing the models to have difficulty learning them properly.
2. **Model Generalizability**: Many models work well on healthy test data but struggle when used with people who have sleep disorders. whichmakes it hard to use in real-world Another important observation ws
3. **Signal Variability and improper feature combination** : While using multiple types of signals (like EEG and EMG),it made hard for models to perform consistently especially with multi-neurophysiological disorders

Slide 9: Research Questions

Based on these findings, several important research questions arise:

- Which PSG signals are the most effective for detecting different sleep stages?
- What feature extraction parameters from these signals best distinguish sleep stages?
- How do PSG signals differ between healthy subjects and those with sleep disorders?
- What is the ideal set of input signals and features for identifying sleep irregularities?

Slide 9: oVERVIEW OF SLEEP STAGING CLASSIFICATION:

FIRSTLY WE ACQUIRE THE DATA FROM THE psg SIGNALS, WHERE WE TAKE eeg, ecg, eog SIGNALS.

GENERALLY PREPROCESSING IS DONE BY REMOVING ARTIFACTS AND SEGMENTING FURTHER, THEN SPLITTING THE DATA INTO TRAINING SET AND TESTING SET.

EVAULATING AND EXTRACTING FEATURES AND SELECTING THE MOST USEFUL ONES,finally PASING THEM THROUGH CLASSIFICATION MODEL. For training and
THE MODEL HELPS TO PREDICT AND CLASSIFY THE STAGES AS PER INPUT DATA.

Slide 10: oVERVIEW OF CHANNELS OF SLEEP STAGING CLASSIFICATION:

The listed channels for **EEG**, **EOG**, **EMG**, and **ECG** relate to specific physiological signals used in **sleep studies** for staging and analysis, typically in a **polysomnography (PSG)** setup. Each of these signals provides insight into different aspects of brain activity, eye movements, muscle tone, and heart activity, all of which help in determining sleep stages like **REM**, **NREM**, or wakefulness.

EEG: helps to demarcate sleep stages (wake, NREM, REM) by identifying distinct brainwave patterns.

EOG: Detects rapid eye movements during REM sleep, a key indicator of dreaming and stage transitions.

EMG: Differentiates muscle tone levels to identify REM sleep (where muscle atonia occurs) and wakefulness or NREM stages (where tone is higher).

ECG: Assesses heart rate variability and rhythm to monitor autonomic responses across different sleep stages.

1. EEG (Electroencephalography):

EEG measures the brain's electrical activity via electrodes placed on the scalp. The channels mentioned here are specific locations for electrode placement, with the naming conventions based on the **10-20 international system** for EEG recording.

- **C3-A2, C4-A1, F3-A2, F4-A1**: These are common EEG derivations used to measure activity in the frontal (F) and central (C) regions of the brain. They help in distinguishing between different sleep stages, especially deeper NREM stages (like N3) and REM sleep.
- **FPZ-CZ/PZ-OZ**: These measure electrical activity from the frontal-polar (FPZ) and central-parietal (CZ, PZ) regions. They are useful for detecting transitions between stages, such as from wakefulness to light sleep (N1), and also provide insight into REM sleep.
- **O1-A2, O2-A1**: These occipital (O) electrodes help monitor brain activity in the visual cortex. They are especially **relevant during REM sleep, as REM is associated with vivid dreams and high brain activity in the occipital lobe.**
- **A1-A2**: This reference channel measures activity between the earlobes and is often used as a baseline for comparison with other EEG channels.

EEG is fundamental for determining **sleep stages**:

- **NREM (Non-Rapid Eye Movement)**: Characterized by slower brain waves like theta and delta.
- **REM (Rapid Eye Movement)**: The EEG during REM sleep looks similar to that during wakefulness (fast and low-voltage waves).

2. EOG (Electrooculography):

- **LEFT, RIGHT, HORIZONTAL**: These channels track the horizontal and vertical movements of the eyes.
  Thus EOG helps in distinguishing REM sleep from NREM stages.

3. EMG (Electromyography):

- **Chin, 1-EMG**: Chin EMG measures muscle tone, especially in the chin and neck region, which is helpful for identifying transitions between different sleep stages. Muscle tone varies significantly:
  - **NREM Sleep**: There is a slight decrease in muscle tone.
  - **REM Sleep**: Muscle tone drops dramatically, leading to atonia (muscle paralysis), which prevents the sleeper from acting out dreams. EMG is particularly useful in distinguishing **REM sleep** from wakefulness or NREM sleep due to the stark difference in muscle tone.

4. ECG (Electrocardiography):

- **ECG**: Records heart rate and rhythm. In sleep studies, it helps to assess the **autonomic nervous system** activity during different sleep stages. Heart rate tends to slow during **NREM sleep** and becomes more variable during **REM sleep**. ECG data can also help detect sleep-related conditions such as sleep apnea, which might cause irregular heart rhythms.

5. Respirational Features

Respiratory signals monitor breathing patterns, which also change across sleep stages. These signals help in identifying irregular breathing events like apnea (pauses in breathing).

From Next Slide onwards, my colleague Aman will continue the presentation