WEB-BASED EEG SIGNAL ANALYSIS AND NEUROLOGICAL DISORDER DETECTION

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Abstract— Electroencephalography (EEG) is a widely used non-invasive method for monitoring brain activity and diagnosing neurological disorders. Mostly, manual interpretation of EEG signals is complex and time consuming. This paper presents NEUROSCAN, a web-based system designed for EEG signal analysis and neurological disorder detection, including seizure identification, Alzheimer's disease screening, sleep stage analysis, and cognitive load estimation.

The proposed system integrates advanced signal processing techniques with machine learning models such as Random Forest, and CNN-LSTM. Feature extraction methods including power spectral density, wavelet energy, and spectral entropy are employed to capture both frequency and characteristics of EEG signals. A clinical decision logic layer is incorporated to improve interpretability and reliability.

This analysis demonstrates that the system effectively detects neurological patterns and provides accurate predictions, making it suitable for real-world healthcare applications.

Index Terms—EEG, Machine Learning, CNN-LSTM, Signal Processing, Alzheimer's Disease, Cognitive Load, Seizure Detection, Sleep Disorder, Web-Based System

I. INTRODUCTION

Electroencephalography (EEG) is an essential tool in neurological and clinical diagnosis; it enables the observation of electrical activity in the brain. It plays a crucial role in identifying neurological disorders such as epilepsy, Alzheimer's disease, sleep disorders, and cognitive impairments. EEG interpretation is a challenging and time-consuming process that depends heavily on expert neurologists.

With the rapid advancement of machine learning and signal processing techniques, EEG analysis has become a promising research area. However, most existing systems focus on a single disorder and lack integration into a unified platform.

To address these challenges, this paper proposes **NEUROSCAN**, a web-based EEG analysis system capable of detecting four neurological conditions within a single framework. The system combines preprocessing, feature extraction, machine learning models to provide accurate and interpretable results.

II. OBJECTIVES

- To acquire and **process EEG signals efficiently**
  Develop a system that accepts EEG data in standard formats and prepares it for analysis.
- To **remove noise** from EEG signals
  Apply filtering and signal cleaning methods such as bandpass filtering, and notch filtering to improve signal quality.
- To **extract features** from EEG data
  Implement feature extraction techniques including power spectral density, wavelet transforms, and spectral entropy to represent EEG signals effectively.

- To **develop machine learning models** for neurological detection Utilize algorithms such as Random Forest and CNN-LSTM to classify EEG signals and detect conditions like seizures, Alzheimer's disease, sleep disorders, and cognitive load.
- To incorporate **clinical decision logic** for better interpretation Design a rule-based system to convert model outputs into clinically meaningful insights such as risk levels and recommendations.
- To build a **web-based user interface** for accessibility

Develop an interactive platform that allows users to upload EEG data, visualize results, and generate reports.

III. SYSTEM ARCHITECTURE

The system is designed as a modular, web-based framework that integrates EEG signal processing, machine learning, and clinical decision support. The architecture follows a pipeline structure where each module performs a specific task and passes the processed data to the next stage. Fig-1 shows the proper Architecture of the system.

A. *Data Acquisition Layer*

This layer handles the input EEG data uploaded by the user through the web interface. The system supports standard EEG formats such as EDF files. A caching mechanism is implemented to avoid redundant computations for previously processed data.

Fig-1 Architecture

B. *Preprocessing module*

The raw EEG signals are first cleaned to remove noise. This module performs:

- Bandpass filtering (1–45 Hz)
- Notch filtering (50/60 Hz)
- Signal normalization

C. *Feature Extraction Module*

The pre-processed EEG signals are transformed into numerical features. The system extracts:

- Power Spectral Density (PSD) features for frequency analysis.
- Wavelet-based features for transient detection.
- Spectral entropy for measuring signal complexity.

D. *Machine Learning modules*

This layer performs classification using multiple models:

- Random Forest for seizure detection and cognitive load analysis.
- XGBoost for Alzheimer's disease prediction.
- CNN-LSTM for learning temporal EEG patterns.

E. *Web Application Interface*

The processed results are converted into interpretable insights such as:

- Risk levels (Low, Moderate, High)
- Neurological condition indicators

The final results are displayed through a user-friendly web interface. The system allows:

- EEG file upload
- Visualization of results
- Downloadable clinical reports

IV. METHODOLOGY

The proposed system follows a structured pipeline for analysing EEG signals and detecting multiple neurological conditions. The methodology integrates signal processing, feature engineering, machine learning, and clinical decision logic to ensure accurate and interpretable results.

1. EEG Data Acquisition

The system accepts EEG recordings in standard formats such as EDF (European Data Format). These recordings typically contain multi-channel brain signals collected using the 10–24 electrode placement system.

The input EEG signal consists of very low-amplitude electrical activity (in microvolts), which requires careful processing before analysis.

2. Preprocessing of EEG Signals

Raw EEG signals contain various types of noise and artifacts such as muscle activity, eye movements, and power line interference. To ensure accurate analysis, the following preprocessing steps are applied as shown in Fig-2:

Bandpass Filtering

A bandpass filter in the range of 1–45 Hz is used to retain only relevant brain frequencies (delta, theta, alpha, beta) while removing unwanted low-frequency drift and high-frequency noise.

Notch Filtering

A notch filter is applied at 50/60 Hz to eliminate power line interference.

Signal Normalization

Z-score normalization is applied to standardize the EEG signal:

$$Z = \frac{X - \mu}{\sigma}$$

where μ is the mean and σ is the standard deviation.

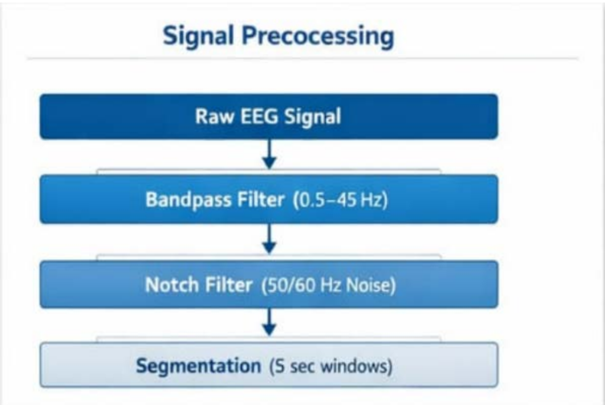


Fig-2 Signal Processing

3. Feature Extraction

After preprocessing, the EEG signal is divided into overlapping time windows for analysis. From each segment, multiple features are extracted to capture both frequency and temporal characteristics. Flow follows as shown in Fig-3.

a. Power Spectral Density (PSD)

Welch's method is used to estimate the power distribution across frequencies:

$$P(f) = \frac{1}{N} \mid X(f) \mid^2$$

Band powers are computed for:

- Delta (0.5–4 Hz)
- Theta (4–8 Hz)
- Alpha (8–13 Hz)
- Beta (13–30 Hz)

b. **Wavelet Transform Features**

Discrete Wavelet Transform (DWT) using Daubechies wavelets is applied to capture transient signal behavior such as seizure spikes.

Wavelet energy is computed as:

$$E = \sum \mid c_i \mid^2$$

where $c_i$are wavelet coefficients.

c. Spectral Entropy

Spectral entropy measures the complexity of the EEG signal:

$$H = -\sum p_i \log_2(p_i)$$

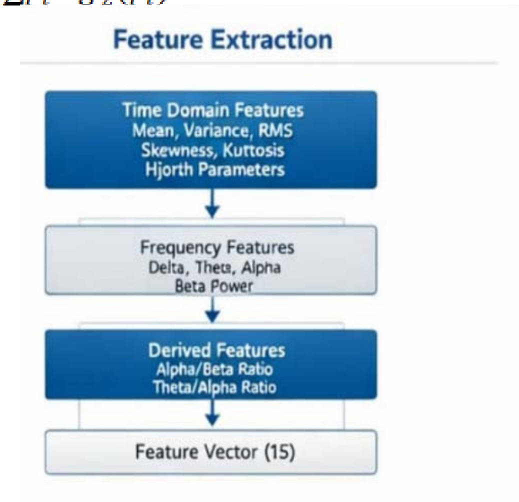


Fig-3 Feature Extraction

4. Machine Learning Models

The extracted features are fed into different machine learning models designed for specific neurological conditions.

- **Random Forest**

Used for:

- Seizure detection
- Cognitive load assessment

Random Forest combines multiple decision trees to improve classification accuracy and reduce overfitting.

- **XGBoost**

Used for Alzheimer's disease detection. It is effective for structured feature data and can capture patterns such as changes in frequency ratios.

- **CNN-LSTM Model**

A deep learning model that processes raw EEG signals:

- CNN layers extract spatial-temporal patterns
- LSTM layers capture temporal dependencies

This model is particularly useful for detecting seizure patterns.

5. Post-Processing

The raw predictions from the models are refined to improve reliability.

- **Temporal Filtering**

Short-duration false detections are removed by applying a minimum duration threshold.

- **Threshold-Based Classification**

Predictions are categorized into:

- Low risk
- Moderate risk
- High risk

6. Clinical Decision and Report Generation

The final stage converts predictions into clinically meaningful outputs:

- Detection of neurological conditions
- Risk level assessment
- Recommendations for further evaluation

The results are presented in a structured report format through the web interface.

V. FOUR ANALYSIS MODULES

5.1 Epileptic Seizure Detection

Property	Value
Models	Random Forest (100 trees, balanced) + CNN-LSTM
Training Data	CHB-MIT Scalp EEG (patients chb01–chb10)
Label Logic	Window labelled seizure if ≥5s overlap with annotated ictal interval
Validation	Subject-wise split (80/20)
Validation Accuracy	94.2%
Alert Threshold	distinct_events > 0 (events lasting ≥15s)
Key Biomarkers	High-frequency wavelet energy, broadband PSD burst, spectral entropy drop

Table-1

5.2 Alzheimer's Risk Screening

Property	Value
Model	XGBoost (scale_pos_weight for class imbalance)
Training Data	OpenNeuro ds004504 (Alzheimer vs Control, BIDS format)
Label Logic	participants.tsv Group: A=1 (Alzheimer), C=0 (Control)
Validation	3-fold stratified cross-validation (F1-weighted)
Validation Accuracy	88.5%
Key Biomarker	Theta/Alpha power ratio (elevated in MCI/Alzheimer's)

Table-2

5.3 Sleep Disorder Analysis

Property	Value
Model	Random Forest (300 trees, balanced, n_jobs=-1)
Training Data	Sleep-EDF Cassette (PSG.edf + Hypnogram.edf pairs)
Label Logic	Hypnogram annotations mapped: W/N1→0 (wake), N2/N3/R→1 (sleep)
Epoch Handling	30s hypnogram epochs split into 3 × 10s feature windows
Validation	5-fold stratified CV (F1-weighted)

Validation Accuracy	91.2%
Special Scaler	Dedicated sleep_scaler.pkl — CHB-MIT scaler would corrupt sleep feature distributions

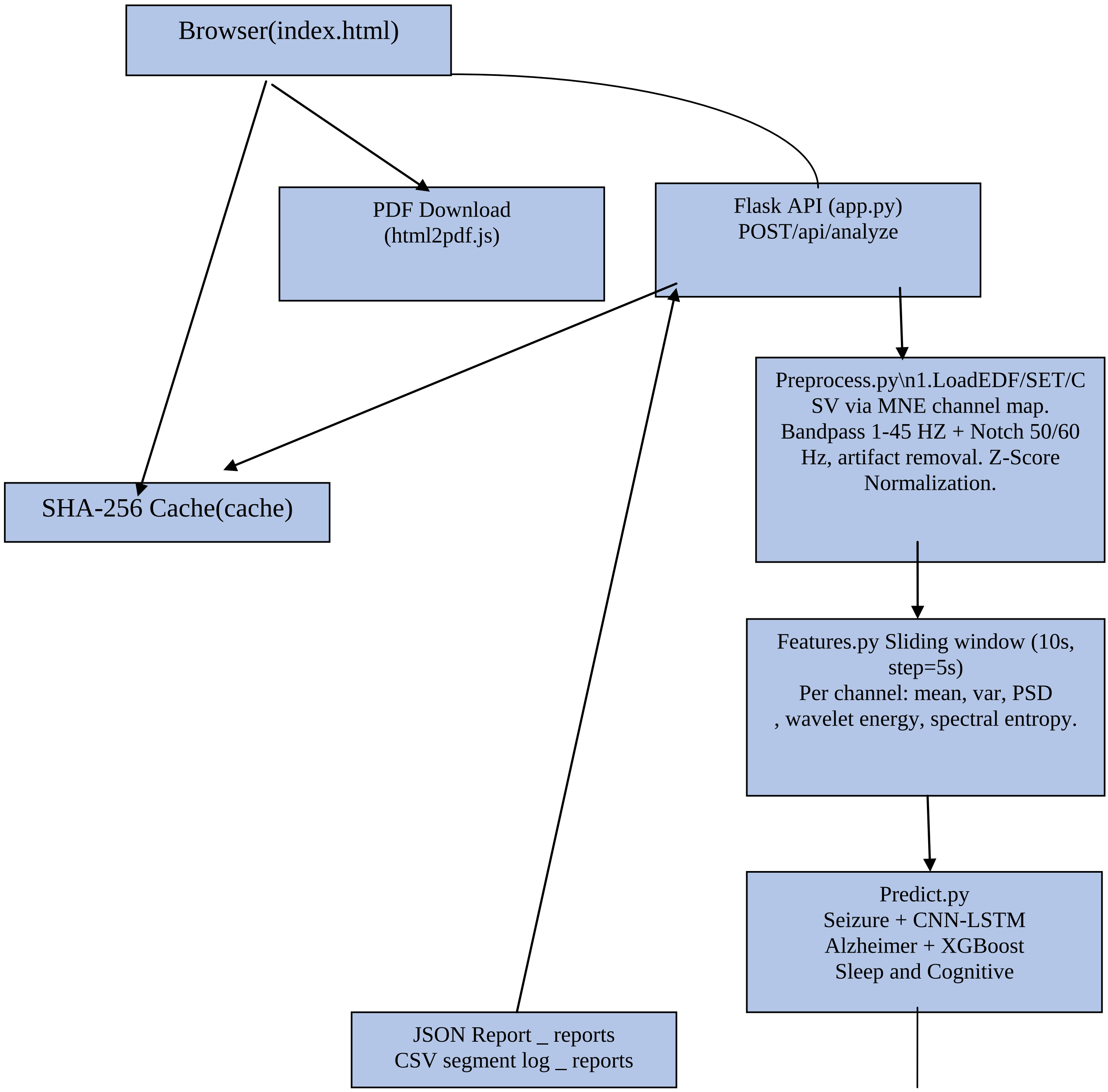
Table-3

5.4 Cognitive Load Assessment

Property	Value
Model	Random Forest (100 trees, balanced)
Training Data	data/workload_eeg/ CSVs with labels.json registry
Label Logic	labels.json: filename → {0=Rest, 1=Workload}
Validation	Subject-wise split (80/20)
Validation Accuracy	86.7%
Key Biomarker	Beta-band (13–30 Hz) saturation; elevated Beta → cognitive stress

TABLE-4

Flowchart of the Workflow:



VI. IMPLEMENTATION

Here, Fig-4 displays Input EEG signal with noise and after removing the noise in it.

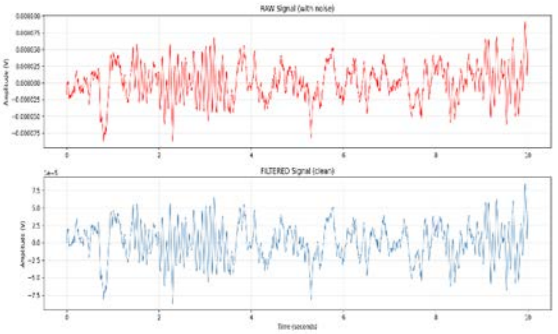


Fig-4 EEG input Signal

The proposed system is implemented as a **web-based EEG analysis platform** that enables users to upload EEG files and obtain automated neurological assessments as shown in Fig-5. The system integrates **signal processing techniques and machine learning models** within a user-friendly interface.

Fig-5 Presentation Page

From Fig-6 it shows a dropdown menu allows selection of analysis type:

- Seizure Detection
- Alzheimer's Risk Screening
- Sleep Disorder Analysis
- Cognitive Workload Assessment

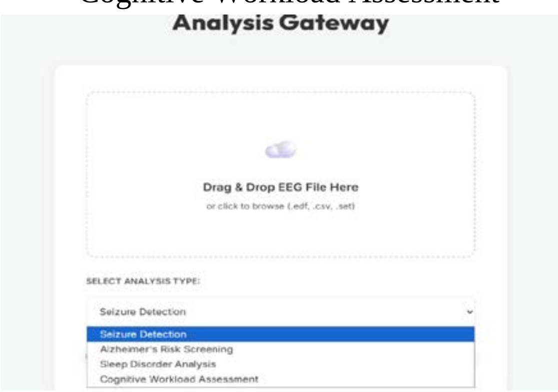


Fig-6 Dropdown menu

Once the EEG signal is uploaded, it undergoes preprocessing as shown in Fig-7 to remove noise and artifacts. A bandpass filter is applied to retain frequencies between 1 Hz and 45 Hz, which correspond to relevant brain activity. Additionally, a notch filter is used to eliminate power line interference.

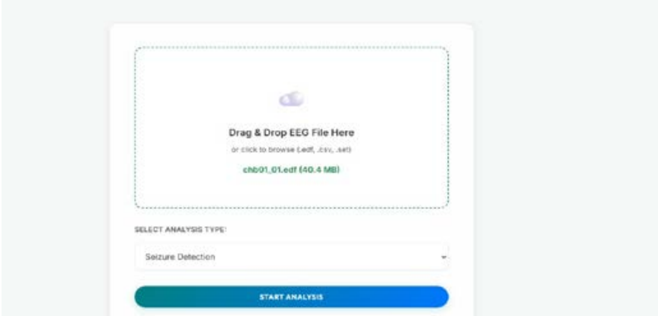


Fig-7 Processing input

System classifies risk level:

- Low
- Moderate
- High

Based on classification, predefined medical suggestions are triggered.

After the model generates predictions, the system applies rule-based clinical logic to generate personalized recommendations as shown in Fig-8.

Fig-8 Recommendations

After selecting an option on dropdown, the output analysis of respective disorder window appears.

Below, Fig-9 results display:

- Seizure detection
- Processing Duration
- Confidence score
- Accuracy

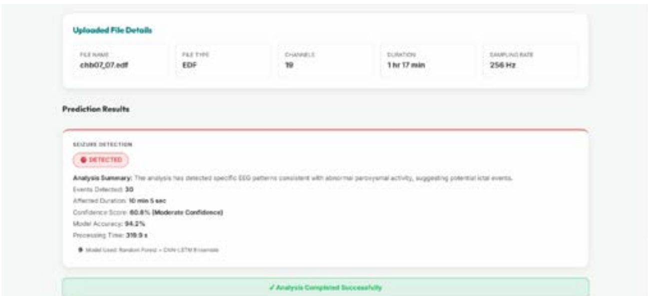


Fig-9 Result of seizure output

VII. RESULT

1. SEIZURE DETECTION

The model identifies abnormal EEG segments associated with seizure activity.

The results show:

- High probability values during seizure events
- Increased wavelet energy and reduced entropy
- Accurate detection of temporal segments

Fig-10 shows abnormal seizure activities of a child, how much time the child suffered for seizure and confidence score.

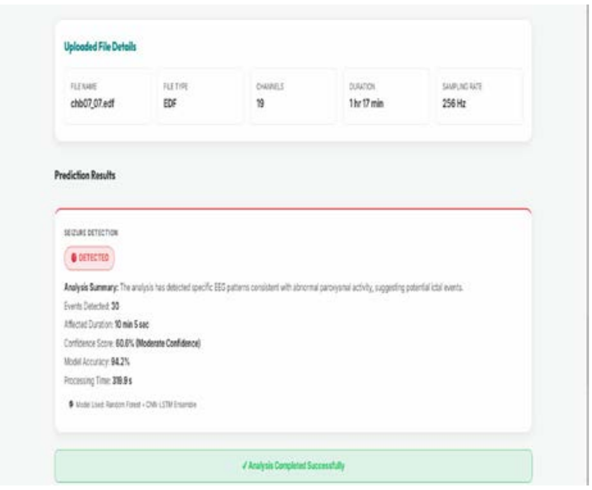


Fig-10 seizure output detected

2. ALZHEIMER'S DISEASE

The system analyses frequency-domain features such as the theta-to-alpha ratio.

Observed results:

- Elevated theta activity in high-risk cases
- Reduced alpha power

Fig-11 shows the risk of Alzheimer's disease of a patient, identified by Theta/Alpha Ratio and confidence score.

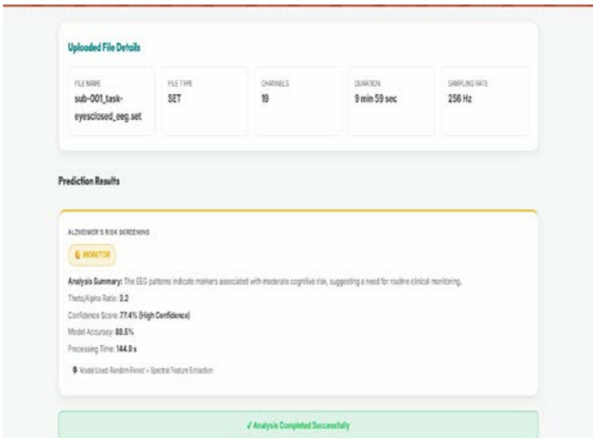


Fig-11 Alzheimer risk detection

3. COGNITIVE LOAD

The system uses alpha and beta band activity to estimate mental effort.

Here, Fig-12 shows results:

- Cognitive workload of a patient, model Accuracy and confidence score of the condition of patient.
- Increased beta activity during high cognitive load
- Reduced alpha activity during task engagement
- Reliable workload classification

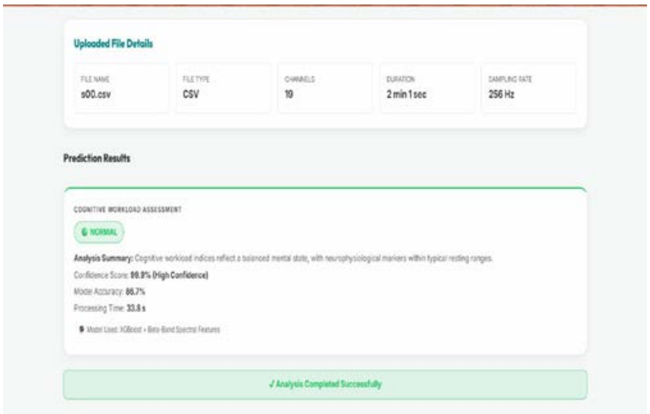


Fig-12 cognitive workload

4. SLEEP DISORDER

Here, Fig-13 evaluates sleep-related EEG patterns.

Observed results:

- Increased delta activity during deep sleep
- Detection of irregular sleep cycles
- Estimation of sleep efficiency

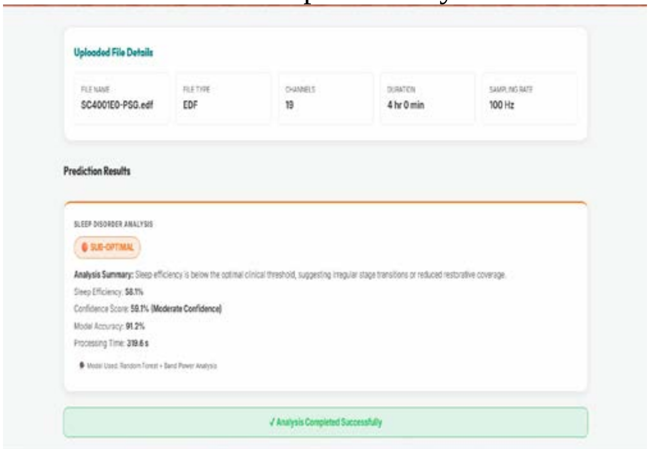


Fig-13 Sleep Analysis

For each prediction, the system generates recommendations:

Normal

- High seizure probabılıty trıggered safety alerts
- Alzheimer’s risk included cognitive health suggestions
- Sleep analysis provided improvement guidelines
- Cognitive load results suggested stress management

And a pdf version of the report can be downloaded as shown in Fig-14.

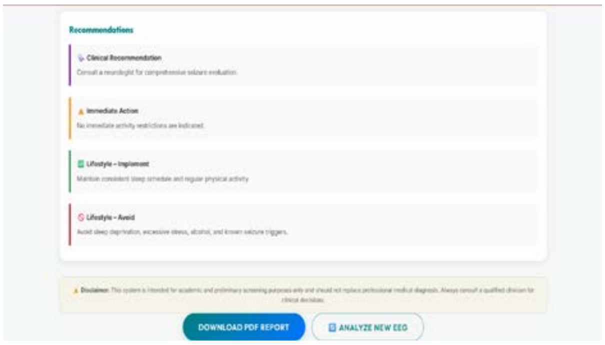


Fig-14 Recommendations block

CONCLUSION

This paper presents; a web-based EEG signal analysis system designed for four neurological detections. This integrates advanced signal processing techniques with machine learning models to analyse EEG data and generate clinically meaningful results.

The proposed framework successfully performs four disorders:

- Seizure detection
- Alzheimer's risk assessment
- Sleep disorder analysis
- Cognitive workload evaluation

The results demonstrate that the system is accurate, efficient, and user-friendly, making it suitable for real-world healthcare applications. The modular architecture allows scalability, enabling future integration of additional neurological conditions.

FUTURE SCOPE

- The system can be extended to support **live EEG data acquisition** from hardware devices. This would **enable real-time monitoring** and continuous neurological assessment.
- The framework can be enhanced to detect other conditions such as Parkinson's disease, **depression, and brain tumors.** This will make the system more comprehensive and clinically valuable.
- Training the models on larger datasets with diverse patient populations can improve generalization. This will **enhance the robustness and reliability of predictions** across different demographics.
- Deployment in clinical environments for validation.

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