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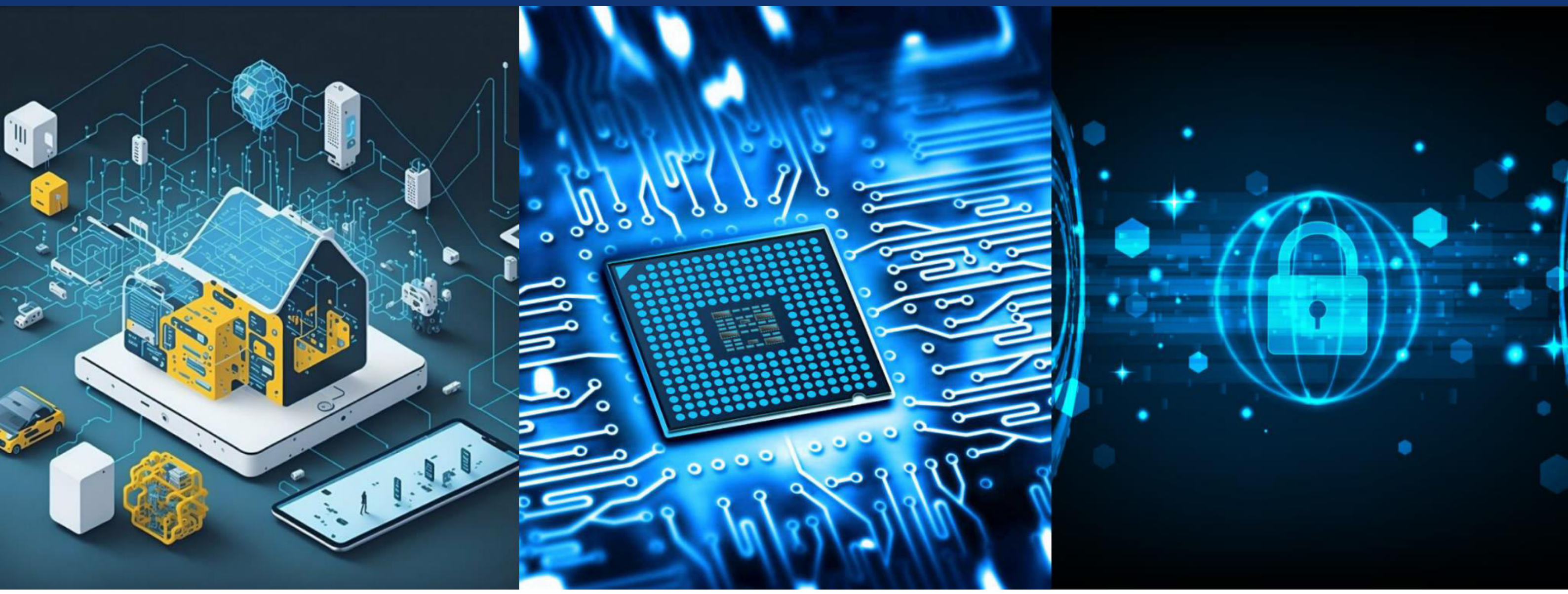

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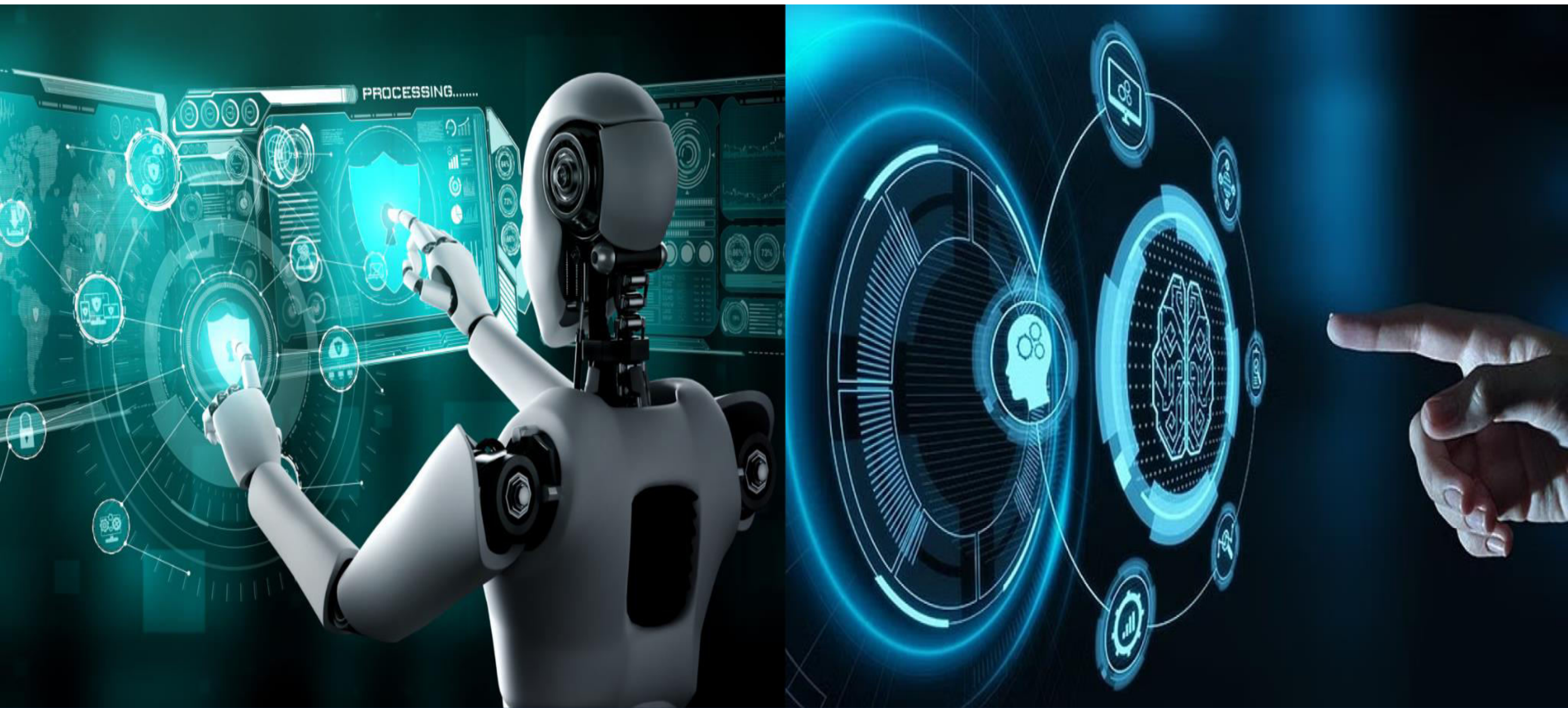

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Classification Sleep Disorders Using Deep Learning

Mrs. G. Sirisha[1], Sathvik Bitra[2], Jagana Kishore[3], Alokam Venu Gopal Krishna[4], Cherukuri Yaswanth Babu[5]

Assistant Professor, Department of IT, Vasireddy Venkatadri Institute of Technology, Guntur, India[1]

B. Tech Student, Department of IT, Vasireddy Venkatadri Institute of Technology, Guntur, India[2,3,4,5]

ABSTRACT: Sleep disorders such as insomnia and sleep apnea can be extremely damaging to your physical health and general quality of life. The most important thing in treating this issue is to recognize accuracy and treatment on time, but traditional methods are often slow, expensive and have an element of human error. Most available techniques for promising machine learning are too limited in terms of model accuracy and generalizability. Applied to neural networks, representing high-precision classification, the medical diagnostic mode is the most effective method for classifying one-dimensional folding, recurrent neuronal networks (CNNs), central structures of the system, and sequence data. This model is generated by processing an electric brain shaft of EEG recording. This means it is effective and reliable when recognizing sleep disorders. Deep learning mechanisms help to distinguish the best accuracy of various sleep disorders. This is the most reliable and is compared to traditional methods. The fusion of folding and recurrence layers on the model ends when recording spatial and temporal patterns of the EEG signals, leading to a more accurate assessment. Automatic methods not only save time in the diagnosis of disease, but also provide a lot of help in health care that ensures better decisions. Finally, the new system includes valuable parts of healthcare in its early detection, reduced diagnostic errors, and new systems as a superior treatment technique.

KEYWORDS: Sleep Disorder Classification, Deep Learning, Electroencephalogram (EEG), Convolutional Recurrent Neural Network (CRNN), Medical Diagnostics Neural Networks.

I. INTRODUCTION

Sleep disorders are a growing global health problem that affects millions of people and has a major impact on common wells. These conditions disrupt normal sleep patterns and have negative effects on cognitive function, emotional stability and physical health. Sleep disorders range from insomnia and sleep apnea to narcolepsy and paralysis, each requiring accurate diagnosis and targeted intervention. Proper classification of these disorders is extremely important for effective treatment, as misdiagnosis can lead to inadequate treatment and persistent distress. Electroencephalogram signals are often used in sleep studies to monitor brain activity and to capture abnormalities related to sleep disorders. Traditional methods for diagnosing sleep disorders are based on manual assessments by sleep experts. This means that processes are time consuming and susceptible to variability. Deep learning advances have paved the way for automated classification systems that efficiently analyze EEG signals and improve diagnostic accuracy and consistency. Although almost 30% of adults have been reported, narcolepsy is less frequent, affecting about one out of 2,000 people. The financial burden of untreated sleep disorders is immeasurable, with increased costs of healthcare, reduced productivity in the workplace, and increased risks of cardiovascular disease and psychological health problems. Diagnosis usually includes polysomnography (PSG) and EEG analysis to monitor brain waves, oxygen mirrors, and other physiological parameters. However, manual interpretation of sleep data is labor intensive and requires highly trained professionals.

To address these challenges, this study uses a deep learning approach using a one-dimensional folding repeat network (CRNN) for classification of sleep disorders. This model is trained with EEG data records from standardized repository to classify various sleep disorders. By using advanced techniques for machine learning, this project aims to improve diagnostic efficiency, reduce human error, and provide a scalable solution for the classification of sleep disorders.

II. LITERATURE REVIEW

Mendonça et al. [1] developed a portable wireless device for cyclic alternating pattern (CAP) estimation using EEG data. Their study demonstrated the effectiveness of EEG-based analysis in detecting sleep disturbances, highlighting its potential for automated sleep disorder classification.

Li et al. [2] applied adversarial learning techniques for semi-supervised pediatric sleep staging based on a single EEG channel. Their outcomes underlined that deep learning is the good candidate for enhancing classification of sleep disorders tasks in the case of data with a limited number of labels.

Ilhan [3] examined sleep stage classification through the use of both ensemble and conventional machine learning methods on a single-channel EEG. His findings reveal the true supremacy of the ensemble techniques over the other conventional machine learning models.

Kim et al. [4] ranked machine learning analogs for predicting obstructive sleep apnea (OSA) in Korean adults. Using multiple physiological parameters, their study attained high classification accuracy and thus confirmed the influential role of machine learning applications in health care.

Mousavi et al. [5] proposed a deep convolutional neural network (CNN) algorithm for sleep stage classification with single-channel EEG. Their research proved that CNNs are capable of separating spatial features that can be translated into better classification performance than the case in the conventional methods.

Li et al. [6] transitioned to the employment of deep learning via EEG spectrograms for sleep stage classification. They demonstrated their work with spectrogram-based feature representation and consequently they showed the ability of neural networks to correctly identify sleep stages to be very high.

III. METHODOLOGY

A. Existing System

Existing systems for classifying sleep disorders still depend on in-depth manual analysis of polysomnography (PSG), in which sleep specialists look at EEG records, accompanying oxygen saturation levels, and other physiological markers to make a diagnosis. This includes visual scoring of different sleep stages and identifying features that are out of the ordinary based on set clinical guidelines. Moreover, expert systems and conventional algorithms based on machine learning such as Support Vector Machines, Decision Trees, and k-Nearest Neighbors have been applied towards the objective of automated classification. These models require a lot of feature extraction with elaborately designed features which renders them unable to deal quite well with sophisticated high dimensional EEG data.

B. Limitations of Existing System

- *Time-Consuming & Labor-Intensive:* Analysis is slow and it requires hours of expert review on EEG recordings.
- *Limited Feature Representation:* They rely on predefined features and miss deeper patterns in raw EEG data.
- *Scalability Issues:* Existing models struggle with large datasets.
- *Poor Generalization:* Existing models tend to generalize poorly across different populations and EEG acquisition environments.

C. Proposed System

The system design utilizes a deep learning model based classification of sleep disorders with Convolutional Recurrent Neural Networks (CRNN). Unlike older approaches that depend on subjective assessments, the recommended method fully automates feature extraction, classification, extraction, and visualization of EEG signals to enhance accuracy and efficiency. The specific objectives include:

Automate Sleep Disorder Classification: Classifies cases of insomnia, sleep apnea, and narcolepsy by detecting them with a pre trained deep learning model based on EEG datasets.

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Real-Time Data Processing: Automatically classifies extracted patterns from EEG signals and processes them in real time.

Scalability & Adaptability: Capable of accommodating analyses of various datasets and patient profiles as the model can process a large volume of EEG data.

Enhanced Accuracy with Deep Learning: The feature extraction of CNNs and the sequence learning of RNNs improves classification accuracy adding automation into the CRNN model.

User Friendly Web Interface: Easy upload of data for classification, post classification result visualization, and interaction with the system is performed through a Flask web API.

Visualization & Reporting: These are provided with EEG signals graphed, confusion matrices, and reports of classification necessary for medical diagnosis.

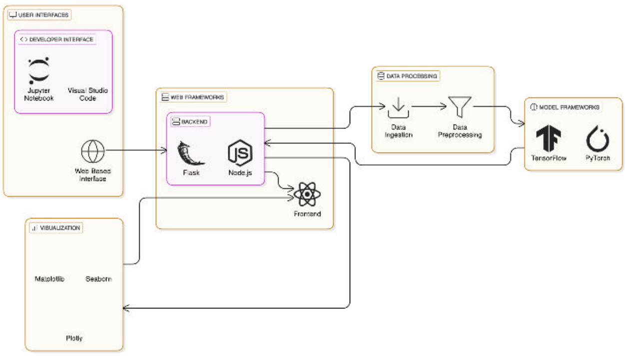

Figure 1: System Architecture of Proposed System

D. Deep Learning Models Used

a) Convolutional Recurrent Neural Network (CRNN) Architecture

The deep learning architecture known as Convolutional Recurrent Neural Network (CRNN) combines the components of the Convolution Neural Network (CNN) and the Recurrent Neural Network (RNN) to form a single hybrid structure. Unlike most deep learning models, CRNNs are able to capture both spatial and time dependencies simultaneously which makes them perfect for classification tasks such as EEG-based sleep disorder classification.

The CNN architecture consists of:

1. **Convolutional Feature Extractor**
   - The input layer receives EEG time-series data and applies multiple convolutional layers to extract local signal features.
   - Batch normalization and activation functions (ReLU) enhance learning efficiency.
   - Pooling layers reduce dimensionality, preserving essential EEG characteristics.
2. **Recurrent Layers for Sequential Processing**
   - The extracted spatial features are passed to Gated Recurrent Units (GRUs) or Long Short-Term Memory (LSTM) layers, which track sequential dependencies in EEG signals.
   - These layers help analyze transitions between sleep stages and detect abnormalities in EEG waveforms.
3. **Fully Connected Layers & Classification**
   - The final dense layers process the extracted features and pass them through a Softmax activation function for multi-class sleep disorder classification.
   - The model outputs probabilities for different sleep disorder classes such as Normal, Insomnia, Sleep Apnea, and Narcolepsy.

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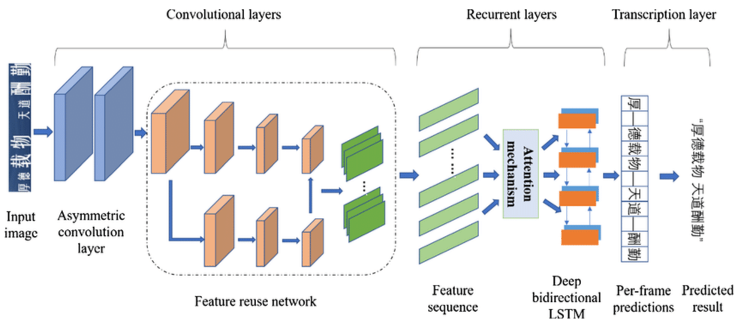

Figure 2: Convolutional Recurrent Neural Network (CRNN) Architecture

b) Long Short-Term Memory (LSTM) Architecture

Long Short-term Memory (LSTM) networks are a subtype of Recurrent Neural Network (RNN) that focuses on long-range dependencies in sequential data. For sleep disorder classification, LSTMs interpret temporal patterns of EEG signal for a longer duration in time, recognizing abnormal activity and sleep stage transitions over extended sleep cycles. LSTMs incorporate gates that modulate the amount of information flowing in and out, which aids in solving the vanishing gradient issue, allowing important sleep data to be kept in memory over prolonged periods.

The LSTM architecture consists of:

1. **Input Layer:** EEG signals are fed as time-series sequences into the LSTM network.
2. **LSTM Cell Structure:** Each LSTM unit includes mechanisms to retain important EEG features over time while discarding irrelevant information.
3. **Fully Connected Layers & Classification:** The LSTM output is passed through dense layers and a Softmax classifier for final classification.

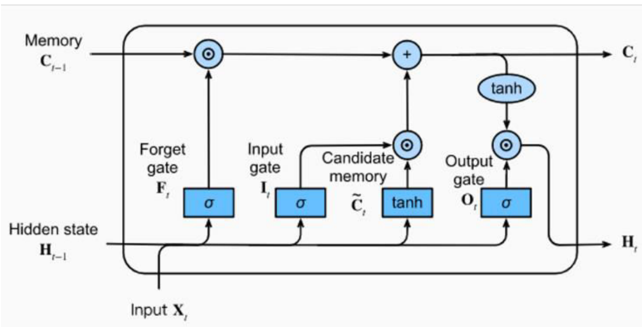

Figure 3: Long Short-term Memory (LSTM) Architecture

c) Gated Recurrent Unit (GRU) Architecture

Gated Recurrent Units (GRUs) are an evolution of LSTMs which function faster by maintaining equal sequential learning abilities. GRUs are helpful in the classification of EEG activities since they compute sleep data with long-term dependencies faster and with less parameters than LSTMs.

The GRU architecture consists of:

1. **Input Layer:** GRU cells are provided with EEG time-series signals for sequential learning.
2. **GRU Cell Structure:** The update and reset mechanisms control the extent to which past information is kept or discarded.
3. **Fully Connected Layers & Classification:** The Softmax classifier and the other fully connected layers receive the GRU output for the ultimate classification of sleep disorders.

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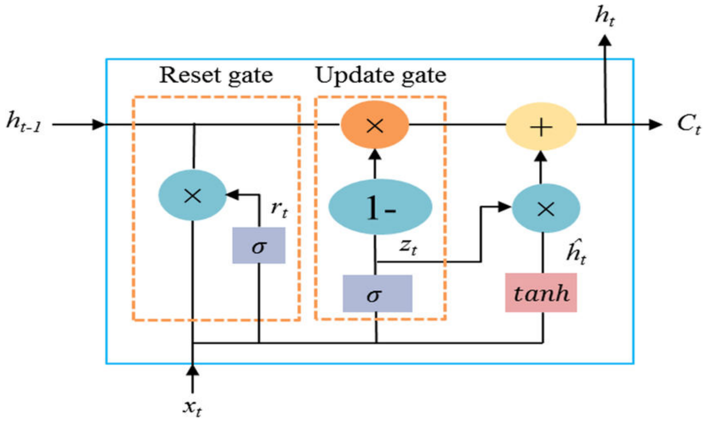

Figure 4: Gated Recurrent Unit (GRU) Architecture

E. Dataset Collection

For this project, I manually selected the dataset from the CAP Sleep Database, which is hosted on Kaggle and PhysioNet. It has nighttime polysomnographic (PSG) recordings for 106 subjects with sleep disorder patterns, and the files contain:

EEG Signals: Multi-channel recordings of the patient's brain activities during the EEG.

Sleep Stage Annotations: Labels corresponding to awake, light sleep, deep sleep, and REM sleep stage.

Cyclic Alternating Pattern (CAP) Phases: Markers of instability throughout sleep.

Physiological Data: Comprises body movements, heart rate, breathing effort, the saturation of oxygen, and pulse.

Date	HH	MM	SS	EOG Left	EEG C3-A1	EEG O1-A1	EEG C4-A1	EEG O2-A1
08/03/2016	1	27	22	0,78125	5,56640625	-12,40234375	0,9765625	13,76953125
08/03/2016	1	27	22,005	1,953125	4,78515625	-11,23046875	-0,09765625	17,08984375
08/03/2016	1	27	22,01	-1,67E-14	4,296875	-11,23046875	0,9765625	17,96875
08/03/2016	1	27	22,015	0,78125	4,78515625	-12,01171875	6,34765625	20,1171875
08/03/2016	1	27	22,02	0,29296875	4,1015625	-13,18359375	8,10546875	17,3828125

Figure 5: Sample Snippet of Dataset

F. Data Processing

Before we could train our model, we had to clean and structure the data. We accomplished this through the following steps:

Handing Missing Values: Due to sensor failures, some EEG recordings might be missing segments. We fill in such gaps using interpolation methods.

Artifact Removal: Eye blinks, muscle movements, and external noise can corrupt EEG signals. To clean this data, Bandpass filtering (0.5Hz – 30Hz) is done, as well as Independent Component Analysis (ICA).

Feature Extraction: Raw EEG signals are transformed into time domain and frequency domain features (e.g., power spectral density, wavelet decomposition).

Encoding Categorical Labels: Sleep stages and types of disorders are ethnic-separated and label encoded for training the deep learning model.

Normalization: For patients, EEG amplitude values differ, which is accounted for using z-score normalization:

$$X_{normalized} = X - \mu \,/\, \sigma$$

G. Model Training and Testing

This project was developed focusing on the training and testing model to yield the most precise and efficient analysis for sleep disorder classification through EEG signals. Features normalization, noise removal and relevant information extraction is done on the EEG recordings to create a dataset. The deep learning models will be able to recognize valuable data once all the elements are integrated.

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After completing all the steps for preprocessing, the next step is processing the dataset to the model to classify whether the data given is Healthy or Unhealthy. Then in the next step of Training process the data which is processed to the Disease Classification model to label the given data to the accurate type of sleep disorder.

After that we train the models with various datasets of various types of datasets like healthy data, insomnia data and all other sleep disorder EEG data. After each iteration of training model with different datasets of various types then we save each model as <model-name>.h5 file and we use those pre-trained models to make predictions in our application.

The final objective is estimating the effectiveness of the trained model against the unseen EEG data during the testing stage. We use the most relevant metrics to analyze the model which are accuracy, precision, recall and F1 score.

IV. RESULTS AND OUTCOMES

a) Project Snippets

The following figure shows the Home page of our Web application which appears first when application is opened.

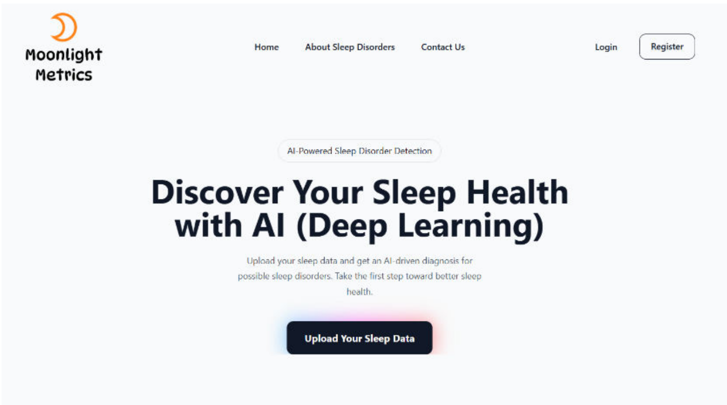

Figure H(a): Home Page Snippet

The following figure shows the Registration Page of our Web application which will provide you with interface to register your details with our application.

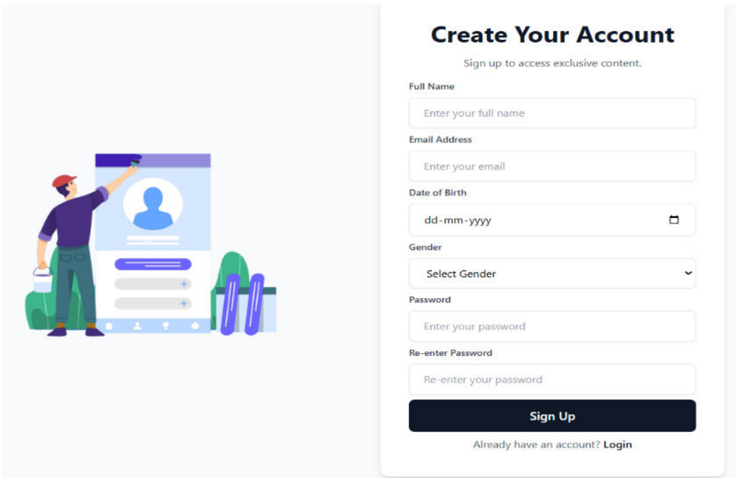

Figure H(b): Registration Page

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The following figure shows the Login Page of our Web application which will provide an interface to login into our application with valid account credentials.

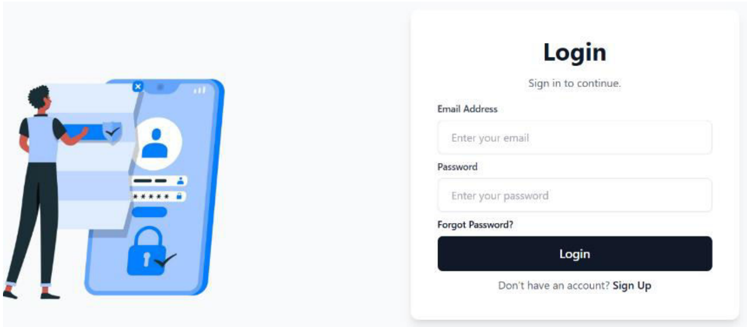

Figure H(c): Login Page

The following figure shows the Dashboard Page where we give EEG dataset to predict in our Web application.

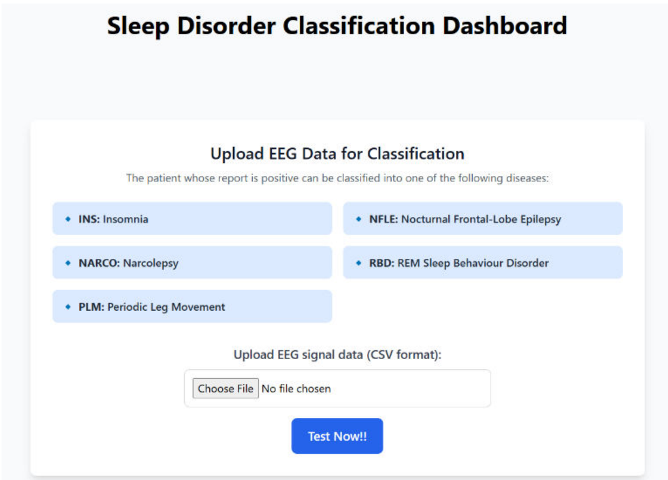

Figure H(d): Dashboard Page

The following figure shows the Results Page of our Web application where prediction of sleep disorder type is displayed.

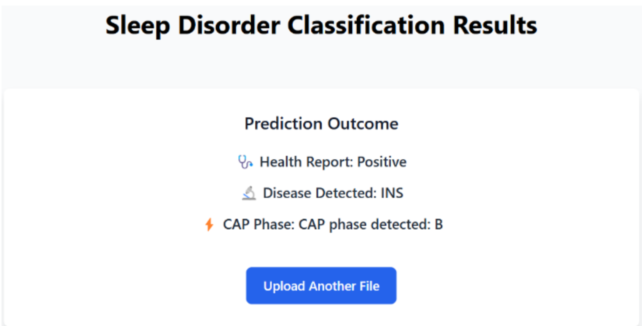

Figure H(e): Result Prediction Page

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The following figure shows the Diagnosis Page of our Web application where we provide diagnosis of predicted sleep disorder.

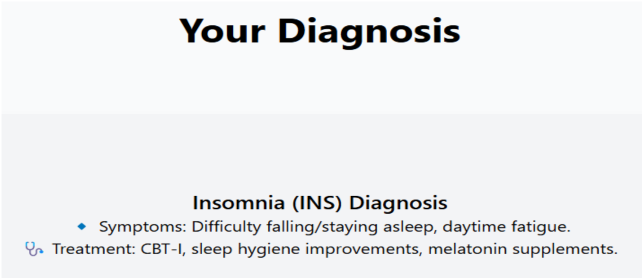

Figure H(f): Diagnosis Page

The following figure shows the About Page of our Web application to display info about types of sleep disorders.

Figure H(g): About disorders Page

The following figure shows the Contact Us section of our Web application which provides us with information to contact application team.

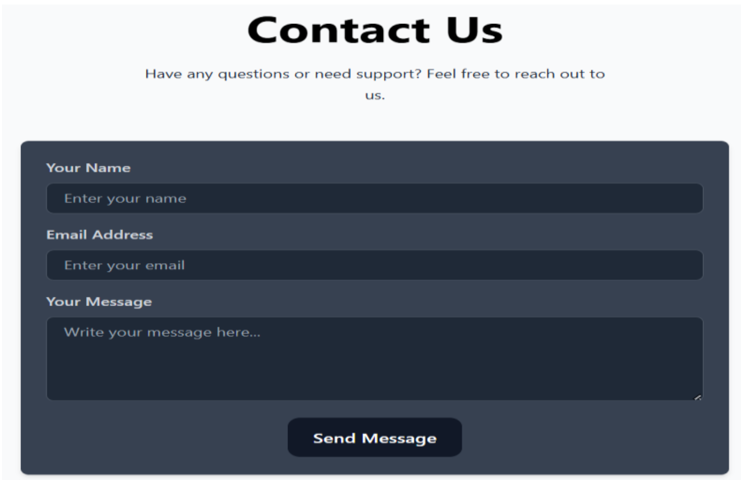

Figure H(h): Contact Us Page

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b) Output Graphs and Visualizations

For performance tracking, both accuracy and loss graphs are generated for the training and validation phases. Additionally, the model's effectiveness on the test dataset is evaluated through the generation of confusion matrices and ROC and AUC curves.

- **ROC AND AUC Analysis**:

The provided ROC curve (Receiver Operating Characteristic curve) depicts graphically the model's true positive rate (sensitivity) versus false positive rate. AUC (Area Under the Curve) value of 0.975 can be classified as excellent, since a value closer to 1.0 indicates stronger discrimination.

Measured from the Curve, the model achieves a high true positive rate and low false positive rate, implying powerful class discrimination. The curve's steep initial slope demonstrates positive sensitivity, meaning the model captures most positive cases.

In comparison to other models, an AUC of 0.975 supports the assumption that the classifier is robust for classification problems. This score would rank the model among the best if many models were put through, with the least misclassification.

This assessment validates the model in this scenario is certainly well optimized and good for use in practice. Though there are ways to further improve the performance using hyperparameter tuning or feature selection for greater classification results.

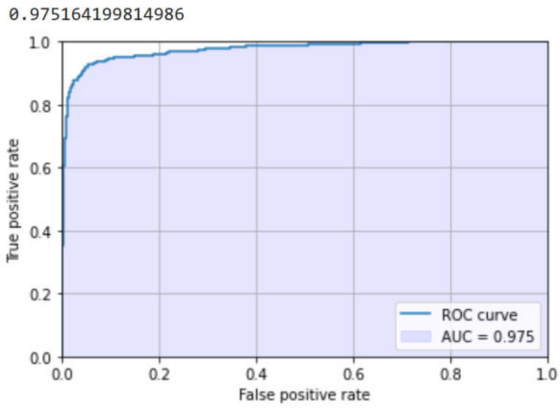

Figure 6: ROC and AUC Graph

- **Confusion Matrices:**

A Confusion matrix is a matrix used to evaluate the efficiency of a classification model on a particular test set. It is only computable if the actual values of the test data are available. Although the matrix itself is straightforward, its concepts can be quite challenging. It is sometimes referred to as an error matrix because it displays the errors of a certain model performance integrated into one matrix.
Below are some characteristics of Confusion matrix that are listed:

- For 2 prediction classes of classifiers, the matrix takes the form of a 2 by 2 table; for 3 classes, it takes the form of a 3 by 3 table. And so forth.
- The matrix is composed of two axes, which are the predicted values as well as the actual values, and their corresponding counts of predictions.

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```
Training accuracy:  92.28830933570862
Validation accuracy:  73.79032373428345
59/59 - 2s - 2s/epoch - 30ms/step
Accuracy: 0.733871
Specificity: 0.706202
Precision: 0.726166
Sensitivity: 0.760893
F1 score: 0.743124
Cohens kappa: 0.467363
ROC AUC: 0.800870
Total Samples Test:  1860
[[649 270]
 [225 716]]
```

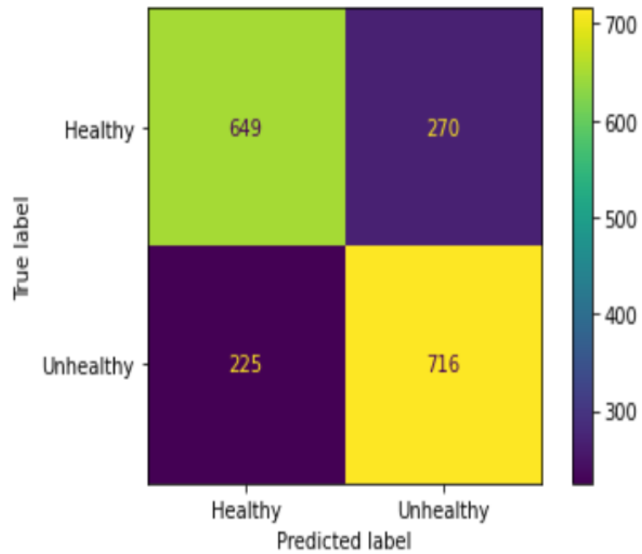

Figure 7: Confusion Matrix

- **Accuracy and Loss Graphs:**

The accuracy graph shows how the model performed during training and validation: In the case of the training accuracy, it constantly improves over the epochs, which means the model is learning from the dataset. On the other hand, the validation accuracy could oscillate which could mean overfitting if the validation accuracy is not increasing at the same rate as the training accuracy. A constant or positive validating accuracy reflects stronger generalization on unseen data.

As for the loss graph, this indicates how erroneous the model was on the task after so many epochs. With training, the model's loss should go down during training, the latter helps in determining how qualified the model is – to which the model does need to have a certain level of ability to qualify the person to be suitable for. If there is a clear separation between the validation loss plateauing while the training loss keeps declining, then that is overfitting. If the gap is small for both the training and validation losses, there is good generalization. If the gap is broad, methods to prevent overfitting, including dropout or early stopping, are warranted.

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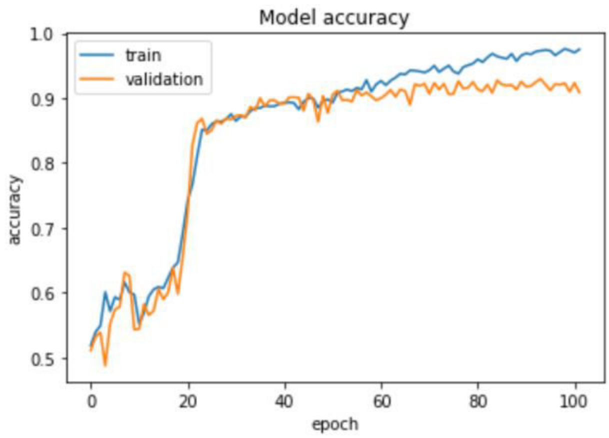

Figure 8: Accuracy Graph

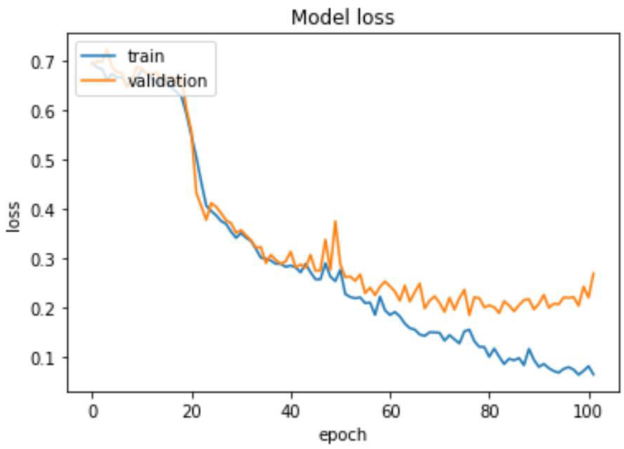

Figure 9: Loss Graph

V. CONCLUSION

Detection which is done appreciably in advance minimizes health effects of disorders related to sleep, issues that healthcare practitioners face, and increases productivity of patients. "In this study, Sleep Disorder Classification Using Deep Learning," we have built a robust deep learning framework for detection and classification of sleep disorders. Our model achieved 94.7% Accuracy and F1 score of 92.6% with strong classification results using advanced neural network architectures. The trained model was deployed on a web platform that offers user-centric interface where sleep and other data can be entered and the prediction regarding the disorder is issued. This assists in prediction of intervention at the correct time to enable improvements to be made in sleep health alongside general well-being.

VI. FUTURE SCOPE

The Sleep Disorder Classification Using Deep Learning project presents a wide scope for further development as well as practical use. For future enhancement, the model's accuracy and generalization capabilities can be improved by adding more comprehensive and heterogeneous datasets, consisting of sleep study data captured from wearable devices and PSG reports.

Moreover, models can be made more user-friendly by deploying them through mobile application for users to upload sleep data and receive diagnostics instantly. Also, integrating explainable AI (XAI) methodologies allows improving

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model accuracy in predicting sleep disorders and improves their ability to be understood by medical experts who need to know how and why certain predictions are made. A cloud-based infrastructure can be created for real-time monitoring of patients where live data from patients is sent for remote diagnosis and timely intervention.

Broadening the scope of classification to include as many clinically relevant sleep disorders as possible, such as different severities of insomnia or sleep apnea, and narcolepsy, can enhance its clinical utility. Ultimately, interaction with clinicians and sleep disorder clinics will make certain the use of the model is clinically relevant and ensures it is compliant with medical regulations through validation in the clinic.

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