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Non-Invasive Intracranial Monitoring for Detection of Epilepsy Using EEG Signals

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***Abstract*—Epilepsy is a lifelong neurological disorder characterized by sudden and unpredictable surges of electrical activity in the brain, resulting in seizures that affect movement, awareness, and behavior. Although electroencephalography (EEG) plays a crucial role in epilepsy diagnosis, conventional EEG monitoring requires sophisticated clinical infrastructure, making long-term and continuous observation impractical for many patients. This work presents a compact, non-invasive, and portable system capable of detecting seizure-like patterns in real time using EEG signals. The proposed system employs lightweight preprocessing, eighteen interpretable EEG features with additional derived measures, and an embedded hybrid CNN–LSTM classifier deployed on a low-cost microcontroller. An IoT layer enables real-time alerts and remote visualization of physiological parameters. Experimental validation using the CHB-MIT Scalp EEG Dataset and supplementary dry-electrode recordings demonstrates that the proposed approach achieves high detection accuracy while remaining cost-effective and suitable for home-based and non-clinical monitoring applications.**

***Index Terms*— Epilepsy, EEG, Embedded Machine Learning, CNN–LSTM, IoT Monitoring, Biomedical Signal Processing**

I. INTRODUCTION

Epilepsy affects almost fifty million individuals all around the world, with a major portion of them residing in places where infrastructure is limited for purposes of diagnosis [1]. Fits and seizures begin from abnormal neuronal firing that randomly changes be- haviour, motor control, and consciousness temporarily [3]. Traditional diagnostic workflows are dependent on EEG monitoring, which needs specialised hospital equipment, an expert's interpretation, and controlled environments that act as barriers that restrict accessibility for patients in previously mentioned low infrastructure areas. [4].

Progress in new wearable and bendable, waterproof sensors, low-power controllers and processors, and embedded machine learning systems has now paved the way for lightweight seizure detection systems that operate outside controlled clinical settings. [2, 5]. These systems combine signal processing techniques with AI-based classifiers to automatically distinguish seizure activity from normal EEG patterns. However, many such solutions depend on computationally heavy algorithms or multi-channel medical hardware, which limits their deployment on low-cost embedded platforms [6].

Our objective in the project is to design a practical, resource-efficient system for continuous, real-world EEG monitoring that integrates preprocessing, features that can be interpreted, and a hybrid CNN-LSTM Deep learning model best suited for deployment onto microcontrollers. We also integrated a lightweight IoT layer for visualisation of the features extracted from the EEG signals and alerting, while carefully evaluating messaging services (e.g., Telegram) against memory and TLS constraints on the embedded device.

II. LITERATURE REVIEW

A. Existing Medical Techniques

Clinical EEG interpretation is the top-tier standard for the diagnosis of epilepsy; doctors inspect the long recordings to identify epileptic activity such as 'spike-and-wave' discharges and sharp and unexplained transients [7]. Intra-cranial EEG (iEEG) im- proves accuracy tremendously but needs surgical action and is primarily reserved for extreme cases [8].

B. AI and Signal Processing Approaches

Automated detection using ML and DL has matured considerably since the time of traditional EEG signal interpretation. Earlier works used classical classifiers such as SVM and Random For- est with hand-picked features [9, 10], whereas recent research into this field employs deep learning architectures such as CNN, LSTM and hybrid CNN-LSTM (such as ours) to capture spatial, temporal patterns in EEG [11, 12]. Entropy-based and wavelet-derived features have also been shown to boost discriminability in the EEG Signals. [13, 14].

C. Deployment and Research Gaps

ML model accuracy on benchmark datasets such as the one by CHB-MIT is excellent however these high-performing models are impractical on microcontrollers due to memory, computation and latency constraints [5, 6]. Also, an end-to-end real-time system involving acquisition, preprocessing, inference, and cloud integration is rarely written about in the literature [32]. Our system can address these gaps by dividing the computation responsibility across an STM32 for acquisition, preprocessing and model deployment and an ESP8266 for the data visualisation and IoT functions. The CNN-LSTM model has been quantised into an 8-bit TFLite model for deployment [21].

III. SYSTEM DESIGN

Figure 1 shows the overall architecture of the entire project: EEG signal acquisition via a single-channel, low-cost dry-electrode system, analogue conditioning and amplification to measurable values, STM32-based conversion to digital signals and then preprocessing, extraction of necessary features. The slave ESP8266 is used for message alerts, buzzer and LED alerts and also the data visualisation through a dashboard.

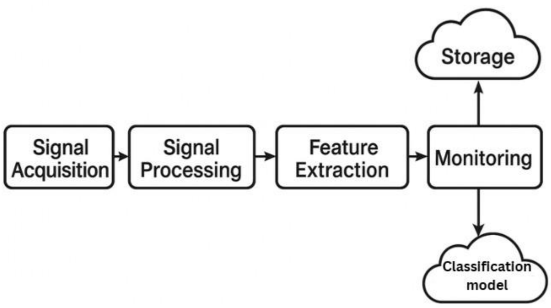

Figure 1: Overall system architecture combining acquisition, processing, classification, and IoT-based monitoring.

A. Hardware Components

The hardware of the entire project consists of:

- Three-channel dry-electrode EEG headset: frontal electrodes to capture relevant waveforms while allowing for wear- ability and general mobility [23].
- BioAmp EXG Pill frontend: an integrated and low-noise electrophysiology analogue frontend sensor and amplifier combination that replaces the traditionally used instrumentation amplifiers such as INA333 or AD8237-class. It gives built-in gain, filtering, and a high CMR ratio (CMRR) for the capturing of EEG signals in the μV value ranges while simplifying the broader hardware design [33].
- STM32 MCU: responsible for the ADC sampling in the 200–512 Hz ranges, bandpass and notch filtering, and for the feature extraction. The STM32 model used in this prototype was an STM32 with the specific model being the F446RE for its DSP capabilities, floating point and DMA support [17].
- ESP8266 MCU: chosen for its Wi-Fi connectivity (used for Twilio and Telegram) and sufficient RAM and flash memory for hosting a lightweight web server (dashboard) [18].
- Power subsystem: for the prototype, power was supplied directly from a laptop USB port, avoiding additional Li-ion battery management hardware to simplify rapid prototyping.
- Local alerting: buzzer and LED controlled by the ESP8266 for immediate alarms on detection.

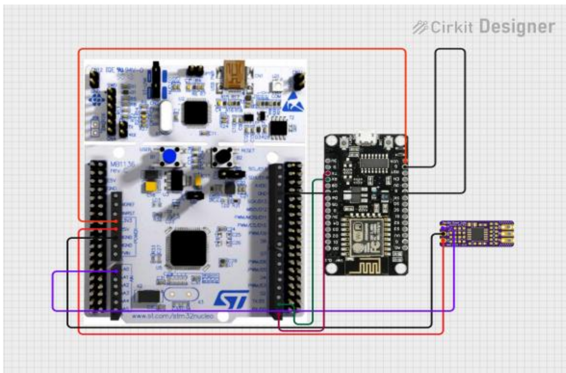

Figure 2: basic circuit diagram of the proposed EEG monitoring system (buzzer and LED omitted).

B. Software and Data Flow

The firmware pipeline (Figure 3) is split across the two controllers to optimise latency as much as possible and allow for better re- source utilisation:

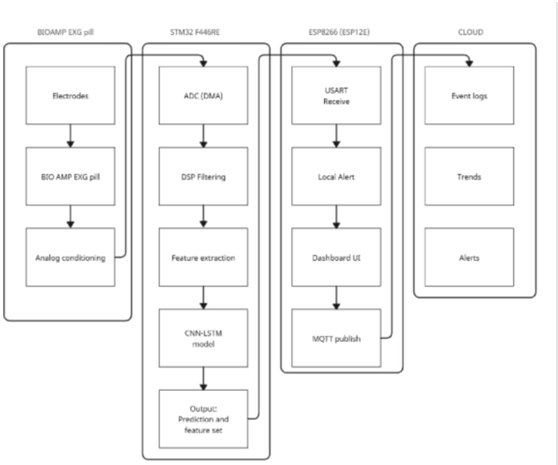

Figure 3: Firmware data flow from acquisition to output.

1. Acquisition (STM32 and BIOAMP EXG pill: The STM32 ADC samples raw EEG through the BIOAMP EXG pill at 256 Hz (configurable between 200 to 512 Hz range) with 'DMA-driven circular buffers' to minimise CPU load as much as possible [19].
2. Preprocessing (STM32): digital 0.5 to 60 Hz bandpass filtering (we used IIR Butterworth), along with a 50/60 Hz IIR notch filter was made using fixed-point routines; then a moving-average smoothing was applied to reduce impulsive noise from the earlier filters [16].
3. Feature extraction (STM32): We computed 18 core features per window, along with a few additional derived features such as crest factor and spectral centroid and Peak to Peak (P2P) and packaged them as a compact feature bundle to be sent to the ESP8266. This feature bundle is ran through a quantised 8-bit TensorFlow Lite model that outputs seizure probability; if the threshold is exceeded, a local alert is also sent along with the message.
4. Communication/Transportation: the feature bundle we spoke about earlier is now transmitted over USART (baud 9600 as we used Software Serial) (simple frame with header and footer and a checksum) to the ESP8266 for alerts and visualisation.
5. Alerts (ESP8266): the ESP8266 is connected to a Buzzer and an LED. If a local alert message is transmitted by the STM32, the local alert is triggered and an MQTT event is published to the cloud dashboard along with the message being sent to the registered phone number.
6. Cloud dashboard: HTTP endpoint receives the MQTT events, displays live feature trends, raw waveform snapshots, and stores event history for clinician review which can also be downloaded if needed.

IV. METHODOLOGY

A. EEG Data Acquisition

Two types of EEG data were collected and turned into a single working dataset, and then used:

- CHB-MIT Scalp EEG Dataset: clinical pediatric recordings sampled at 256 Hz with precise seizure annotations used for training and offline evaluation, and is available as an open source library for EEG classification model training. [22].
- Wearable dry-electrode recordings: three frontal channels were used to collect values in semi-controlled daily activities to evaluate robustness to motion and common ambient noise [23, 24].

Figure 4 shows the standard 10–20 layout (for reference); our wearable used two frontal placements along with a reference be- hind the ear (temporal), approximating Fp1/Fp2/T5 for comfort while extracting meaningful signals [25].

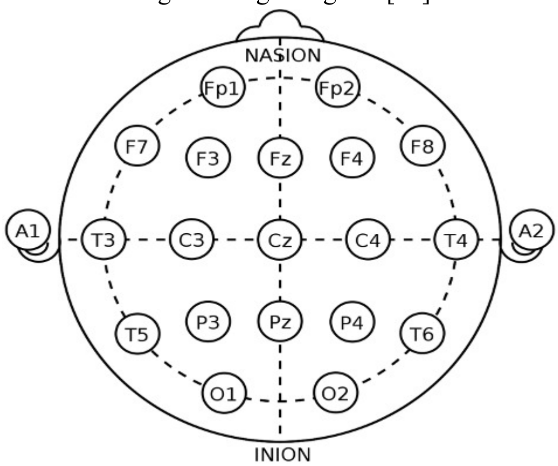

Figure 4: Standard international 10-20 electrode layout [25].

B. Signal Processing and Feature Extraction

Raw EEG signals are mixed with ocular artefacts, EMG, motion artefacts, and mains interference acting as noise. This noise acts as a major barrier to extraction and further preprocessing. The preprocessing pipeline shown below was designed to be operated on a microcontroller:

- Bandpass filter: 0.5-60 Hz fourth-order Butterworth IIR filter (implemented as cascaded biquads in the program) to retain bands relevant to the project [16].

- Notch filter: narrowband IIR notch filter at 50 Hz (you can also use 60 Hz, depending on your region) with high Q value to suppress mains interference (50 Hz in India) [20].

- Smoothing: short-window moving average windows (length= 5 to 11 samples, depending on the sampling rate used) was used to reduce the impulsive noise from the filters used before, while providing minimal noise towards the temporal resolution.

- Artefact handling: Thresholding and an epoch rejection scheme for extreme amplitude transients (such as those greater than 500 μV) was made and also channel-wise cor- relation checks were added to avoid processing gross motion artefacts received.

The STM32 computes features for sliding windows (we used windows with 2 s length with 50% overlap) and generates the 18-feature bundle described below that is sent to the ESP8266.

C. Feature Set

The extracted feature set includes time-domain statistics (mean, variance, RMS, skewness, kurtosis), nonlinear measures (entropy, zero-crossing rate, Hjorth parameters), and frequency-domain descriptors (band powers, dominant frequency, spectral centroid, flatness, and crest factor).

V. CNN–LSTM CLASSIFICATION MODEL

A. Motivation

The layers of the Convolutional Neural Network (CNN) capture short-term spatial dependencies in the received feature vector, while the LSTMs capture temporal evolution across adjacent win- dows. This comes out to be very important because seizures exhibit slow and gradual temporal buildup [11, 12].

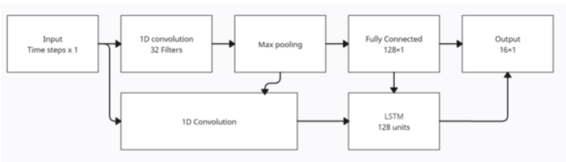

Figure 5: CNN-LSTM Architecture.

B. Architecture

Figure 5 shows the model (placeholder).

- 1D Convolution (kernel=3, filters=32)
- Max Pool
- LSTM(32 units)
- Dense (16 units, ReLU)
- Output (1 neuron, Sigmoid)

C. Training

Training was performed on a dataset comprising of normal values obtained by using the BIOAMP EXG pill and seizure values from the CHB-MIT dataset. [22].
Loss: Binary cross-entropy
Optimiser: Adam
Epochs: 80
Batch size: 32

D. TFLite Quantization

We converted the model we trained above to an 8-bit quantised (int 8 size) TensorFlow Lite Micro model [21]. The Benefits of which are:

- 4x smaller model size
- 2x faster inference on STM32
- slightly RAM usage

Final model size: 102 kB(it may vary depending on compile flags used).
Inference time on the STM32: 0.23 seconds.

VI. FIRMWARE ARCHITECTURE AND REAL-TIME LOGIC

A. STM32 Data handling

The complete signal processing and inference pipeline is done on the STM32:

- ADC sampling at 256 Hz using a DMA circular buffer [19]
- ISR-triggered processing on a 2 second window
- Feature extraction using DSP (18+ temporal and spectral features) [17]

- 8-bit quantised TF Lite-Micro CNN-LSTM inference
- UART transmission of the features, prediction, and system status to the ESP8266 in the form of a packet

B. ESP8266 Runtime Loop

Algorithm 1 ESP8266 Runtime Loop

```
Init WiFi, MQTT, WebServer
Init UART buffer
loop
  Wait for STM32 status packet
  Parse prediction, probability and device status
  if prediction == seizure then
    Trigger buzzer and LED
    Publish MQTT alert
  end if
  Update dashboard JSON buffer
end loop
```

C. Latency Breakdown

Table 1: Measured End-to-End Latency (STM32 + ESP8266)

Task	Time (ms)
STM32: preprocessing	5–10
STM32: feature extraction	8–12
STM32: TFLite inference	40–55
UART transfer	3–5
ESP8266: packet parsing	2–3
ESP8266: dashboard refreshing	10–20
ESP8266: MQTT publishing	15–25
Total end-to-end	85–130 ms

VII. MEMORY AND RESOURCE ANALYSIS

A. STM32 Memory Use

- TFLite Micro arena (8-bit model): 25–35 kB
- DSP buffers: 8–12 kB
- ADC and DMA buffers: 1–2 kB
- Feature arrays: 1–2 kB
- Stack and system: 8–10 kB
- Total SRAM usage: 45–60 kB (within operational limits)

B. ESP8266 Memory Use

Since STM32 does all the heavy computation and mathematical work, the ESP8266 only handles the networking and UI:

- Web server (HTML and CSS buffers): 20-40 kB
- MQTT client: 6-10 kB
- UART parsing: 1-2 kB
- Dashboard JSON buffer: 3-5 kB
- Free heap at runtime: 20-35 kB (5%)

VIII. IoT DASHBOARD AND CLOUD INTEGRATION

A. Dashboard Overview

The ESP8266 hosts a lightweight local dashboard providing live EEG visualisation, feature trends, alert logs, and system status, with periodic auto-refresh. Data are synchronised with a cloud MQTT broker for remote clinician access.

IX. RESULTS AND DISCUSSION

A. Classification Performance

The hybrid CNN-LSTM classifier showed us good results on the combined CHB-MIT dataset and wearable recordings. Performance metrics given below followed the standard evaluation procedure for optimal seizure detection [26].

Table 2: Performance Metrics of the Proposed Seizure Detection System

Metric	Value (%)
Accuracy	93.12
Recall (Sensitivity)	94.1
Specificity	92.42
Precision	93.26
F1-Score	94.4

B. Confusion Matrix

The confusion matrix given below (Fig. 6) shows us the distribution of classification outcomes from the CNN-LSTM model.

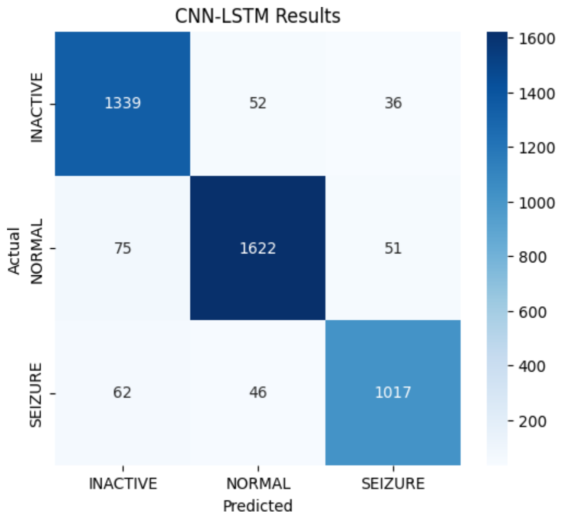

Figure 6: Confusion matrix of CNN–LSTM classifier.

C. Latency and On-Device Real-Time Performance

The end-to-end system latency of both devices was consistently below roughly 300 ms (Table 3). This allows us not to worry about the real-time monitoring constraints [5] of the devices.

Table 3: Latency Breakdown and On-Device Performance

Process	Latency (ms)
UART reception	3–5
Feature normalization	2–4
TFLite inference	180–200
MQTT publish	15–25
Dashboard update	10–20
Total	200–260

X. APPLICATIONS

A. Rural Healthcare and Low-Resource Settings

Since low-cost microcontrollers and dry electrodes were used, the system can be used in rural clinics where EEG labs are lacking, enhancing accessibility and care in even the remotest of areas [27].

B. Telemedicine and Remote Neurology

Using MQTT and cloud dashboards, doctors can observe trends, snapshots, and event histories remotely, allowing for better long- term care [28].

C. Predictive Healthcare Pipelines

As the system also stores feature trajectories, it can be mixed into seizure forecasting algorithms [29], allowing for personalised risk predictions.

XI. LIMITATIONS AND FUTURE WORK

A. Motion Artifacts

Dry electrodes suffer due to motion artefacts, which mimic epileptic activities of the brain [24].

B. Dataset Diversity

CHB-MIT contains only children and pediatric subjects. Gener- alisation between adults and seniors requires multicenter datasets [26].

C. Hardware Constraints

Only 3 channels are used; future versions may include:

- 8-channel designs
- Virtual electrode synthesis
- Custom wearable PCB with case

D. Seizure Prediction

The current model can only detect seizures post-onset. Future goals:

- Pre-ictal prediction models
- Temporal convolution networks (TCN)
- Transformer-based EEG forecasting

XII. ETHICAL CONSIDERATIONS

All EEG data that we took from the CHB-MIT comply with its open-access license [22].

The other wearable data that we collected followed proper ethical guidelines such as:

- Informed consent
- No personal identifiers stored
- Encrypted MQTT transport using TLS lightweight profiles

These measures adhered to biomedical principles of autonomy, beneficence, and confidentiality followed throughout the world [31].

XIII. CONCLUSION

This work presents a finished, completely non-invasive EEG monitoring system integrating STM32-based preprocessing, CNN– LSTM-based seizure detection and an IoT dashboard on an ESP8266.

The ML model-based system achieved 93.1% accuracy using a lightweight, quantised TFLite model best suited for embedded deployment was deployed on the STM32.

Comprehensive debugging addressed the TLS/HTTPS limitations we encountered on ESP8266 and also the UART desynchronization, and the dashboard rendering issues.

The system's portability, low cost, and good accuracy make it best suitable for rural healthcare and long-term EEG supervision. Future extensions may include predictive modelling, multi-channel EEG, and wearable PCB miniaturisation with its own custom case.

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Use of Generative AI: Generative AI tools were used for language refinement and formatting assistance. All technical content, analysis, and conclusions are the sole responsibility of the authors.

Conflict of Interest

We, the authors, declare that we have no known competing financial interests or personal relationships that may have influenced the work reported in this paper.

Data Availability

The CHB-MIT Scalp EEG Dataset that we used in this study is publicly available at https://physionet.org/content/chbmit/1.0.0/.

Additional wearable dry-electrode EEG recordings collected for this project can be made available from the corresponding authors upon reasonable request.

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