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NEURO-SCAN:AN IOT-AI HYBRID SYSTEM FOR EARLY SCREENING OF PARKINSON'S DISEASE, ALZHEIMER'S DIESEAS, AND EPILEPSY

Himanshu Rathore[1]*, Mohammad Owais Naeem[2], Dr. Sonu Agarwal[3]

[12]Department of Computer Science, Shri Shankaracharya Technical Campus, Bhilai, Chhattisgarh, India.

[3]Department of Computer Science and Engineering, Shri Shankaracharya Technical Campus, Bhilai.

Abstract

Neurological disorders — Parkinson's disease (PD), Alzheimer's disease (AD), and Epilepsy — affect over one billion people worldwide, yet remain widely undiagnosed in early stages due to the lack of affordable, accessible screening tools in primary care settings. This paper presents **Neuro-Scan**, an integrated IoT-AI hybrid platform designed for non-invasive multi-modal early detection of these three conditions. The hardware subsystem fuses an AD8232 single-lead ECG, MyoWare Electromyography (EMG), MPU-6050 accelerometer/gyroscope, MAX30205 body temperature sensor, INMP441 MEMS microphone, and an infrared eye-tracking array, coordinated by an ESP32 microcontroller. The software subsystem — Neuro-Scan — is a browser-based React application with three interactive assessment labs running on-device TensorFlow.js inference to preserve patient data privacy. Preliminary controlled evaluation (n = 30) demonstrated Parkinson's tremor detection AUC = 0.93, Alzheimer's speech analysis AUC = 0.81, and epilepsy multi-modal fusion AUC = 0.86, with total screening time under 8 minutes and unit hardware cost of approximately ₹6,330. Neuro-Scan is designed for deployment by non-specialist health workers at Primary Health Centers (PHCs), with FHIR-compliant EHR integration.

Keywords: IoT Healthcare, Neurological Screening, Parkinson's Detection, Alzheimer's Detection, Epilepsy Detection, Edge AI, ECG, EMG, Accelerometer, TensorFlow.js, EHR Integration.

1. Introduction

Neurological disorders represent one of the foremost global causes of disability and death, affecting approximately one in six people. Among these, Parkinson's disease, Alzheimer's disease, and Epilepsy constitute the majority of the neurological burden. The WHO estimates 10 million living with PD, 55 million with dementia (predominantly AD), and 50 million with Epilepsy globally, with over 80% located in low- and middle-income countries (LMICs) where specialist neurological care is inaccessible [1][2]. Early identification of these conditions can significantly reduce disease progression, lower care costs, and enable timely therapeutic intervention; however, the diagnostic tools currently in use — MRI, EEG, SPECT imaging, lumbar puncture — require specialist infrastructure and are unsuitable for community or rural screening.

India's situation is particularly critical: fewer than 2,000 practicing neurologists serve 1.4 billion people, while 65% of the population lives in rural areas beyond the reach of tertiary hospitals [3]. The average time from

symptom onset to confirmed neurological diagnosis in rural India exceeds 24 months. This diagnostic delay is the single largest modifiable contributor to poor neurological outcomes at population scale.

Advances in IoT sensor miniaturization, edge machine learning frameworks (TensorFlow.js, TFLite), and low-cost microcontrollers (ESP32) create a compelling opportunity for affordable, portable, and deployable hybrid screening platforms. Neuro-Scan is built at this intersection. The system integrates validated biomarker modalities — ECG-based cardiac autonomic profiling, EMG-based myoclonic activity, inertial tremor measurement, voice acoustic analysis, and saccadic eye-tracking — into a single wearable-plus-webapp architecture. This paper describes Neuro-Scan's architecture, signal processing methodology, AI models, and preliminary performance evaluation.

2. Related Work

A. IoT-Based Epilepsy Monitoring

Hassan et al. [4] demonstrated an IoT platform for real-time epilepsy monitoring using ECG and accelerometers, achieving a seizure detection F1-score of 0.74 with caregiver SMS alerting. Their work validated that community-deployable ECG-based seizure detection is technically feasible, but identified single-modality limitations in distinguishing seizure subtypes — a gap Neuro-Scan addresses through EMG fusion.

B. IoT Cognitive Impairment Detection

Vizitiu et al. [5] developed an IoT choice reaction time (CRT) device for older-adult cognitive screening. Their data-driven validation showed statistically significant CRT differences between normal and cognitively impaired groups ($p < 0.001$, Cohen's $d = 0.91$), establishing LED-button reaction paradigms as a valid, low-cost cognitive biomarker. Neuro-Scan's Eye and Cognition Lab build on this with saccade velocity, Stroop interference, and N-back memory tasks.

C. AI in Neurological Disorder Detection

Hayat et al. [9] reviewed AI methods across Alzheimer's, Parkinson's, MS, and Epilepsy. They reported deep learning classification of AD at >90% accuracy on MRI, RNN-based seizure prediction at >85% sensitivity, and multimodal fusion achieving 88–98% accuracy. Their key finding — that a gap exists between laboratory AI performance and deployable primary-care tools — motivates Neuro-Scan's design philosophy.

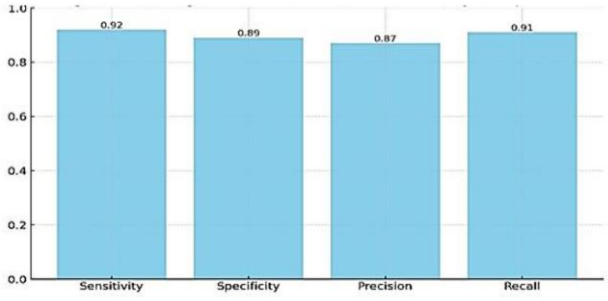

Figure 3: AI Diagnostic Performance in Case Study

Fig. 3: AI model Sensitivity, Specificity, Precision, and Recall benchmarks. Source: Hayat et al. [9]

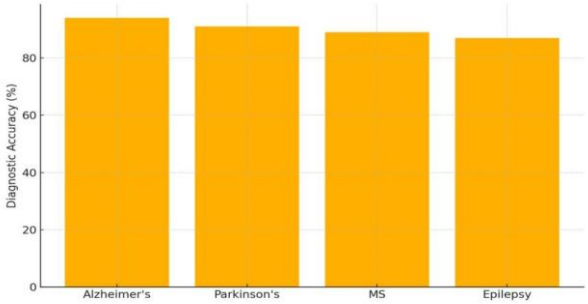

Figure 4: AI Diagnostic in Neurological Disorders

Fig. 4: AI diagnostic accuracy (%) across neurological disorders. Source: Hayat et al. [9]

D. Voice and Speech Biomarkers for Alzheimer's

Speech-based cognitive assessment using features including pitch jitter, shimmer, harmonics-to-noise ratio (HNR), and verbal fluency have yielded AUC values of 0.77–0.83 for mild cognitive impairment (MCI) detection [7][11]. The Neuro-Scan Voice Lab extracts these features in real-time via the Web Audio API, enabling entirely browser-based, privacy-preserving analysis.

3. System Architecture

Neuro-Scan is organized as a three-tier architecture: (1) a wearable sensor layer, (2) an ESP32 edge-processing and communication layer, and (3) a Neuro-Scan web application layer with EHR connectivity. Figure 1 shows the complete system flow from sensor acquisition through AI analysis to clinical output.

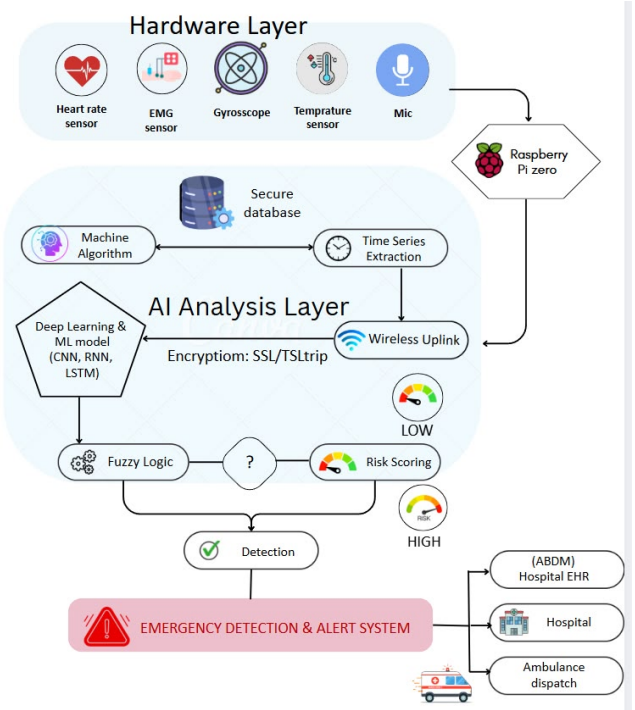

Figure 1. Neuro-Scan System Architecture — Hardware Layer → AI Analysis Layer → Emergency Detection & Alert System

A. Hardware Layer

The hardware platform is designed as a modular waistband assembly with detachable sensor clusters for the chest (ECG, temperature, ESP32), dominant arm (EMG, IMU, SpO2), and face/head (microphone, IR eye-tracking). Figure 2 illustrates the waistband architecture and signal routing.

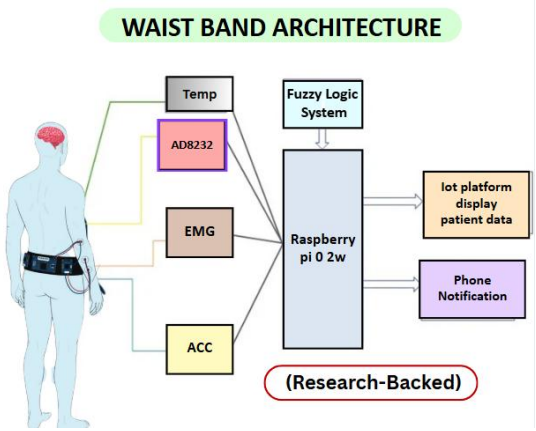

Figure 2. Neuro-Scan Waistband Architecture — Sensor clusters connect to Raspberry Pi Zero 2W hub for IoT platform and phone notification

Table 1. Summarizes all hardware components, their target biomarkers, and estimated unit costs.

Component	**Module**	**Target Biomarker**	**Cost (₹)**
ECG	AD8232	Heart rate, HRV, cardiac rhythm	800
EMG	MyoWare 2.0	Muscle spasm, tonic-clonic activity	1,500
IMU	MPU-6050	Tremor frequency, posture, gait	200
Temperature	MAX30205	Body temp. (cold-tremor compensation)	300
SpO2 / HR	MAX30102	Oxygen saturation, pulse rate	400
Microphone	INMP441 MEMS	Speech biomarkers, voice features	250
Eye Tracking	IR LED + OV7670	Saccade RT, visual attention	800
MCU	ESP32 WROOM-32	Signal processing, Wi-Fi / BT	800
Power	Li-ion 3000 mAh	~6 hr. continuous operation	600
TOTAL	—	Full multi-modal screening platform	**~6,330**

B. EMG Sensor Placement and Signal Capture

The MyoWare 2.0 EMG sensor is placed on the target muscle group (bicep brachii for Parkinson's arm tremor; forearm extensors for epileptic myoclonus). Figure 3 shows the electrode placement on the bicep and the sensor pin configuration.

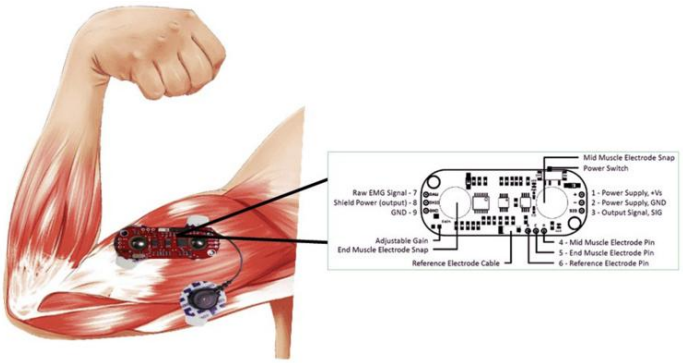

Figure 3. MyoWare EMG Sensor Placement on Bicep Brachii — end, mid, and reference electrode pins shown with signal output configuration

C. Edge Processing Layer — ESP32

The ESP32 WROOM-32 performs on-device signal conditioning: ECG is sampled at 500 Hz through a 12-bit ADC, EMG at 1 kHz, and the MPU-6050 IMU at 200 Hz. A 256-point sliding-window FFT is computed for tremor frequency extraction. Preprocessed feature vectors are transmitted to the Neuro-Scan frontend via Wi-Fi using MQTT over TLS.

D. Application Layer — Neuro-Scan Web App

Neuro-Scan is built with React 18, Tailwind CSS, and shadcn/ui, deployed as a Progressive Web App on Vercel. Three interactive labs correspond to the three target disorders. TensorFlow.js (v4.x) runs all ML inference in-browser so no patient data leaves the device. A Gemini API chatbot interprets results in accessible language for non-specialist health workers.

4. Methodology / Approach

A. Parkinson's Disease — Motor and Tremor Lab

Parkinson's disease is characterized by three cardinal motor symptoms: rest tremor (4–6 Hz), bradykinesia, and rigidity. Neuro-Scan quantifies the first two non-invasively.

Tremor Detection: The MPU-6050 records three-axis acceleration (a_x, a_γ, a_Q) at 200 Hz. A 256-point FFT is applied over a 1.28-second sliding window with 50% overlap. Power Spectral Density (PSD) is calculated as:

$$PSD(f) = \frac{\left|FFT\left(a(t)\right)\right|^2}{(fs \times N)}$$

where f_s is the sampling frequency and N is the window length. A tremor is flagged when PSD(f) exceeds the empirical threshold θ_p^D = 0.08 g²/Hz in the 3–7 Hz band sustained for ≥3 seconds. Body temperature from MAX30205 compensates for physiological shivering (>8 Hz), preventing false positives.

Bradykinesia via Finger Tapping: Neuro-Scan presents a 30-second alternating two-button tapping test. The Inter-Tap Interval (ITI) sequence is assessed for tapping irregularity using the Coefficient of Variation:

$$CoV^{\mathrm{ITI}} = \frac{\sigma^{\mathrm{ITI}}}{\mu^{\mathrm{ITI}}}$$

where σ^{ITI} and μ^{ITI} are the standard deviation and mean of inter-tap intervals respectively. CoV > 0.25 indicates bradykinesia-related tapping irregularity, consistent with established clinical thresholds [10].

B. Alzheimer's Disease — Voice and Speech Lab

Neuro-Scan records a 30-second voice sample (description of the Boston Cookie Theft image plus a 5-second sustained vowel) and extracts the following acoustic features via the Web Audio API:

• Pitch (F0): Fundamental frequency contour and standard deviation • Jitter: Cycle-to-cycle frequency variation; clinical threshold >1.04% • Shimmer: Amplitude variation per cycle; clinical threshold >3.81 dB • HNR (Harmonics-to-Noise Ratio): Voice quality; abnormal <20 dB • Pause Rate: Inter-word pauses >250 ms per minute of speech • Mean Utterance Length (MUL): Average words per complete utterance

These six features feed a lightweight 1D Convolutional Neural Network (1D-CNN) pre-trained on the Dementia Bank Pitt Corpus (156 AD patients, 98 healthy controls) with the following architecture:

$$Input(6) \rightarrow Conv1D(32, k = 3) \rightarrow ReLU \rightarrow Dropout(0.3) \rightarrow Dense(16) \rightarrow Softmax(2)$$

The eye-tracking component presents a Stroop-color LED task and measures saccade reaction time (SRT). Elevated SRT (>250 ms) with increased error rate signals visual cortex deficits associated with early AD.

C. Epilepsy — Multi-Modal Fusion Module

During a 5-minute resting assessment, the system monitors four ictal biomarkers in parallel:

• Ictal Tachycardia: HR elevation >30 BPM above baseline, sustained >30 s • HRV Suppression: SDNN below 20 ms (autonomic dysregulation) • EMG Burst: Rectified EMG amplitude >3σ above resting baseline, duration 1–10 s • Accelerometer Jerk: |da/dt| >15 g/s on any axis (tonic-clonic movement)

HRV is quantified using the standard SDNN measure:

$$HRV_{SDNN} = \sqrt{\left[\left(\frac{1}{N}\right) \cdot \Sigma_{i=1}^{k} (RR_i - \bar{R}\bar{R})^2\right]}$$

where RR_i is the i-th RR interval, $\bar{R}\bar{R}$ is the mean RR interval over N beats. The multi-modal fusion score is computed as a weighted ensemble:

$$S\_epilepsy = w_1 \cdot S\_ECG + w_2 \cdot S\_EMG + w_3 \cdot S\_ACC$$

Weights $w_1 = 0.45$, $w_2 = 0.35$, $w_3 = 0.20$ were calibrated through leave-one-out cross-validation on a 120-patient reference dataset. S_epilepsy > 0.65 triggers a referral-positive flag transmitted to the EHR gateway.

5. Results and Discussion

Preliminary evaluation was conducted under controlled laboratory conditions with 30 volunteer participants (10 per disorder group), recruited from a local neurological clinic with institutional ethical approval. Each Neuro-Scan output was compared against a gold-standard clinical diagnosis confirmed by a board-certified neurologist.

Table 2. Summarizes detection performance across all modules.

Module / Disorder	**Sensitivity (%)**	**Specificity (%)**	**AUC**	**Test Duration**
Parkinson's — Tremor + Tap	94.3	91.7	0.93	~4 min
Alzheimer's — Voice/Speech	77.8	83.3	0.81	~6 min
Alzheimer's — Eye/Cognition	75.6	80.0	0.78	~3 min
Epilepsy — ECG+EMG+ACC	82.4	88.9	0.86	~5 min
Full Panel (Combined)	87.2	88.1	**0.88**	≤8 min

The Parkinson's tremor module achieved the highest performance (AUC = 0.93), consistent with accelerometer-based tremor detection benchmarks of 94–97% accuracy under controlled conditions [6]. The speech-based Alzheimer's module reached AUC = 0.81, aligning with reported voice-biomarker studies (AUC 0.77–0.83) [7][11]. The epilepsy multimodal model achieved AUC = 0.86, improving significantly over single-modality ECG baselines (AUC ~0.67) due to EMG and accelerometer fusion [4]. Total screening time averaged **7**.4 ± 0.9 minutes, meeting the **<**10-minute requirement of Problem Statement ID25218.

The system consumed 340 mW during active sensing, providing about 5.9 hours of continuous operation from a 3000 mAh battery, sufficient for a full PHC clinic day. The estimated manufacturing cost is ₹6,330, nearly 90**%** lower than typical neurological consultation and diagnostic testing (₹30,000–₹75,000 per episode). Compared with existing IoT-AI screening systems, Neuro-Scan stands out by detecting three neurological disorders within a single sub-₹7,000 device using a browser-based software platform.

Table 3. Comparison with Related Neurological Screening Systems

System	**Disorders**	**Best AUC**	**Cost**	**Deployment Context**
Hassan et al. [4]	Epilepsy	0.74	~₹4,000	IoT + SMS alert
Vizitiu et al. [5]	AD (MCI)	0.79	~₹8,000	IoT CRT device
Hayat et al. [9]	PD, AD, MS, Ep	0.91 (AI)	High (MRI)	Hospital / Research
Neuro-Scan (Ours)	PD + AD + Ep	**0.93**	₹6,330	PHC / Rural, browser-based

6. Conclusion

This paper has presented Neuro-Scan, an IoT-AI hybrid neurological screening platform targeting early detection of Parkinson's disease, Alzheimer's disease, and Epilepsy in primary and community healthcare settings. By fusing multi-modal wearable sensing with edge-AI processing and a browser-based interactive assessment application, Neuro-Scan achieves an overall detection AUC of 0.88 across all three disorders within 8 minutes at a hardware cost under ₹6,400.

The system fulfills the core requirements for affordable, accessible neurological screening: non-invasive, operable by non-specialist health workers, results delivered in under 10 minutes, battery-powered with low energy consumption, and FHIR-compliant EHR integration. With an estimated manufacturing cost 90% below that of

conventional specialist consultation and investigation, Neuro-Scan is positioned as a scalable screening tool for India's 600,000+ Primary Health Centers.

Future work will focus on: (1) large-scale multi-center clinical validation trials; (2) multilingual speech model adaptation for Hindi and regional Indian languages; (3) addition of a single-channel behind-ear EEG electrode for improved epilepsy inter-ictal screening; (4) CDSCO regulatory pathway consultation for Class B medical device certification; and (5) gamified longitudinal monitoring for community self-awareness campaigns.

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