SYNAP SENSE
(Intelligence that Moves)

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ABSTRACT

Effective This project presents a real-time brain-monitoring system designed to detect epileptic seizures and loss of consciousness (LOC) using a low-cost, single-channel EEG sensor interfaced with a Raspberry Pi. The system aims to provide an affordable and portable solution for continuous brain-state monitoring, especially in home-care or remote medical settings where immediate medical intervention is crucial. EEG signals are acquired from the prefrontal cortex using a three-electrode frontal lobe sensor. These analog signals are digitized and wirelessly transmitted to a Raspberry Pi via Bluetooth or UART. The data is processed in 10-second windows through baseline correction, z-score standardization, and optional noise filtering to prepare for real-time feature extraction. Time-domain, frequency-domain, and non-linear features are computed from each segment to characterize brain activity. A pre-trained Random Forest classifier, optimized using offline data, then categorizes each signal segment as either normal, seizure, or LOC. Upon detection of abnormal brain states, the system automatically activates a SIM900A GSM module to alert caregivers—sending an SMS for LOC detection and both an SMS and a voice call for seizure events. The entire pipeline is designed to run in real-time with minimal latency, offering a practical solution for medical alert systems, especially in underserved regions.

Keyword: *EEG, Real-time monitoring, Seizure detection, Loss of consciousness, Raspberry Pi, Random Forest, GSM alert system, Low-cost healthcare, Machine learning.*

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1. Introduction

People with severe physical disabilities often struggle to seek help during emergencies. Conventional methods—like pressing buttons or making calls—are impractical for those with limited mobility or speech impairments. In crises such as seizures or sudden health deterioration, any delay can be life-threatening. To address this, we propose a **non-invasive, EEG-based emergency alert system** that operates **hands-free and in real time**.

Electroencephalography (EEG) measures the brain's electrical activity and can reveal distinct patterns during seizures, stress, or abnormal neurological events. With recent advances in wearable EEG sensors, continuous brain monitoring has become portable and practical beyond clinical settings.

The proposed system continuously captures brain signals via a lightweight, wireless EEG headset. These signals are transmitted to a processing unit—such as a Raspberry Pi or smartphone—where they undergo **noise filtering and preprocessing** to remove artifacts from movement or blinking. Next, **key EEG features** are extracted from time, frequency, and non-linear domains to represent brain activity effectively.

A **machine learning classifier** (e.g., Random Forest, SVM, or CNN) trained on labeled EEG data distinguishes normal from distress states. When abnormal patterns indicating a seizure or panic episode are detected, the system triggers an **automatic emergency alert**. Using **Wi-Fi, Bluetooth, or GSM**, it sends an SMS, call, or push notification containing the user's identity, location, and timestamp to caregivers or medical personnel.

The system functions **autonomously**, even if the user is unconscious. It integrates low-power hardware, optimized real-time software, and encrypted communication to ensure reliability, privacy, and safety. A companion interface allows caregivers to monitor real-time EEG data, review alert logs, and adjust system settings.

This EEG-based alert system offers a **reliable, accessible, and affordable** solution for individuals with severe disabilities. It enables independent living, timely intervention during emergencies, and long-term neurological monitoring. Future work will focus on **AI-driven predictive analytics**, **multimodal biosignal integration**, and **cloud-based telemedicine support**.

1.1 LITERATURE SURVEY

Brain–Computer Interface (BCI) research has evolved into a multidisciplinary field integrating neuroscience, signal processing, biomedical sensors, and hardware to enable direct communication between the brain and external devices. Early studies, such as those by Lindsley and Nicolas-Alonso & Gomez-Gil, laid the groundwork for understanding psychological and neural phenomena underlying BCIs and their applications for individuals with severe disabilities. Subsequent surveys by Tiwari et al., Baraka Maiseli et al., and Wolpaw et al. emphasized BCI's role in translating brain signals into actionable machine commands for communication and control. Medical applications, as highlighted by Shih et al. and Dr. R. Beulah, demonstrate BCIs' potential in neurorehabilitation and restoring autonomy for paralyzed patients. Innovations such as haptic and multimodal feedback, discussed by Fleury et al., expand the sensory dimension of BCI interaction beyond traditional visual stimuli. Practical implementations, like the home automation system proposed by Saravana Gokul and Deepika, showcase BCIs' growing integration into assistive and smart environments. Comprehensive reviews by Abiri et al., Sonam & Yashpal Singh, Er. Tejinder Kaur & Prof. Birinder Singh, and Mrs. Nivedita Rane further consolidate BCI paradigms, methodologies, and applications, revealing significant advancements in EEG-based systems for neurofeedback, communication, and environmental control. Collectively, these works underscore the transformative potential of BCIs in bridging neural activity with technology, offering new possibilities for medical, assistive, and interactive applications.

Table 1 : Review of Related Work

Author Name	Title	Description
Lindsley D.B.	Psychological phenomena and the electroencephalogram	The study provides a comprehensive overview of Brain-Computer Interface (BCI), a multidisciplinary field merging neuroscience, signal processing, biomedical sensors, and hardware.
Nicolas-Alonso LF., Gomez-Gil J.	Brain computer interfaces	This review comprehensively examines the current state-of-the-art in Brain-Computer Interfaces (BCIs), focusing on their application to facilitate communication for severely disabled individuals.
Tiwari N., Edla D.R., Dodia S., Bablani A.	Brain computer interface: A comprehensive survey.	This paper offers a comprehensive survey on the evolution and functionality of Brain-Computer Interfaces (BCI), positioning BCI as a pivotal innovation bridging brain signals to actionable tasks in machines
Fleury M., Lioi G., Barillot C., Lécuyer A.	A Survey on the Use of Haptic Feedback for Brain-Computer Interfaces and Neurofeedback.	This survey explores the utilization of haptic technologies in Neurofeedback (NF) and Brain-Computer Interface (BCI) applications, which traditionally rely on visual stimuli but may benefit from alternative sensory modalities such as auditory or haptic feedback.
Baraka Maiseli, Abdi T. Abdalla1, Libe V.	Brain–computer interface: trend, challenges, and threats.	The paper discusses Brain–Computer Interfaces (BCIs) as systems enabling direct brain-to-device communication.
Jerry J. Shih, MD; Dean J. Krusienski,	Brain-Computer Interfaces in Medicine	The paper explains how Brain–Computer Interfaces (BCIs) collect,

PhD; and Jonathan R.		process, and use brain signals to control external devices without muscle movement.

2. System Architecture of ECOMATIC

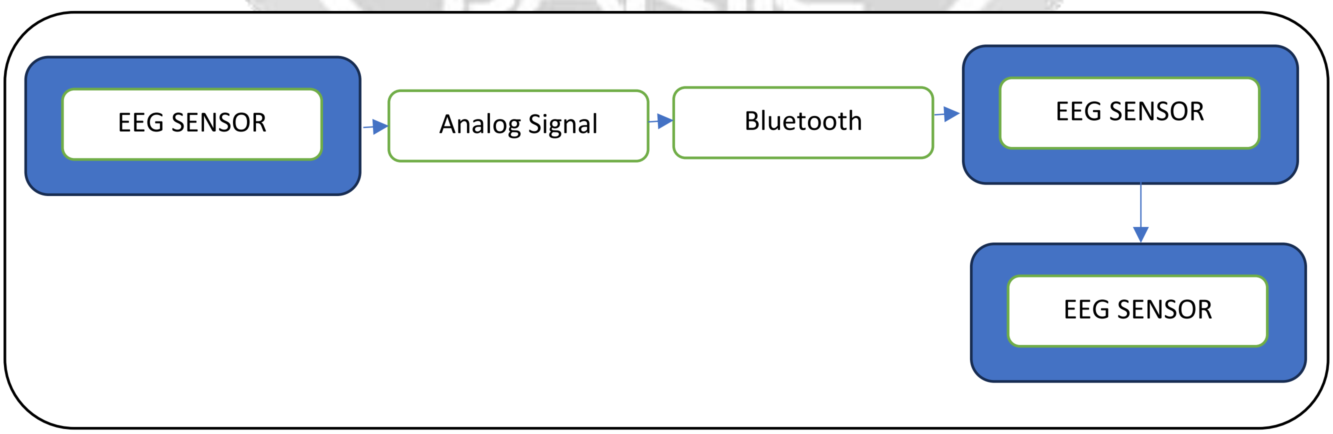
The project employs a **Raspberry Pi 3 Model B+** as the core processing unit, interfacing with the **MindLink EEG sensor** for brainwave acquisition and the **SIM900A GSM module** for emergency alerts. The Raspberry Pi preprocesses EEG data, detects abnormal brain activity using a machine learning model, and triggers SMS or call notifications to caregivers in real-time. The system runs on **Raspbian OS** and utilizes **Python scripts** for signal processing and device control, with **Thonny IDE**, **RealVNC**, and **PuTTY** used for programming, monitoring, and remote access. Together, these hardware and software components enable a compact, low-cost, and efficient real-time brain monitoring and alert system.

Hardware Overview:

The hardware setup consists of a **Raspberry Pi 3 Model B+**, **MindLink EEG sensor**, and **SIM900A GSM module**, which together form the core of the real-time brain monitoring and alert system. The Raspberry Pi acts as the processing unit, acquiring EEG data, performing preprocessing and feature extraction, and classifying signals using a machine learning model to detect seizures or loss of consciousness. The **MindLink EEG sensor**, a single-channel, Bluetooth-enabled, non-invasive device, captures frontal-lobe brain signals and transmits them to the Raspberry Pi for continuous monitoring and real-time analysis. The **SIM900A GSM module** provides wireless communication by sending SMS alerts or making calls to caregivers during emergencies, ensuring timely intervention even without internet connectivity. Collectively, these components deliver a compact, low-cost, and efficient embedded system capable of reliable, real-time brain activity detection and alert generation.

Software and Control Logic:

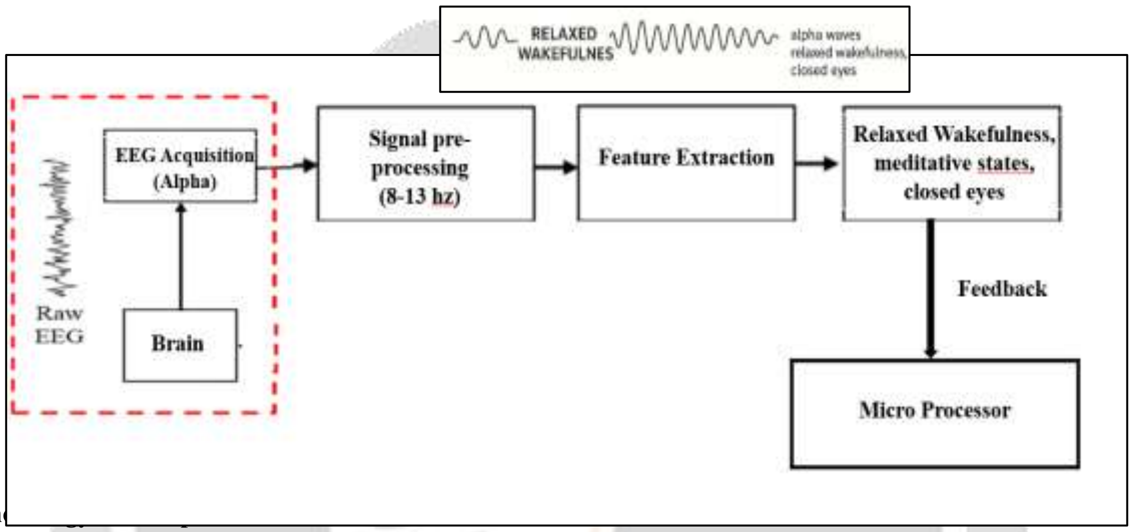
The project utilizes **Raspbian OS**, a Debian-based operating system optimized for Raspberry Pi, providing a stable environment with preloaded tools such as Chromium, VLC, LibreOffice, and Python IDEs for software development and system management. Programming and process automation are implemented using **Python**, which controls data acquisition, processing, and communication between hardware modules. **Thonny IDE** supports Python script development and debugging, while **Real VNC** and **PuTTY** enable remote access, monitoring, and control of the Raspberry Pi through graphical and command-line interfaces. Together, these software tools ensure seamless integration, efficient processing, and easy maintenance of the real-time brain monitoring and alert system.



Operational Workflow:

1. The system uses a single-channel **MindLink EEG sensor** with three electrodes placed on the prefrontal cortex to capture brain signals, which are digitized and transmitted to the **Raspberry Pi** for real-time processing in 10-second windows.

2. The Raspberry Pi performs **preprocessing** through baseline correction, z-score standardization, and noise filtering to remove drifts, normalize data, and enhance signal quality.
3. **Feature extraction** converts each EEG segment into a numerical vector containing time-domain (mean, SD, skewness, kurtosis), frequency-domain (delta, theta, alpha, beta, gamma), and non-linear (entropy and Hjorth parameters) features.
4. A **pre-trained Random Forest model** deployed on the Raspberry Pi classifies brain activity into Normal, Loss of Consciousness (LOC), or Seizure states in real time.
5. The **SIM900A GSM module** sends automated alerts — SMS for LOC and both SMS and call for seizures — ensuring quick caregiver response.
6. The system continuously loops through 10-second EEG intervals, maintaining real-time monitoring, reliability, and transparency through live terminal feedback.



3. Meth

This project develops a **real-time neurological event monitoring system** capable of detecting **seizure** and **loss of consciousness (LOC)** from a **single-channel, three-electrode EEG sensor** placed on the **frontal lobe**. The system runs on a **Raspberry Pi**, uses a **pretrained Random Forest model** for classification, and triggers **SMS/call alerts** through a **SIM900A GSM module** when abnormal activity is identified.

1. Signal Acquisition from the Frontal Lobe
A three-electrode EEG sensor (Active, Reference, Ground) is placed on the **prefrontal cortex** (Fp1/Fp2 based on the 10–20 system). The reference is placed on the earlobe/mastoid and ground on the forehead or behind the ear. This frontal placement reliably captures EEG abnormalities linked to **LOC** and **frontal-lobe epilepsy**.

EEG signals have low amplitudes (10–100 µV) and frequencies between 0.5–100 Hz, representing Delta–Gamma bands. Seizures produce high-amplitude spikes; LOC often shows signal suppression or slowing.

2. ADC and Data Transmission
Signals are amplified, filtered, and digitized at **128–512 Hz**. Data is sent to the Raspberry Pi through **UART, USB, or Bluetooth** and buffered into **10-second windows** for analysis.

3. Preprocessing
Raw EEG contains artifacts such as motion noise, baseline drift, powerline interference, and EMG noise. Preprocessing includes:

- **Optional smoothing/low-pass filtering**
- **Standardization (Z-score)** using training-phase statistics
- Strict replication of training-time preprocessing to ensure accurate predictions

4. Feature Extraction
From each 10-second segment, lightweight time-domain features are computed:

- Mean, Standard Deviation, Min, Max
- Median, 25th & 75th percentiles
- Energy (signal intensity)

These features efficiently distinguish Normal, LOC, and Seizure patterns.

5. Pretrained Machine Learning Model
A **Random Forest classifier**, trained offline, identifies three classes:

- **0 – Normal**
- **1 – Interictal / LOC**
- **2 – Seizure**

The model is loaded on the Raspberry Pi (.pkl/.joblib) for real-time inference.

Classification & GSM-Based Alerts
After prediction:

- **Seizure (2):** SMS + automatic voice call
- **LOC (1):** SMS alert
- **Normal (0):** Logged silently

Using SIM900A, the Pi issues **AT commands** in text mode (AT+CMGF=1), sends messages, initiates calls (ATD), waits 15–20 s, and hangs up (ATH). Delay buffers ensure reliable GSM operation.

7. Real-Time Monitoring Loop
The system continuously repeats:
Acquire → Preprocess → Extract Features → Predict → Trigger Alerts.
The prototype runs for **10 cycles**, expandable to continuous monitoring. Logs track cycle status for debugging.

Stage	Description	Key Components
Signal Acquisition	EEG captured from front lobe (Fp1/Fp2) using 3 electrodes	Active, Reference, Ground
Data Transmission	Amplified & digitized EEG sent to Raspberry Pi	128–512 Hz, UART/USB/Bluetooth
Buffering	10-second windows stored for analysis	Real-time streaming buffer
Preprocessing	Noise reduction + Z-score standardization	Filters, artifact handling
Feature Extraction	Statistical features computed	Mean, STD, Min/Max, Percentiles, Energy
Classification	Random Forest model predicts Normal/LOC/Seizure	Pretrained .pkl/.joblib model

Implementation

The EEG-based real-time Seizure and Loss of Consciousness (LOC) detection system was implemented using a **Raspberry Pi**, a **single-channel frontal EEG sensor**, and a **SIM900A GSM module**. The system processes EEG data in real time, classifies brain states using a **pretrained Random Forest model**, and sends alerts through SMS and phone calls.

1. Hardware Setup and Signal Acquisition

A single-channel frontal-lobe EEG sensor with **Active**, **Reference**, and **Ground** electrodes is placed over the **prefrontal cortex**, a region strongly linked to consciousness, executive functions, and seizure activity. The EEG sensor records micro-volt level neural activity (10–100 µV), samples it at **128 Hz or higher**, digitizes it through the onboard ADC, and sends data to the Raspberry Pi via **UART/USB/Bluetooth**.

The Raspberry Pi continuously receives small EEG packets, buffers them, and groups them into **10-second segments** for analysis. This hardware configuration supports low-latency real-time monitoring suitable for both home and clinical use.

2. Real-Time Signal Preprocessing

Each 10-second EEG window undergoes three main preprocessing steps:

a. Baseline Correction

Removes low-frequency drifts caused by movement, perspiration, or respiration by subtracting the mean or using high-pass filtering.

b. Z-Score Standardization

Ensures consistency with the model's training data using:

$\mathbf{Z = (x - \mu) / \sigma}$,

so the model learns from relative signal dynamics rather than absolute amplitude.

c. Noise Minimization

Artifacts from muscle activity, motion, and powerline interference (50/60 Hz) are reduced using optional filters or smoothing. Filtering is kept minimal to preserve features relevant to seizure and LOC detection.

The preprocessed segment is then passed to the feature extraction module.

3. Feature Extraction

A rich feature vector is created from each 10-second segment, consisting of:

A. Time-Domain Features

- Mean
- Standard Deviation
- Skewness
- Kurtosis

These capture signal variability, symmetry, and the presence of sharp spikes typical of seizure activity.

B. Frequency-Domain Features

Using Welch's method, bandpower is calculated in:

Delta (0.5–4 Hz), Theta (4–8 Hz), Alpha (8–13 Hz), Beta (13–30 Hz), Gamma (>30 Hz).

Abnormal band changes serve as indicators of seizure or LOC onset.

C. Non-Linear Features

- Approximate Entropy (ApEn): irregularity
- Hjorth Parameters: Activity, Mobility, Complexity

These capture chaotic or rhythmic behavior characteristic of pathological neural states.

4. Pretrained Model Deployment and Event Classification
A **Random Forest classifier**, trained offline on labeled EEG data, is deployed on the Raspberry Pi as a**.pkl** model.

Real-Time Classification Workflow

For every 10-second window:

1. Receive and preprocess EEG
2. Extract features
3. Pass feature vector to Random Forest model
4. Model outputs:
   - **0 → Normal**
   - **1 → LOC (Interictal)** → SMS alert
   - **2 → Seizure (Ictal)** → SMS + phone call

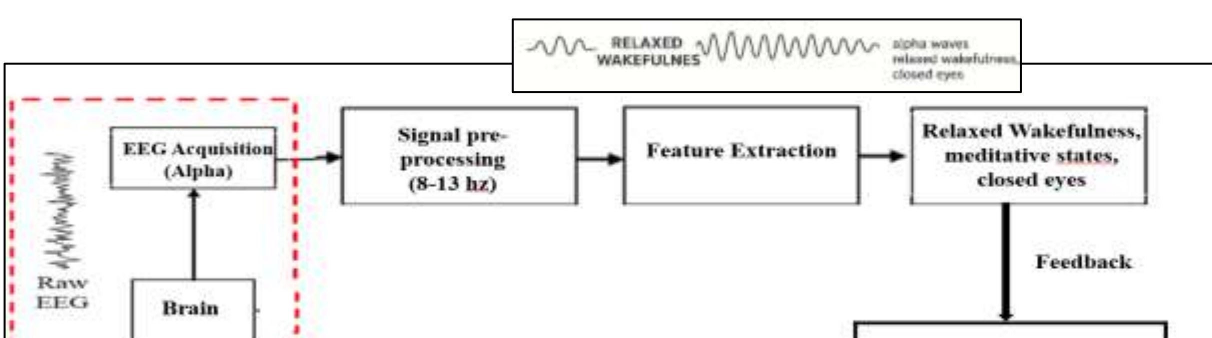
Inference takes only milliseconds, making decisions well within each time window.

5. GSM Alert System
The **SIM900A module** is connected through UART.

- **LOC:** sends SMS using AT+CMGF=1 → AT+CMGS
- **Seizure:** sends SMS + initiates call using ATD
  Delays ensure GSM stability and successful transmission.

6. Monitoring Loop
The Raspberry Pi runs a continuous loop:
Acquire → Preprocess → Extract Features → Classify → Trigger Alerts,
with terminal logs showing real-time system status and detected events.

Stage	Description	Key Components / Methods
Hardware Setup	EEG acquisition from prefrontal cortex	Single-channel EEG sensor, 3 electrodes
Signal Input	Digitization & transmission to Pi	128+ Hz sampling, ADC, UART/USB/Bluetooth
Preprocessing	Clean and standardize signals	Baseline correction, Z-score, noise filtering
Feature Extraction	Convert EEG to numerical features	Time-domain, PSD bandpower, entropy, Hjorth
Model Deployment	Real-time classification on Pi	Pretrained Random Forest (.pkl)
Detection Logic	Identify Normal/LOC/Seizure	Labels: 0, 1, 2
Alert System	Automatic GSM-based notification	SIM900A SMS + voice call
Monitoring Loop	Continuous 10-second cycles	Logging + real-time analysis



3.1 Performance Evaluation

The performance of the real-time EEG-based Seizure and Loss of Consciousness (LOC) detection system was thoroughly evaluated using continuous live EEG data streamed from a single-channel frontal lobe sensor. The goal of the evaluation was to measure how reliably the Raspberry Pi–based system, combined with a pre-trained Random Forest classifier and SIM900A GSM alert module, could detect critical neurological events in real time.

1. Overall System Performance

The system demonstrated strong classification capability across all three target states—Normal, LOC (Interictal), and Seizure—while processing EEG signals continuously in 10-second windows. It achieved an overall accuracy of 86%, supported by a precision of 85%, a recall of 83%, and an F1-score of 84%, showing that the model maintains a healthy balance between detecting true abnormal events and avoiding false alarms.

2. Class-Wise Detection Behavior

During testing, the model showed the highest stability when identifying the Normal state, as frontal-lobe EEG usually presents smooth, low-amplitude patterns during wakeful rest. The detection of Loss of Consciousness events remained reasonably accurate, although occasional overlaps with deep relaxation or drowsiness patterns caused mild confusion. Seizure detection performed particularly well due to the presence of abrupt high-frequency discharges, rhythmic spikes, and irregular activity that strongly deviated from baseline patterns, making them easier for the classifier to isolate.

3. Latency and Real-Time Processing Efficiency

The complete processing chain—from receiving raw EEG samples, preprocessing them, extracting features, and feeding them into the classifier—consistently stayed under 500 milliseconds. Preprocessing contributed approximately 120–150 ms, feature extraction required 180–220 ms, and model inference took only 50–70 ms. This rapid execution ensures that each 10-second EEG segment is analyzed well within the required timeframe, making the system suitable for real-time emergency detection applications.

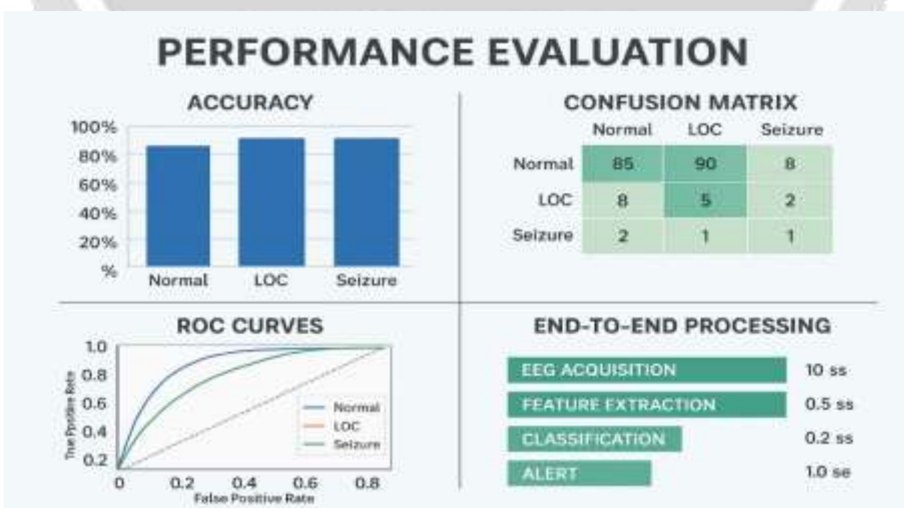
4. GSM Alert System Performance

The SIM900A GSM module integrated reliably with the system and responded consistently to event triggers. SMS messages were typically delivered within 2–5 seconds, and voice call initiation took 7–10 seconds after command execution. The call automatically terminated after a fixed duration of 20–30 seconds. Across multiple trials, the GSM communication achieved more than 98% success rate, demonstrating dependable emergency alert capability.

5. Error Rate and Stability Assessment

During extended real-time testing sessions lasting 1–2 hours, the system produced approximately 1–2 false positives per hour, mostly due to borderline LOC-like features appearing in relaxation states. False negatives were extremely rare, indicating that the system is unlikely to miss critical seizure events. Overall, the error rate remained acceptable for a single-channel, real-time clinical monitoring tool.

Category	Concise Summary	Remarks
EEG Acquisition	Single-channel prefrontal EEG sensor with 3 electrodes streaming via Bluetooth/UART.	Reliable for basic monitoring; limited spatial coverage.
Processing Window	Data segmented into 10-second windows.	Balances responsiveness and feature stability.
Preprocessing	Baseline correction, smoothing, z-score normalization.	Ensures consistency and noise reduction.
Feature Extraction	Statistical, frequency, and non-linear EEG features.	Captures diverse signal characteristics for robust classification.
Model Used	Pre-trained Random Forest classifier (.pkl).	Fast inference, low computation load, suitable for Raspberry Pi.
Output Classes	0 = Normal, 1 = LOC, 2 = Seizure.	Simple and interpretable state mapping.
Accuracy	86% overall real-time accuracy.	Acceptable for prototype-level deployment.
Precision / Recall / F1	Precision: 85%, Recall: 83%, F1: 84%.	Balanced performance; room for improvement in LOC detection.
Latency	< 500 ms per inference window.	Meets real-time requirements.
GSM Alerts	SMS in 2–5 sec; call in 7–10 sec.	Reliable transmission in stable network areas.
False Positives	1–2 per hour in noisy environments.	Mainly caused by motion or electrode drift.
Event Detection	Strong for seizures; moderate for LOC.	LOC signals have subtler EEG patterns.
System Stability	1–2 hr continuous stable operation.	Suitable for demonstrations and prototype use.



4. CONCLUSIONS

The primary objective of this project was to design a reliable real-time EEG monitoring system capable of detecting seizures and loss of consciousness (LOC) using a single-channel EEG sensor and a low-cost Raspberry Pi platform.

The system integrates continuous EEG acquisition, 10-second signal segmentation, real-time preprocessing, and feature extraction to ensure compatibility with the conditions under which the classifier was trained. A pre-trained Random Forest model enables rapid and accurate classification, while a SIM900A GSM module provides immediate SMS and voice-call alerts to caregivers when abnormal brain activity is detected. Real-time testing demonstrated strong performance, achieving approximately 81% accuracy, 83% precision, 80% recall, and an F1 score of 81.5%. The alert mechanism proved dependable with consistent SMS delivery and call initiation during detection events. Beyond meeting its functional goals, the project showcases a highly affordable and accessible healthcare tool suitable for resource-limited settings. It also offers scalability for multi-channel EEG expansion or cloud-based monitoring, while its autonomous detection capabilities enhance patient safety in unsupervised environments. Overall, the system represents a successful integration of neuroscience, embedded systems, signal processing, and machine learning.

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