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AI-POWERED MULTIMODAL SCREENING AND RISK ASSESSMENT FOR EARLY NEUROMOTOR ABNORMALITY DETECTION

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Abstract : ***Neuromotor disorders can develop gradually and may initially manifest through subtle abnormalities in tremor, gait, balance, grip strength, and voice. Early identification of such abnormalities can support timely clinical evaluation. This paper presents an AI-powered multimodal screening system for preliminary detection of neuromotor abnormalities using wearable sensors, embedded data acquisition, signal processing, and machine learning. The proposed system integrates an ESP32-S3 microcontroller with inertial measurement units (IMUs), force-sensitive sensors, and a microphone to acquire movement, force, and voice signals. Hand-mounted sensing is used for tremor and grip-related measurements, while foot-mounted inertial sensing is used for gait and balance assessment. Voice signals are acquired through a microphone for complementary speech analysis. The acquired signals undergo preprocessing operations including noise filtering, normalization, and windowing. Time-domain and frequency-domain features are then extracted using statistical measures and Fast Fourier Transform (FFT). Features obtained from tremor, gait, balance, grip, and voice modalities are fused into a unified feature representation and provided to a machine learning model for classification or anomaly detection. A risk-score generation module combines the assessment outputs and compares the resulting risk factor with a predefined threshold. If the threshold is exceeded, the system recommends further clinical evaluation. The proposed system provides a portable, non-invasive, and multimodal approach for preliminary neuromotor screening and is intended to support, rather than replace, professional clinical diagnosis.***

IndexTerms **- Neuromotor screening, wearable sensors, inertial measurement unit (IMU), tremor detection, gait analysis, voice analysis, machine learning, risk assessment.**

I. INTRODUCTION

Neurological and neuromotor disorders represent a significant healthcare challenge because their symptoms may develop progressively and remain subtle during the early stages. Conditions associated with neuromotor impairment may exhibit symptoms such as tremors, gait irregularities, postural instability, reduced grip strength, and changes in speech characteristics. These symptoms can be difficult to quantify using simple visual observation, particularly when they occur at an early stage.

Conventional neurological assessment generally relies on clinical examinations and specialist evaluation. Although these methods are essential for diagnosis, they may require repeated hospital visits and specialized equipment. Consequently, there is a need for portable systems capable of acquiring objective measurements that can support preliminary screening outside conventional clinical environments.

Recent advances in wearable sensing and machine learning have created opportunities for objective analysis of neuromotor characteristics. Inertial sensors can capture acceleration and angular velocity associated with movement, while force sensors can quantify grip and force variations. Similarly, speech signals can provide additional information related to neuromotor function. Combining these modalities can provide a more comprehensive representation of an individual's motor characteristics than relying on a single measurement.

The proposed system addresses this requirement through a **multimodal hardware and artificial intelligence architecture**. An ESP32-S3 microcontroller is used as the central embedded controller for sensor acquisition and communication. IMU sensors are used for movement-related measurements, force-sensitive sensors are used for grip and force-related measurements, and a microphone is used for voice acquisition. The project presentation identifies these components as the primary hardware elements of the proposed system.

The acquired signals are transmitted for further processing, where filtering, normalization, windowing, feature extraction, and machine learning are performed. The project methodology specifically identifies time-domain and FFT-based frequency-domain features followed by multimodal feature fusion and risk-score generation.

II. LITERATURE REVIEW

Recent research has increasingly explored machine learning, deep learning, wearable sensors, and multimodal analysis for the early detection and monitoring of neurological disorders.

Wearable inertial sensors have been investigated for distinguishing Parkinson's disease from other forms of parkinsonism. A study using wearable accelerometer and gyroscope data demonstrated the feasibility of extracting movement characteristics from a timed-up-and-go assessment and applying machine learning for classification [1]. Such approaches demonstrate the potential of wearable movement sensing for objective neurological assessment.

Deep-learning techniques have also been investigated for tremor assessment. Image-based approaches have been developed for essential tremor severity estimation, demonstrating that artificial intelligence can support remote and low-cost assessment [2]. Similarly, inertial-data-based deep-learning methods have been investigated for pathological gait recognition, showing that appropriate preprocessing and feature optimization can reduce model complexity while maintaining classification performance [3].

IoT-based neurological screening architectures have also been proposed. Such systems combine wearable sensors with edge or cloud processing to support continuous neurological monitoring [4]. Multimodal approaches using voice and handwriting have demonstrated that combining different behavioural characteristics can improve Parkinson's disease prediction compared with relying on an individual modality [5].

Research has additionally explored EEG-based neurological assessment, tremor analysis, gait analysis, voice-based Parkinson's disease prediction, and wearable monitoring systems [6]. These studies demonstrate the usefulness of machine-learning algorithms including Support Vector Machines (SVM), Random Forest, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks.

Wearable tremor-monitoring systems have used accelerometers and gyroscopes together with frequency-domain techniques such as FFT and wavelet transforms to quantify tremor characteristics [17]. Gait-based approaches using foot-mounted IMUs have also demonstrated the feasibility of non-invasive Parkinson's disease screening [13].

However, the literature indicates several limitations. Many of the existing systems use relatively small and non-diverse datasets, which can limit generalization to real-world populations. Several approaches are sensitive to noise and recording conditions, while some require multiple bulky wearable components that can reduce user comfort. Clinical validation is also limited in several existing systems. These limitations are identified in the project's literature survey.

The proposed system therefore focuses on combining **hand and foot sensing with voice-based analysis** while using signal preprocessing, multimodal feature fusion, and machine learning to produce an overall neuromotor risk score.

III. METHODOLOGY

The proposed system is an integrated, AI-enabled framework for the early detection and evaluation of neuromotor abnormalities through the combined use of multiple sensing modalities, signal processing, and machine learning. Movement, force, and speech signals are captured simultaneously, and each sensing component contributes complementary information: force-sensing resistor (FSR) sensors measure pressure distribution, IMUs monitor motion and balance, and a microphone records speech characteristics. Drawing on several domains gives a more comprehensive and dependable assessment than single-sensor solutions, since neuromotor disorders often affect several functional systems at once.

After acquisition, the raw data is subjected to signal conditioning and preprocessing to eliminate noise, artifacts, and inconsistencies caused by environmental influences or sensor constraints. Meaningful features are then extracted in both the time and frequency domains. Time-domain features capture observable signal variations such as gait irregularities, while frequency-domain analysis using the Fast Fourier Transform (FFT) reveals periodic patterns such as tremor or oscillatory instability. The modality-specific features are integrated through multimodal feature fusion into a unified representation of the individual's neuromotor profile, which is processed by a machine-learning model. In the final stage, the outputs are converted into interpretable scores across multiple functional domains and an overall risk level, on the basis of which the system can recommend further observation, follow-up assessment, or formal clinical evaluation. The overall architecture is shown in Fig. 3.1 and the detailed process is explained below.

A. Multimodal Inputs and Signal Acquisition

Fig. 3.1 presents the major components of the system and shows how data move from the input modalities to the screening output. The system receives finger-tapping movement data measured using MPU sensors, gait data measured using MPU and FSR sensors, balance-related movement data measured using MPU sensors, and voice input captured through a microphone. The wearable hand sensor captures tremor and finger-tapping behaviour, the wearable foot sensor provides gait and balance information, and the voice-input module (a mobile-device microphone or a dedicated module) records speech. The signals from these modalities are collected by the signal-acquisition stage and prepared for further processing.

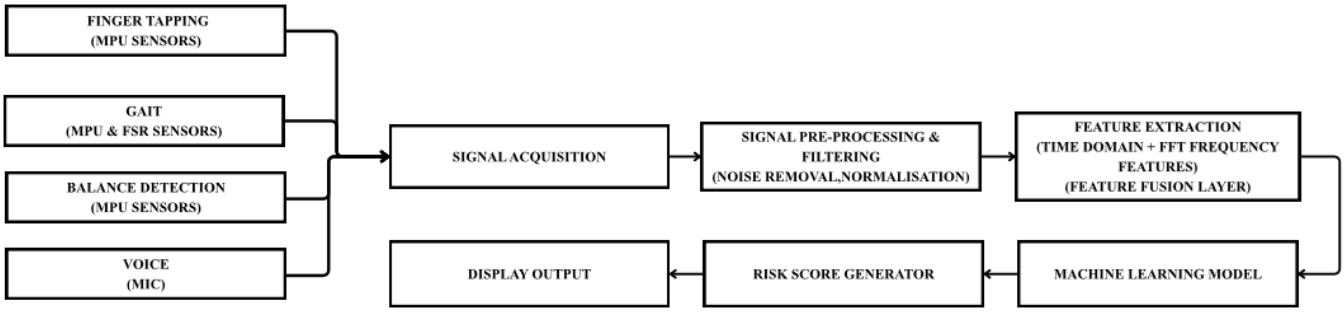


Fig. 3.1. Block diagram of the proposed multimodal neuromotor screening system

B. Signal Preprocessing and Filtering

After acquisition, the signals pass through preprocessing and filtering, which includes noise removal and normalization. Noise removal reduces unwanted variation in the recorded signals, while normalization prepares the measurements for feature analysis.

The voice recording is additionally cleaned so that voice-related features can be derived from it. The continuous sensor signals and audio recording are then divided into smaller time windows or frames (windowing and segmentation), which allows local temporal characteristics to be analyzed in manageable units and provides standardized inputs for feature extraction.

C. Feature Extraction and Fusion

The preprocessed segments proceed to feature extraction. Time-domain features describe signal behaviour over time, while frequency-domain features, obtained using the FFT, represent signal components by frequency; voice-feature analysis is applied to the audio input. The extracted features are organized according to their source into three groups, as given in Eq. 1,

$$F = \{F_T, F_G, F_V\} \tag{1}$$

where F_T represents tremor and finger-tapping features (hand IMU), F_G represents gait and balance features (foot IMU), and F_V represents voice features (audio). This grouping preserves the contribution of each modality. The groups are then brought together in the feature-fusion layer, as given in Eq. 2,

$$F_{combined} = F_T \oplus F_G \oplus F_V \tag{2}$$

where $\oplus$ denotes the combination or fusion of the individual feature sets. The fused representation contains information from finger tapping, gait, balance, and voice for use by the machine-learning model. In parallel, the extracted features are directed to a data collection and storage stage so that screening data can be retained for future model retraining and improvement.

D. Machine-Learning Analysis and Output Display

The fused features are supplied to the machine-learning model, which performs the required classification, regression, or anomaly-detection operation. The model results are passed to the risk-score generator, which produces the tremor, gait, balance, and voice scores and the overall risk factor. Finally, the display-output component presents the results to the user through the interface.

E. Operational Workflow

The sequential processing and decision-making procedure is shown in the flowchart of Fig. 3.2 and consists of the following steps.

1. **Sensor data collection:** data are collected from the wearable hand and foot sensors and the microphone.
2. **Data acquisition:** the collected sensor signals and voice recording are transferred to the processing unit and organized for the next stages.
3. **Signal processing:** the sensor signals are filtered and normalized, and the audio recording is cleaned.
4. **Windowing and segmentation:** continuous signals are divided into smaller time windows or frames.
5. **Feature extraction:** time-domain and FFT-based frequency analysis is applied to the sensor signals, along with voice-feature analysis for the audio.
6. **Modality-specific feature grouping:** features are organized as finger-tapping, gait and balance, and voice feature groups.
7. **Machine-learning analysis:** the feature groups are provided to the model for classification, regression, or anomaly detection.
8. **Risk-score generation:** the model results are used to generate the screening risk score and the modality-related scores.
9. **Data collection and storage:** assessment data are stored to support future model retraining.
10. **User-interface output:** the tremor, gait, balance, and voice scores are presented to the user.
11. **Threshold-based decision:** the generated risk factor R is compared with the defined threshold, as given in Eq. 3.

$$R > R_{threshold} \tag{3}$$

If the condition is satisfied, the system suggests further clinical evaluation; otherwise, the screening process ends without that recommendation.

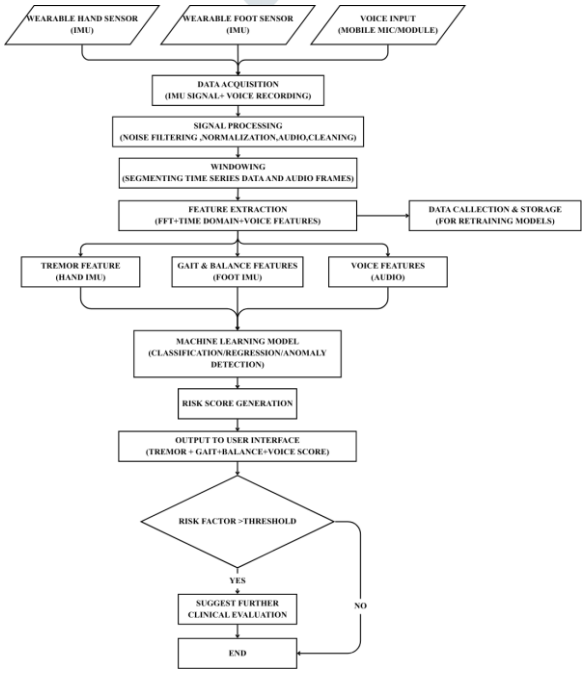


Fig. 3.2. Flowchart of the sequential processing and decision-making procedure

F. Hardware and Software Tools

Hardware. The **ESP32** microcontroller (ESP32-WROOM-32 module; dual-core processor, Wi-Fi and Bluetooth, GPIO, I²C, SPI, and UART interfaces; 3.0–3.6 V supply) collects readings from the sensors and transmits the data to the processing system. The **MPU6050** is a six-axis motion sensor combining a three-axis accelerometer (±2 to ±16 g) and a three-axis gyroscope (±250 to ±2000 °/s) with an I²C interface; it provides the motion data for tremor, finger-tapping, gait, and balance analysis. The **FSR sensor** is a passive two-terminal device whose resistance decreases as the applied force increases; it is connected in a voltage divider so that the ADC of the ESP32 can measure the resulting voltage. A **microphone** converts sound waves into an electrical signal for the voice-based modality. A rechargeable battery or USB supply provides a stable voltage to the ESP32 and the connected sensors; the ESP32 input and GPIO pins are not exposed directly to 5 V.

Software. The **Arduino IDE** (C/C++) is used to write, compile, and upload the embedded programs to the ESP32. **IntelliJ IDEA** is used for developing the Java-based Spring Boot backend, and **Visual Studio Code** is used for the remaining programming and application development.

G. Backend Processing

The backend of the proposed system is developed using **Spring Boot** and acts as the central communication layer between the data-processing module, machine-learning service, database, and user interface. Once the sensor data has been acquired and the required preprocessing and feature extraction have been completed, the extracted features are transferred to the Spring Boot backend for further processing and management.

The backend coordinates the transfer of the combined hand, foot, and voice features to the machine-learning service, which returns the corresponding prediction and risk-related information. The result is then associated with the corresponding **patient and screening session**, and the tremor, gait, balance, and voice results, along with the overall risk score, are stored in the database so that the screening history of each patient can be maintained and retrieved. The extracted feature data is also stored for creating additional training datasets and retraining the model as more screening data becomes available.

In addition, the backend manages the healthcare-related application functions, including **patient registration, patient information, authentication, screening records, risk assessment results, and report management**, and provides the REST APIs through which the frontend submits screening data and retrieves the assessment results. The machine-learning component is maintained as a separate service so that the computational AI processing can be performed independently. The **Spring Boot backend thus functions as the integration layer** connecting the data-acquisition system, machine-learning service, database, and user interface.

IV. RESULTS

The proposed neuromotor screening system was evaluated using the developed machine-learning models and the implemented application interface. The experimental results demonstrate the ability of the system to analyze voice and gait-related parameters and generate corresponding screening outputs. In addition, the developed web application successfully provides authentication, patient management, and patient-information views.

A. Voice-Based Screening Results

The voice-based screening module was evaluated using an **XGBoost model**. The example prediction shown in the experimental results produced a **78.56% probability of the subject being classified as healthy**, while the probability of a voice-disorder classification was **21.44%**. This demonstrates that the trained model can provide class probabilities rather than only a binary output.

The overall performance of the voice XGBoost model is presented in Fig. 4.1. The model achieved an **accuracy of 94.87%**, **precision of 100.00%**, **recall of 93.10%**, and an **F1-score of 96.43%**. The high precision indicates that the model produced very few false-positive predictions for the voice-disorder class, while the recall value indicates that the majority of relevant disorder samples were correctly identified.

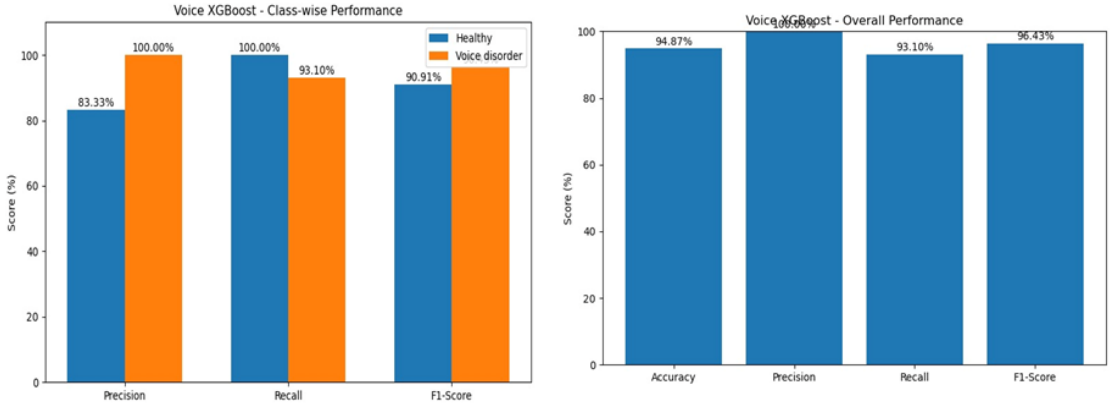


Fig. 4.1. Voice XGBoost overall performance

The confusion matrix shown in Fig. 4.2 provides further insight into the classification performance. The model correctly classified **10 healthy samples** and **27 voice-disorder samples**. It incorrectly classified **2 voice-disorder samples as healthy**, while no healthy samples were classified as voice disorder. The resulting confusion matrix demonstrates the model's ability to distinguish between the two voice-related classes. The example prediction and confusion-matrix results together indicate that the voice-processing module provides a useful classification output for the proposed multimodal screening system.

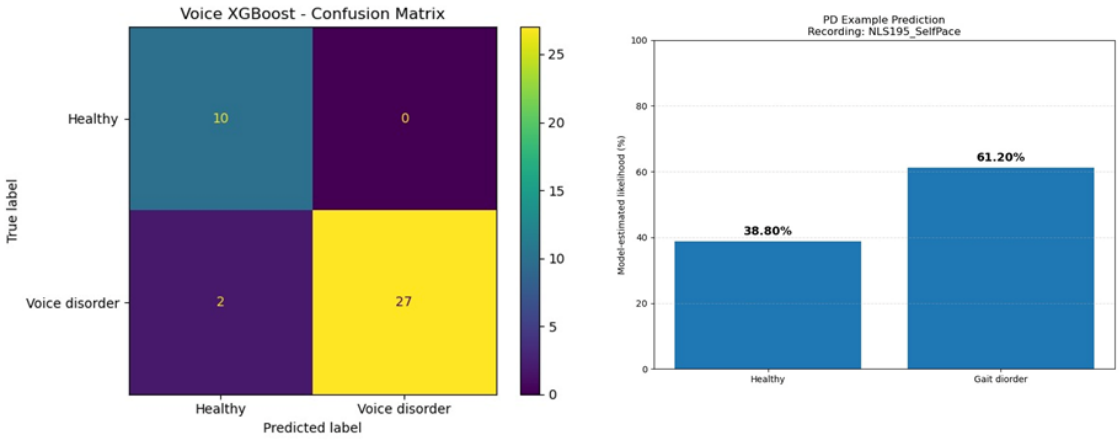


Fig. 4.2. Voice XGBoost confusion matrix

B. Gait-Based Screening Results

The gait-analysis module was evaluated using the developed machine-learning model. An example prediction shown in the results produced a **38.80% probability for the healthy class** and a **61.20% probability for the gait-disorder class**, indicating that the analyzed sample was more strongly associated with the gait-disorder category.

The overall performance of the gait model is presented in Fig. 4.3. The model achieved an **accuracy of 79.33%**, **precision of 78.18%**, **recall of 86.87%**, and an **F1-score of 82.30%**. The recall of **86.87%** indicates that the gait model was able to identify a relatively high proportion of the relevant gait-disorder samples. The F1-score of **82.30%** provides a combined measure of precision and recall and indicates that the model provides a reasonable level of classification performance for gait-based screening.

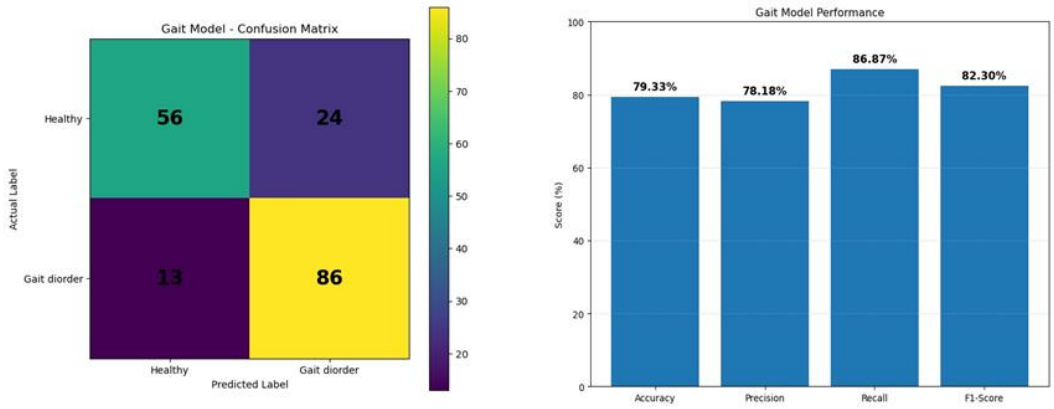


Fig. 4.3. Gait model performance

C. Web Application and Patient Management Results

In addition to the machine-learning results, the proposed system includes a web-based application for managing the screening process. The implemented interface provides an authentication page through which authorized users can access the neuromotor screening system, as shown in Fig. 4.4. After successful authentication, the system provides a dashboard for managing patient information and screening activities. The dashboard displays the available patient records and provides options for adding and accessing patient information, as shown in Fig. 4.5.

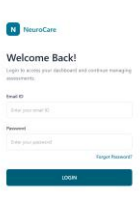


Fig. 4.4. Login interface



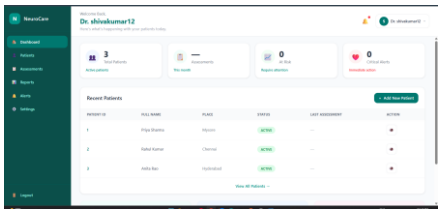


Fig. 4.5. Patient dashboard

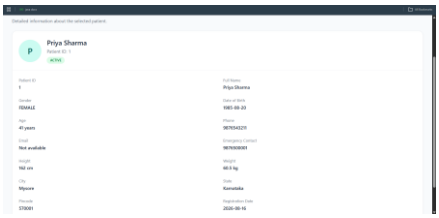


Fig. 4.6. Patient details interface

The patient-management interface enables the authorized user to select an individual patient and view the corresponding information. The detailed patient-information page shown in Fig. 4.6 presents the selected patient's stored details. These results demonstrate that the developed application provides the required software interface for organizing patient information and integrating the neuromotor screening workflow with patient records.

D. Hardware Implementation and Sensor Output

The physical implementation of the proposed neuromotor screening system was developed using wearable sensing modules and an ESP32-based controller. The implemented hardware integrates force-sensitive and inertial sensing components for acquiring the measurements required for neuromotor assessment. The wearable hand-sensing arrangement used for hand-related assessment is shown in Fig. 4.7. The foot-sensing prototype developed for the acquisition of foot-related measurements is shown in Fig. 4.8. The prototype consists of an ESP32 development board mounted on the footwear platform and a force-sensitive sensing element

positioned on the footbed. The sensor is electrically connected to the controller to acquire variations in applied pressure during the assessment.

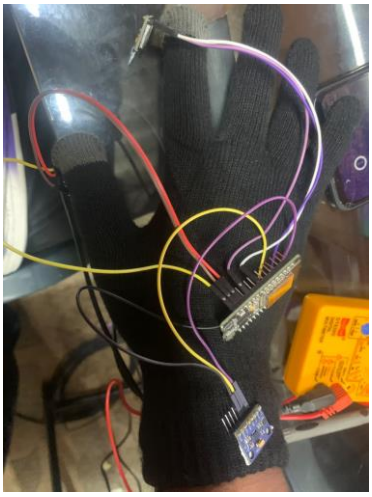
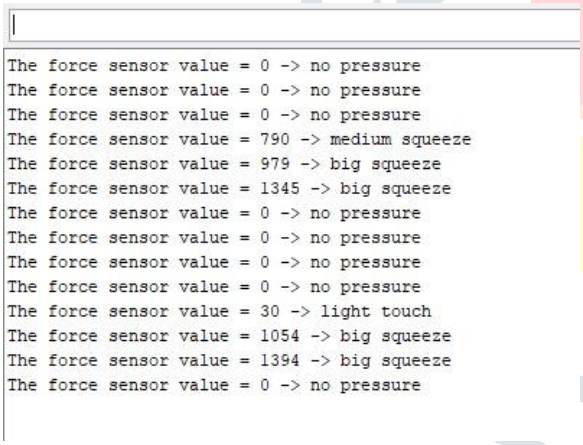


Fig. 4.7. Implemented wearable hand-sensing prototype



Fig. 4.8. Implemented wearable foot-sensing prototype

The functionality of the force-sensitive sensing system was verified using the serial-monitor output shown in Fig. 4.9. Different levels of applied pressure produced corresponding variations in the sensor readings. The observed readings included **0 under no-pressure conditions, approximately 30 for light touch, values around 790–979 for medium to strong pressure, and values above 1000 for higher pressure conditions**. These observations demonstrate that the implemented force-sensitive sensing arrangement responds to different levels of applied force. The inertial sensing module was also tested using the ESP32 development environment. The serial-monitor output shown in Fig. 4.10 demonstrates the acquisition of acceleration and gyroscope measurements along multiple axes. The displayed acceleration and gyroscope values vary continuously, confirming the successful acquisition of motion-related data from the implemented IMU sensing module.



```
The force sensor value = 0 -> no pressure
The force sensor value = 0 -> no pressure
The force sensor value = 0 -> no pressure
The force sensor value = 790 -> medium squeeze
The force sensor value = 979 -> big squeeze
The force sensor value = 1345 -> big squeeze
The force sensor value = 0 -> no pressure
The force sensor value = 0 -> no pressure
The force sensor value = 0 -> no pressure
The force sensor value = 0 -> no pressure
The force sensor value = 30 -> light touch
The force sensor value = 1054 -> big squeeze
The force sensor value = 1394 -> big squeeze
The force sensor value = 0 -> no pressure
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Fig. 4.9. Serial-monitor output showing force-sensitive sensor response to different pressure conditions

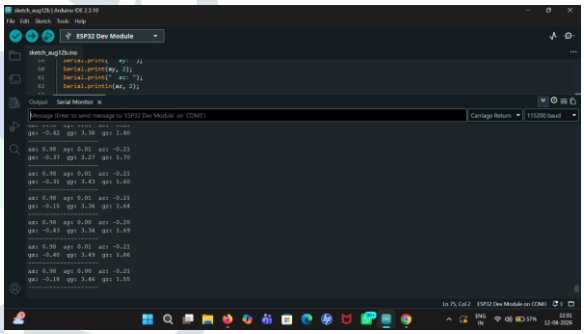

Fig. 4.10. Serial-monitor output showing accelerometer and gyroscope measurements from the IMU

The hardware-level results confirm the functional operation of the implemented sensing modules and demonstrate their ability to acquire the force and motion data required for the subsequent signal-processing and machine-learning stages. Thus, the physical implementation provides the sensing foundation for the proposed multimodal neuromotor screening system.

V. CONCLUSION

The proposed system presents a multimodal neuromotor screening platform that integrates wearable hardware, sensor-based data acquisition, signal processing, machine learning, and a Spring Boot-based healthcare management backend for assessing hand tremor, finger tapping, gait, balance, and voice characteristics. The acquired signals are processed through filtering, normalization, windowing, and time- and frequency-domain feature extraction before being analyzed using machine-learning models to generate neuromotor risk scores. The experimental results demonstrate promising performance, with the voice-based XGBoost model achieving 94.87% accuracy and an F1-score of 96.43%, while the gait model achieved 79.33% accuracy and an F1-score of 82.30%. The developed Spring Boot backend integrates the sensing, AI-processing, database, and user-interface components while maintaining patient and screening records. The system is intended as a preliminary screening and risk-assessment tool rather than a replacement for clinical diagnosis, and further validation using larger and clinically validated datasets is required to improve its reliability and generalizability.

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