EOG BASED EYE MOVEMENT ANALYSIS FOR HEALTH MONITORING AND ASSISTIVE COMMUNICATION IN PARALYZED INDIVIDUALS

PHASE I REPORT

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BONAFIDE CERTIFICATE

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Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

This project explores the idea of Electrooculography (EOG)-based eye movement analysis for enhancing health monitoring and developing assistive communication tools for individuals with paralysis. EOG is a technique to record eye movements by detecting the electrical potentials changes generated by the movements of eyeballs. The objective is twofold. The methodology involves multiple stages, including hardware configuration, signal processing, feature extraction and model integration. EOG electrodes are positioned to detect eye movements accurately and a data acquisition system will capture real – time signals. The data is pre-processed to remove noise, normalized and analyzed in both time and frequency domains to identify the health-related abnormalities.

Conditions such as nystagmus, Parkinson’s disease, progressive supranuclear palsy and internuclear ophthalmoplegia exhibit unique eye movement characteristics that can be detected through EOG. For instance, rapid oscillations may indicate nystagmus, slowed saccadic movements with tremors are common in Parkinson’s disease. The unusual patterns are detected which are indicative of a health issue to support early diagnosis and treatment.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
CNN	Convolutional Neural Network
EOG	Electrooculography
INO	Internuclear Ophthalmoplegia
k-NN	K Nearest Neighbors
PD	Parkinson’s Disease
PSP	Progressive Supranuclear Palsy
RNN	Recurrent Neural Network
SVM	Support Vector Machine

CHAPTER 1
INTRODUCTION

Electrooculography (EOG)-Based Eye Movement Analysis presents a transformative approach for health monitoring and assistive communication, specifically catering to individuals with paralysis and other mobility challenges. This project, titled EOG-Based Eye Movement Analysis for Health Monitoring and Assistive Communication in Paralyzed Individuals, focuses on capturing and analysing eye movements to provide critical insights into neurological health and support alternative communication methods for non-verbal individuals.

This project leverages the EOG technique, which records electrical potentials generated by eye movements, to monitor the physiological behaviour of the eye and interpret it in a meaningful way. By accurately tracking eye directionality (up, down, left, right) and blinks, the project aims to identify distinctive patterns associated with various neurological disorders, such as Parkinson’s Disease (PD), Progressive Supranuclear Palsy (PSP), Internuclear Ophthalmoplegia (INO), and Nystagmus. The EOG signals are processed and analyzed using a Support Vector Machine (SVM)-based classification model, which helps distinguish between these conditions based on recorded eye movement characteristics.

1.1 BACKGROUND AND SIGNIFICANCE

The ability to track and interpret eye movements has gained prominence across various fields, including healthcare, assistive technology, and human-computer interaction. In individuals with severe mobility restrictions, such as those affected by paralysis, EOG provides a non-invasive means of communication and interaction. By interpreting basic eye movements and blinks, this project seeks to empower such individuals to communicate through simplified commands or Morse code, enhancing their autonomy and engagement with their environment.

Moreover, eye movements serve as indicators for neurological health. Changes in eye movement patterns, blink frequency, and directional control are often early symptoms of neurological disorders. For instance, PD is characterized by reduced blink rate and limited vertical/horizontal movements, while PSP primarily affects vertical gaze. These variations enable early diagnosis and monitoring, contributing to improved disease management and quality of life for affected individuals.

1.2 OBJECTIVE OF THE PROJECT

The core objectives of is comprised into two domains:

1.2.1 Health Monitoring

To create a reliable EOG-based system that identifies eye movement patterns indicative of neurological diseases. The project’s SVM classifier analyzes eye movement data and categorizes it to detect diseases such as PD, PSP, INO, and Nystagmus.

1.2.2 Assistive Communication

To develop an interface that translates eye movements into simple communication commands. For individuals with paralysis, this feature allows basic communication by mapping specific eye movements to Morse code, controlling cursors, or even managing basic interfaces on devices. This communication pathway provides an essential lifeline, allowing individuals to interact with caregivers and family members.

1.3 SYSTEM ARCHITECTURE AND COMPONENTS

The EOG-based system architecture integrates several essential components to achieve real-time monitoring and communication support.

1.3.1 Data Acquisition and Hardware Setup

The system utilizes an ESP32 microcontroller, a BioAmp EXG module, and gel electrodes strategically placed to capture EOG signals corresponding to vertical and horizontal eye movements. The electrodes are arranged to monitor up/down and left/right movements, as well as blink frequency. The signals are then transmitted to the ESP32, which sends data to a processing platform for logging and analysis.

1.3.2 Data Transmission and Processing

Real-time EOG data is processed using serial communication protocols between the ESP32 and Python-based processing scripts.

Each data line, containing time-stamped eye movement counts (up, down, left, right, blink), is decoded, processed, and stored in a CSV file for further analysis.

1.3.3 SVM-Based Disease Classification Model

The SVM model is trained to classify various neurological conditions by analyzing features such as blink count, vertical movement frequency, and horizontal movement asymmetry. For example, PD typically exhibits a low blink count, PSP shows limited vertical movement with normal horizontal activity, and INO displays significant horizontal asymmetry. By comparing real-time data with these established patterns, the model effectively classifies eye movement data to predict neurological conditions.

1.3.4 Assistive Communication Interface

The project also incorporates an interface to convert EOG data into assistive commands. These commands translate into Morse code or cursor movements, allowing paralyzed individuals to interact with devices. This interface opens up avenues for controlling basic software applications and providing alternative communication options to enhance independence and quality of life.

CHAPTER 2
LITERATURE REVIEW

Fatma Latifoğlu et al. (2020) focused on the detection of specific eye movement patterns—such as reading backtracking and line skipping—from EOG signals, providing insights into diagnosing reading disorders, particularly dyslexia. This study involved capturing EOG signals while participants read a passage of text, where backtracking (re-reading) and skipping lines generated distinct EOG patterns. Using classifiers like Random Forest and k-Nearest Neighbours (k-NN), the researchers achieved high classification accuracy of 98%. The results support the development of diagnostic tools for reading disorders by identifying involuntary eye movements that are more frequent in individuals with dyslexia. This novel application of EOG highlights its potential for educational diagnostics and learning support, making it possible to diagnose reading issues objectively and early in life.

Md. Mahtab Alam et al. (2021) explored the use of Artificial Neural Network (ANN) models to develop a high-precision eye-tracking system based on EOG signals, specifically tailored for applications in smart technology. Their study addressed the challenge of manoeuvring smart wheelchairs, particularly for individuals suffering from neurodegenerative diseases like Parkinson’s and Huntington’s, who often retain cognitive abilities but experience severe motor impairments.

Thibhika Ravichandran et al. (2021) investigated the classification of eye movements using deep learning models to support ALS patients in performing daily tasks. By using Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models, the researchers classified EOG signals that captured eye movements in horizontal and vertical directions. Their approach involved directly feeding EOG data into these neural networks, bypassing traditional feature extraction methods. The CNN model achieved a high accuracy of 90.3%, while the LSTM model followed closely with 88.33%. This study contributes significantly to the field of human-machine interaction, demonstrating that deep learning models can effectively interpret EOG signals to support device control, such as wheelchairs, without the need for invasive procedures or complex equipment. The implications for ALS patients are profound, as these methods can restore some level of autonomy and interaction, facilitating a better quality of life and enhancing the usability of assistive devices through improved classification performance

M. Thilagaraj et al. (2021) explored the use of EOG based Human-Computer Interfaces (HCI) for individuals with paralysis or limited mobility. The research addressed limitations in traditional eye-tracking technologies, such as involuntary blinking, by establishing a robust protocol to differentiate intentional eye movements from non-intentional events. The study achieved an accuracy of over 90%, demonstrating the system’s potential for real-time HCI applications that can help paralyzed individuals regain control over their environment and improve their quality of life.

Smriti Bhatnagar and Bhawna Gupta (2022) examined the acquisition, processing, and applications of EOG signals in human-machine interactions, presenting a comprehensive overview of the benefits and challenges of EOG over other eye-tracking methods, such as Video Oculography (VOG). The paper underscores the effectiveness of EOG as an inexpensive and straightforward solution for various assistive applications, including wheelchair control, virtual keyboard use, and drowsiness detection. By comparing EOG and VOG, the authors highlighted several key advantages of EOG: it is more convenient as it requires only electrodes and offers a broader range of eye-tracking capabilities. Their analysis also covered applications in neurological disorder diagnosis and everyday assistive technology. This study illustrates how EOG has evolved as a versatile technology, with applications extending from communication aids for disabled individuals to broader health monitoring solutions

Mohamed Ezzat et al. (2023) developed the Blink-To-Live eye-based communication system, a novel solution tailored for users with speech impairments. The system was inspired by the Blink-To-Speak language, which uses eye gestures as an alternative means of communication for patients affected by conditions like Amyotrophic Lateral Sclerosis (ALS) and Primary Lateral Sclerosis (PLS). This approach relies on a mobile phone camera to capture and track real-time video frames of eye movements, subsequently analyzed using computer vision modules. Compared to traditional sensor-based eye-tracking systems, Blink-To-Live is cost-effective and requires no specialized hardware, making it a highly accessible option for low-income regions.

Yuxiang Shi et al. (2023) proposed a cutting-edge active eye-tracking system that uses a transparent, flexible electrostatic interface. This interface leverages electrostatic induction to achieve real-time eye tracking without direct contact, making it suitable for continuous, comfortable use. The system’s triple-layer structure, including a silver nanowire layer, provides high charge storage, allowing it to maintain electrostatic charges over numerous cycles. This setup enhances angular resolution and enables precise decoding of eye movements, applicable in virtual reality, medical monitoring, and commercial user interface design. By minimizing physical discomfort and infection risks associated with traditional electrode-based systems, this electrostatic interface is a breakthrough for long-term applications in human-machine interfaces and wearable health monitoring

CHAPTER 3
EOG BASED HEALTH MONITORING

3.1 INTRODUCTION

The proposed methodology of the project involves health monitoring and creating an assistive communication system that interprets eye movements into commands. This system includes signal acquisition, pre-processing, feature extraction, and machine learning-based classification of eye movements.

3.2 DATASET DESCRIPTION

The dataset for this project comprises two main components: real-time EOG data collected from a healthy individual aged approximately 20 years, and synthetic data generated to mimic eye movement patterns associated with specific neurological conditions. The real-time data provides a baseline reference of normal eye movement patterns, while the synthetic data simulates altered patterns, allowing for the detection and classification of conditions such as PD, PSP, INO, and Nystagmus. This dual approach enables the SVM classifier to distinguish between normal and abnormal patterns with greater accuracy, enhancing its effectiveness for health monitoring applications. The data collection process is divided into two phases: real-time data collection for normal conditions and synthetic data generation for neurological conditions.

3.2.1 Data Collection

(i) Real Time Data Collection

The real-time data collection process is fundamental in establishing baseline EOG signals that represent normal eye movements. By capturing EOG data from a healthy individual, this process provides reference patterns for eye movements in various directions and natural blink rates.

(a) Experimental Setup

Fig 3.1 illustrates the experimental setup used for signal acquisition, where gel electrodes are strategically placed around the eyes to capture electrical activity generated by eye movements. The electrodes are connected to the BioAmp EXG module, which amplifies these low-level bioelectric signals and sends them to the ESP32 microcontroller for further processing. The precise placement of electrodes ensures that vertical and horizontal eye movements, as well as blinks, are accurately recorded, providing reliable input data for analysis.

Fig. 3.1 Experimental Setup

(b) Signal Transmission

Fig 3.2 shows an example of the signal as transmitted by the ESP32 microcontroller. In this setup, the ESP32 captures the amplified signals from the BioAmp EXG module and transmits them in real-time via a serial connection to a connected computer or data logger.

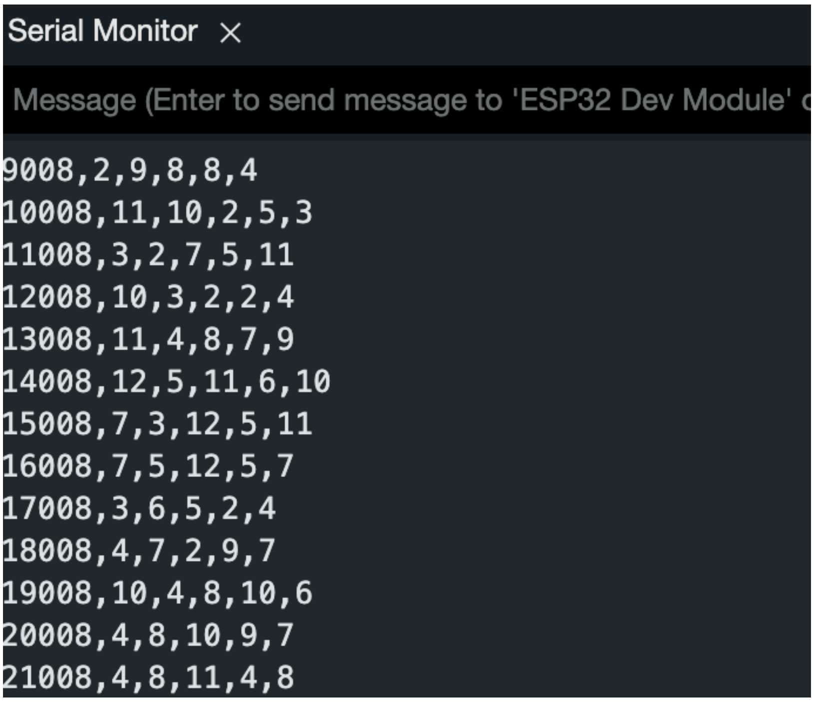

Fig. 3.2 Signal Transmission from ESP32

The purpose of baseline data is crucial for:

(a) Pattern Recognition

Establishing standard eye movement patterns, including natural blink rates and eye movements.

(b) Comparative Analysis

Differentiating normal eye behaviour from abnormal patterns observed in neurological conditions.

(c) Model Training

Providing the machine learning model with a reliable dataset of normal conditions to learn from, ensuring accurate classification during real-time inference.

(ii) Synthetic Time Data Collection

To train the SVM model for accurate classification, synthetic data was generated for various neurological conditions. The table 3.1 shown in the image represents a sample of the synthetic training dataset used for this purpose.

Table 3.1 Training dataset for diseases

	Up Count	Down Count	Right Count	Left Count	Blink Count	Condition
1	332	352	1095	1100	538	Normal
2	172	192	897	911	175	Parkinson's
3	364	375	1070	1104	534	Normal
4	180	176	908	924	174	Parkinson's
5	179	165	887	911	192	PSP
6	186	177	915	905	167	PSP
7	361	372	1077	1044	534	Normal
8	179	172	896	902	179	PSP
9	202	160	893	915	180	PSP
10	364	365	1077	1085	540	Normal
11	191	176	2519	2527	552	Nystagmus
12	178	178	2513	2552	521	Nystagmus
13	368	363	1088	1110	527	Normal
14	361	373	1106	1100	532	Normal
15	520	545	2149	539	526	INO
16	540	539	2157	546	538	INO
17	375	370	1069	1093	542	Normal
18	544	541	2165	542	535	INO
19	187	177	913	895	185	PSP
20	541	548	2140	533	547	INO
21	165	185	2514	2548	531	Nystagmus
22	176	173	891	902	190	PSP
23	549	531	2162	551	537	INO
24	168	178	2504	2517	546	Nystagmus
25	531	549	2164	538	546	INO
26	543	535	2161	554	548	INO
27	560	533	2154	540	541	INO

The dataset consists of the following key features:

(a) Up Count, Down Count, Right Count, Left Count

These counts represent the number of eye movements in each direction during a specific time interval. For example, a reduced Up Count and Down Count in the PSP condition captures the limitation in vertical eye movements commonly seen in patients with this disorder.

(b) Blink Count

The number of blinks detected during each interval. For PD, the blink count is generally lower due to reduced spontaneous blinking, while conditions like Nystagmus may show normal blink rates but increased oscillatory movement counts.

(c) Condition Labels

Each row is labeled with the specific neurological condition it represents (e.g., Normal, PD, PSP, INO, Nystagmus). These labels enable the model to learn the distinctive movement and blink patterns associated with each condition, facilitating accurate classification.

In the table 3.1, each row of data provides an example of a recorded interval with feature counts for each eye movement direction and blinks, associated with a labelled condition. The structured format enables easy handling of the data for model training and evaluation.

3.2.2 Data Transmission and Format

The ESP32 microcontroller plays a crucial role in capturing and transmitting EOG data in real-time, enabling continuous monitoring and analysis of eye movements. The data is sent via a serial connection to a connected device, where each line of data provides a comprehensive record of individual measurements. This structured transmission format is essential for tracking the timestamp and movement details with high precision, allowing the system to operate in real time.

(i) Timestamp

Each data entry is tagged with a millisecond-based timestamp, providing a precise temporal reference for when each measurement was collected. This timestamp enables researchers to analyze the timing, frequency, and patterns of eye movements, which is crucial for detecting abnormalities. By examining time-based patterns, the system can differentiate between natural, consistent movements and irregular ones that may indicate a health concern.

(ii) Movement Counts

The ESP32 records and transmits counts for each eye movement direction (Up, Down, Left, Right), along with blink counts. These counts provide quantitative insights into eye activity, capturing the intensity and frequency of each movement type within a defined interval. The recorded data is then stored in a CSV file (serial_line_data.csv), allowing for seamless data handling and analysis in Python or other data-processing environments.

The CSV format not only supports easy data manipulation and visualization but also facilitates batch processing for training machine learning models. Fig 3.3 shows the Serial Line Data Input used for Signal Processing and Feature Extraction.

```
        time.sleep(0.1)  # Small delay to prevent overwhelming the CPU
Starting to read data from serial port with baud rate 115200...
Received: 4008,12,4,11,7,5
Data saved: 4008,12,4,11,7,5
Received: 5008,4,12,9,3,6
Data saved: 5008,4,12,9,3,6
Received: 6008,8,12,3,2,8
Data saved: 6008,8,12,3,2,8
Received: 7008,6,7,7,8,5
Data saved: 7008,6,7,7,8,5
Received: 8008,3,12,2,4,6
Data saved: 8008,3,12,2,4,6
Received: 9008,2,9,8,8,4
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Data saved: 19008,10,4,8,10,6
Received: 20008,4,8,10,9,7
Data saved: 20008,4,8,10,9,7
Received: 21008,4,8,11,4,8
Data saved: 21008,4,8,11,4,8
```

Fig. 3.3 Serial Line Data Input

3.2.3 Data Recording Process

Data was recorded across multiple sessions:

(i) Session Duration

Each data collection session lasted for 10 minutes, capturing a substantial amount of eye movement and blink activity to reflect typical behaviour.

(ii) Number of Sessions

Separate sessions were conducted at different times of the day. This helps account for natural variations in eye movements

(iii) Total Data Collection

With three 10-minute sessions, a total of 30 minutes of EOG data was collected, equating to approximately 180,000 data points at a sampling rate of 500 Hz. This extensive dataset provides a reliable reference for normal eye movement patterns.

3.2.4 Sampling Rate and Data Resolution

The EOG signals were sampled at 500 Hz, a high sampling rate that captures fine-grained details of eye movements, including rapid blinks and subtle directional changes. The high sampling rate allows the system to capture these rapid movements accurately, ensuring that no important data points are missed.

3.2.5 Feature Extraction for Baseline Analysis

(i) Blink Rate

Normal blink rates typically fall between 12–15 blinks per minute for a healthy individual, providing a baseline for detecting abnormally high or low rates associated with certain neurological conditions.

(ii) Movement Counts

The average counts for upward, downward, leftward, and rightward movements are recorded. These counts help establish typical eye movement patterns.

(iii) Symmetry Ratios

Ratios between left-right and vertical-horizontal movements are computed. In normal conditions, these ratios are expected to be balanced, reflecting symmetrical eye behavior. Significant deviations in these ratios could be indicative of conditions like INO or PSP.

3.2.6 Data Logging and Storage

The captured data is stored in the serial_line_data.csv file, where each row represents a timestamped entry with corresponding movement counts (Up, Down, Right, Left) and blink counts. This structured CSV file allows for easy loading and manipulation within Python, streamlining the preprocessing and feature extraction process needed for machine learning tasks.

The CSV format not only facilitates data visualization and exploratory analysis but also enables efficient segmentation of data for model training and testing. Furthermore, by dividing the dataset into **5-second intervals**, each interval captures short-term eye movement patterns, providing the SVM classifier with granular input that reflects dynamic changes in behavior. This approach helps the model to detect nuanced differences between normal and abnormal conditions, improving its accuracy in real-time classification and health monitoring applications.

3.3. HARDWARE AND SOFTWARE REQUIREMENTS

3.3.1 Hardware Requirement

(i) ESP32 Microcontroller

It acts as the central processing unit for collecting EOG signals. It is responsible for acquiring analog signals from the BioAmp EXG module and transmitting the data via serial communication to a connected computer. Fig 3.4 depicts the ESP32 Microcontroller that is used in the acquisition of signals.

Fig. 3.4 ESP32 NodeMCU

(ii) BioAmp EXG Module

It is an analog front-end designed for capturing EOG. By amplifying the signals before they reach the microcontroller, the accuracy is enhanced. The BioAmp EXG is depicted in Fig 3.5.

Fig. 3.5 BioAmp EXG

(iii) Gel Electrodes

The EOG system relies on gel electrodes to capture bioelectrical signals. In this setup: Two electrodes are placed for detecting the vertical EOG component, positioned above and below one eye. Two electrodes to capture the horizontal EOG component**,** placed on the outer canthi of each eye and two reference electrodes to stabilize the signal. Fig 3.6 shows the position of electrodes in this setup.

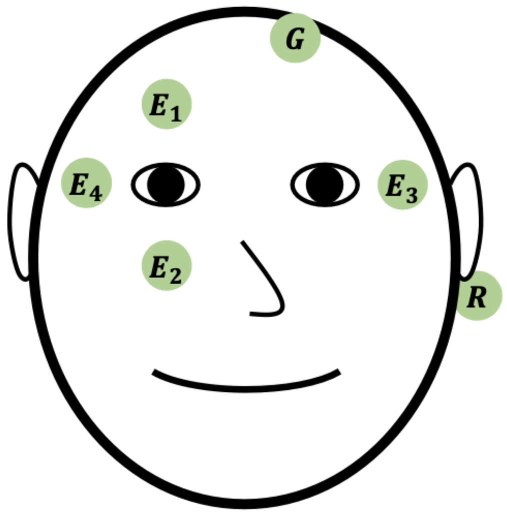

Fig. 3.6 Electrodes configuration

(iv) Serial Communication

The ESP32 microcontroller uses serial communication to send the acquired EOG signals to a Python-based data logging and processing system. Serial communication enables a stable and consistent transfer of data from the ESP32 to a computer, where the data can be logged, analyzed, and interpreted in real-time.

3.3.2 Software Requirement

The software setup for this project consists of two main components: the Arduino Integrated Development Environment (IDE) for managing the ESP32 NodeMCU hardware functions, and the Python environment for advanced data processing, feature extraction, and classification. Together, these components enable efficient and accurate interpretation of EOG signals, allowing real-time response and reliable classification of eye movements.

(i) Arduino IDE

The Arduino IDE is essential for handling real-time data acquisition from the hardware, enabling seamless data flow to the Python environment. With the ESP32’s dual-core processor and multiple ADC channels, the Arduino IDE allows simultaneous handling of multiple data streams from various electrodes. Additionally, the IDE ensures reliable and consistent data transmission, forming the foundation for the system’s real-time capabilities.

(ii) Python Environment

Python plays a crucial role in transforming the raw EOG data into actionable insights. The data undergoes several processing steps, including baseline correction, filtering, and feature extraction, to ensure only the most relevant information is passed to the classifier. The SVM model, trained on EOG signal patterns, is implemented in Python to classify eye movements and detect neurological conditions.

3.4 METHODOLOGY

The methodology aims to develop an EOG-based system that enables health monitoring and assistive communication for users with impairments, integrating hardware for real-time signal acquisition and software for processing, feature extraction, and classification of diseases. This system captures bioelectrical signals from eye movements to analyze distinctive patterns associated with neurological conditions. The hardware components, including the ESP32 microcontroller and BioAmp EXG module, ensure accurate and real-time data collection. The software pipeline, leveraging machine learning models, classifies eye movement patterns to detect diseases providing proactive health alerts and a communication interface for enhanced user autonomy. The sections detailing the methodology include: Hardware Configuration, Signal Processing and Feature Extraction, and Health Monitoring. Fig 3.4 depicts the methodology of EOG based Eye Movement Analysis.

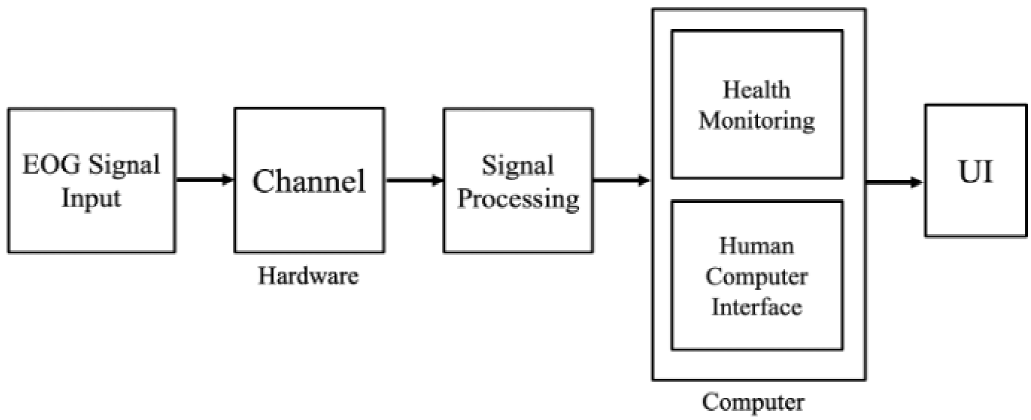

Fig. 3.7 Block Diagram of Proposed Methododolgy

3.4.1 Hardware Configuration

(i) Real-Time Data Acquisition

It is essential for systems that require minimal delay between data collection and processing, enabling timely decision-making. By continuously gathering, processing, and storing data in real-time, eye movement patterns are detected promptly, allowing for both the applications.

3.4.2 Signal Processing and Feature Extraction

The signal processing and feature extraction stages in this project are central to transforming raw EOG data into actionable features that enable the SVM classifier to differentiate between normal and disease specific patterns. The dataset includes multiple features, such as eye movement counts and blink detection, to represent unique eye movement patterns characteristic of neurological conditions. This section describes the specific algorithms and processes implemented with justifications for their selection.

Data is initially collected through the ESP32 microcontroller and stored in serial_line_data.csv. The features serve as the foundation for identifying disease-specific eye movement patterns. The raw data is saved in a CSV format, facilitating easy loading, manipulation, and processing within Python for further analysis.

Each feature is summed across intervals to form a cumulative hourly dataset. This approach enables the system to capture longer-term trends and avoid misclassifications due to short-term variations.

(i) Signal Transmission to ESP32

The amplified signals are then read by the ESP32 microcontroller, where they are sampled and prepared for transmission. The microcontroller continuously monitors the input signals, converting them into digital format and sending them through serial communication.

(ii) Real-Time Data Transfer

Through a stable serial connection, the ESP32 sends the processed EOG signals to a Python environment on a connected computer. This Python script receives the data in real-time, logging each data point with a timestamp for traceability and further analysis.

(iii) Data Processing and Logging

The Python environment logs the received data and performs real-time analysis to detect specific eye movements, such as up, down, left, right, and blinks. This data is then used for health monitoring and assistive communication, enabling quick responses and accurate classification of eye movement patterns.

3.4.3 Health Monitoring

The health monitoring component of the system leverages EOG signals to detect eye movement patterns that are indicative of various neurological conditions.

Below are the key steps involved in health monitoring and an overview of the specific diseases addressed by this project.

(i)Feature-Based Health Pattern Analysis

Features such as blink rate, movement asymmetry, and vertical-horizontal ratios are analysed to classify diseases. The diseases that can be classified based on certain factors and conditions are:

(a) Parkinson's Disease (PD)

Characterized by slowed or reduced eye movements and a significantly lower blink rate. Individuals with Parkinson's often display reduced vertical and horizontal movement, as well as decreased spontaneous blinking due to bradykinesia (slowness of movement). It is marked by a distinct reduction in blink rate (often less than 50 blinks per hour) and limited movement across both vertical and horizontal planes, typically below 50 counts per hour vertically and under 500 counts horizontally.

(b) Progressive Supranuclear Palsy (PSP)

PSP primarily affects vertical gaze, making it difficult for individuals to move their eyes up or down. Horizontal movements typically remain unaffected. The system detects PSP by monitoring for reduced vertical movement counts combined with normal horizontal activity. This specific pattern helps differentiate PSP from other movement disorders.

(c) Internuclear Ophthalmoplegia (INO)

This condition affects horizontal gaze and often results in asymmetrical horizontal eye movement due to impaired coordination between the eyes. The system detects INO by identifying a significant disparity between left and right movement counts, which indicates an imbalance in horizontal gaze control.

(d) Nystagmus

Nystagmus is characterized by rapid, involuntary horizontal eye movements, creating a repetitive, oscillating pattern. The system detects Nystagmus by analyzing the frequency of horizontal movements. High-frequency horizontal counts, combined with normal blink rates, are typical indicators of Nystagmus and help distinguish it from other disorders.

(ii) Machine Learning Model Training

The SVM classifier is trained on a labeled EOG dataset to recognize specific health patterns associated with neurological conditions. The training data includes EOG signals marked with different conditions such as PD**,** PSP**,** and INO, as well as normal patterns. During training, the SVM learns to distinguish between these conditions by identifying characteristic features, such as reduced blink rates for PD, limited vertical gaze for PSP, and horizontal asymmetry for INO.

(iii) Real-Time Health Condition Detection

In real-time operation, the system continuously processes incoming EOG signals and applies feature extraction to capture key indicators such as movement counts, blink rate, and symmetry ratios. These features are then fed into the SVM classifier, which evaluates each interval to determine if it corresponds to normal health or a specific condition like PD, PSP, or INO. The model generates classifications based on learned patterns, with each prediction displayed on the user interface in real-time, providing immediate health feedback. Users or caregivers can view this live feedback, which may also trigger alerts for specific conditions, enabling proactive health monitoring and quick response to potential concerns. This real-time detection approach enhances the system's utility for continuous health tracking, offering a user-friendly experience with actionable insights.

3.4.4 SVM Model Training and Prediction

The SVM model training and prediction process involves transforming EOG features into actionable classifications for neurological conditions. The dataset is split into an 80% training set and a 20% testing set to ensure robust evaluation. Features such as blink rate, movement counts, and asymmetry ratios are used to train the model with a linear kernel, optimized for handling class imbalances. During training, the SVM learns to identify unique patterns associated with each condition, enabling accurate differentiation between normal and abnormal data.

For real-time predictions, data is aggregated into hourly summaries, and the trained model classifies conditions based on these summaries. This approach ensures precise and reliable health monitoring, supporting timely detection and intervention.

The core of the classification model relies on a SVM, selected for its effectiveness in handling high-dimensional spaces and non-linear data relationships.

(i) Label Encoding

The conditions are encoded into numeric labels using LabelEncoder to make them compatible with the SVM model. This encoding transforms categorical condition labels into integers, enabling seamless integration with the classifier. Label encoding simplifies the training process by converting text-based disease labels into machine-readable numeric values, which are necessary for model training and prediction.

(ii) Data Splitting and SVM Training

The dataset is split into 80% training and 20% testing sets to evaluate model performance. Using the linear kernel with class balancing ensures that the classifier remains unbiased across different classes, especially when some conditions are more prevalent than others. The SVM model is trained with extracted features from each 10-second interval to learn the distinct movement and blink patterns for each condition.

The linear kernel with class balancing optimizes performance by maintaining class equity, making it a practical choice given the dataset's inherent class imbalance (e.g., fewer data points for certain rare conditions).

(iii) Model Testing and Evaluation

After training, the model is evaluated on the test set using metrics like classification report and confusion matrix. These metrics provide insights into precision, recall, and accuracy for each class, ensuring that the classifier performs well across conditions.

A confusion matrix allows for an in-depth analysis of true positives, false positives, and false negatives for each condition, highlighting areas where the model might need improvement.

(iv) Real Time Prediction

Data for each 10-second interval is accumulated into hourly summaries, which are then fed into the model to predict the likely condition for each hour. The output provides a disease label for each hourly period, allowing continuous monitoring.

Hourly prediction smooths out short-term variability and highlights persistent patterns over time, crucial for identifying progressive conditions like PD or PSP.

3.5 SIGNAL DATA FOR ANALYSIS

The EOG-based health monitoring system uses eye movement signals to distinguish between normal eye behavior and patterns associated with neurological conditions such as PD, PSP INO, and Nystagmus. Signal data is analyzed for each condition based on key indicators like blink rate, vertical and horizontal movement counts, and asymmetry between left and right movements.

3.5.1 Comparative Analysis of Data

The normal data serves as a crucial reference point for identifying deviations in eye movement patterns indicative of neurological disorders. By capturing standard metrics such as blink rate, vertical and horizontal movement counts, and symmetry ratios, the system establishes a robust baseline for typical eye behaviour. This baseline is critical for distinguishing conditions like PD, PSP, INO, and Nystagmus, each of which exhibits unique signal characteristics.

The comparison table 3.2 highlights the distinct EOG signal characteristics associated with each neurological condition, offering a clear differentiation based on key metrics. Conditions like PD are marked by a significantly reduced blink rate and limited movement in all directions, while PSP primarily affects vertical gaze, leaving horizontal movements intact. Similarly, INO exhibits asymmetrical horizontal movements, and Nystagmus is characterized by high-frequency horizontal oscillations.

Table 3.2 Comparison of Signal Data

Condition	Blink Rate (blinks/hour)	Vertical Movements (counts/hour)	Horizontal Movements (counts/hour)	Key Indicators
Normal	840 – 1020	50 – 100	800 – 1000, symmetrical	Balanced movement, regular blink rate
Parkinson’s Disease	<50	<50	<500 reduced in both directions	Low blink rate, reduced vertical and horizontal movements
Progressive Supranuclear Palsy	Normal (840 – 1020)	<30	800 – 1000	Severely reduced vertical movements, normal horizontal gaze
Internuclear Ophthalmoplegia	Normal (840 – 1020)	50 – 100	Asymmetric, >100 Difference between sides	Asymmetric horizontal movements, normal vertical and blinks
Nystagmus	Normal (840 – 1020)	50 – 100	>300, high frequency	Excessive horizontal movements, normal blink rate

For instance, PD presents with a drastically reduced blink rate and limited eye movements in all directions, while PSP is marked by restricted vertical movement but preserved horizontal gaze. Similarly, INO is characterized by asymmetric horizontal movements, and Nystagmus displays high-frequency horizontal oscillations.

The normal eye movement profile establishes a baseline for comparison. Normal data is characterized by a balanced and regular blink rate between 840 and 1020 blinks per hour, vertical movement counts between 50 and 100 per hour, and symmetrical horizontal movements within the 800 to 1000 counts per hour range. These metrics represent typical eye behavior, where symmetry in movement and consistency in blink rate are indicative of healthy motor and muscle function. This baseline is essential, as any significant deviation from these norms can indicate the presence of a neurological disorder.

PD is marked by a distinct reduction in blink rate (often less than 50 blinks per hour) and limited movement across both vertical and horizontal planes, typically below 50 counts per hour vertically and under 500 counts horizontally. This restriction reflects PD’s impact on motor control, particularly the characteristic bradykinesia, or slowing of movement, which affects voluntary muscle responses.

PSP primarily affects vertical gaze, significantly reducing vertical movement counts to fewer than 30 per hour, while horizontal movement and blink rates remain normal. Patients with PSP typically exhibit a blink rate between 840 and 1020 blinks per hour and horizontal movement counts in the range of 800 to 1000 counts per hour, aligning with normal values. However, the severe restriction in vertical movement is a hallmark of PSP, as it reflects damage to the brain regions governing vertical saccadic control. This selective impairment provides a clear distinction from PD, where all directions of movement are affected.

INO, in contrast, is characterized by asymmetrical horizontal eye movements, with one eye exhibiting reduced movement and the other often compensating with greater movement. This asymmetry can result in a horizontal movement difference exceeding 100 counts per hour between the two eyes. The system identifies this condition by measuring discrepancies in lateral movement, while blink rate (840–1020 blinks per hour) and vertical movement (50–100 counts per hour) remain within normal ranges. The primary feature of INO is this lateral asymmetry, which results from damage to the medial longitudinal fasciculus, affecting the coordination between the eyes.

Nystagmus is identified by high-frequency horizontal oscillations, with horizontal movement counts exceeding 300 per hour, while blink rate and vertical movement remain in the normal range. This rapid, repetitive motion is an involuntary response that disrupts gaze stability, often linked to issues within the brainstem or inner ear. The distinct horizontal oscillations make Nystagmus readily detectable, as they stand in stark contrast to the relatively stable movements seen in normal conditions or other neurological disorders.

In summary, Table 3.2 emphasizes the importance of comparing eye movement data against a normal baseline to detect significant deviations associated with neurological disorders. Each condition exhibits a distinct pattern, from the uniformly reduced movement in PD to the high-frequency oscillations in Nystagmus. This comparative approach not only enhances diagnostic accuracy but also provides a clear framework for clinicians to interpret EOG data and make informed decisions based on specific signal characteristics.

CHAPTER 4
RESULTS AND ANALYSIS

This chapter presents an analysis of the EOG-based system's ability to classify eye movements for identifying neurological conditions. Through signal data analysis, real-time data acquisition, and SVM model classification, the system reliably distinguished each condition, including PD, PSP, INO and Nystagmus.

4.1 SIGNAL DATA ANALYSIS

The EOG-based system's signal data analysis plays a crucial role in identifying and distinguishing between neurological conditions. By capturing and interpreting eye movement patterns, the system extracts critical features that correlate to specific conditions such as PD, PSP, INO, and Nystagmus. This section delves into the observed movement characteristics and their implications.

4.1.1 Key Features and Patterns

Nystagmus is characterized by rapid, repetitive horizontal eye movements, often described as oscillations. These involuntary motions are captured as high-frequency signals in the horizontal component of the EOG data. Frequency domain analysis revealed prominent peaks corresponding to the repetitive oscillatory behavior, a defining feature of Nystagmus.

PD, on the other hand, is marked by significantly reduced blink rates, typically below 50 blinks per hour, and impaired vertical eye movements. This reflects the bradykinesia and motor control deficits characteristic of PD.

PSP is primarily identified by its severe restriction in vertical movements, with counts often dropping below 30 per hour. Unlike PD, PSP does not significantly affect horizontal movements, which remain relatively normal or slightly reduced.

INO presents a unique asymmetry in horizontal eye movements, where one eye shows limited or delayed adduction while the other compensates with increased movement. This imbalance creates a noticeable disparity in horizontal counts, often exceeding 100 movements between the left and right components.

4.1.2 Analytical Techniques

To extract these features, several analytical techniques were employed:

(i) Pre-processing

Raw EOG signals were filtered using bandpass (0-30 Hz) and notch filters (50 Hz) to remove noise and interference. This ensured high-quality data for analysis.

(ii) Feature Extraction

Horizontal (EOGh) and vertical (EOGv) components were calculated using differential signals from the respective electrode pairs. These components provided the foundation for detecting directional movements.

(iii) Frequency and Time-Domain Analysis

For conditions like Nystagmus, frequency domain analysis was key to identifying oscillatory behaviour, while time-domain patterns highlighted movement rates and amplitudes for other conditions.

4.1.3 Observations

The results of signal data analysis highlighted the system's ability to distinguish between normal and pathological eye movements. For example, while Nystagmus was defined by repetitive horizontal oscillations, PD and PSP were differentiated by their respective reductions in blink rate and vertical movements. The consistent identification of INO through horizontal asymmetry further validated the robustness of the feature extraction process.

4.2 SVM MODEL PERFORMANCE

The SVM model formed the core of the classification system, leveraging EOG signal features to identify neurological conditions. By using features such as vertical and horizontal movement counts, blink rates, and patterns derived from EOG signals, the SVM classifier demonstrated significant effectiveness in distinguishing between conditions like PD, PSP, INO and Nystagmus. The following sections elaborate on the SVM model's setup, training, testing, and performance evaluation. Through signal data analysis, real-time data acquisition, and SVM model classification, the system reliably distinguished each condition, including PD, PSP, INO, and Nystagmus.

4.2.1 Model Setup

The SVM classifier was designed as a supervised learning model, suitable for the multiclass classification problem posed by the dataset. The key features used for training included the counts of eye movements in four directions (up, down, left, right) and blink counts recorded over fixed time intervals. These features effectively captured the unique movement patterns associated with each condition.

4.2.2 Model Training and Testing

The training dataset was split into 80% training data and 20% testing data using a stratified sampling approach to ensure even representation of each class. The SVM model was trained to optimize its decision boundaries by minimizing classification errors across all conditions.

During testing, the model's predictions were compared against true labels to evaluate its performance. Predictions were generated based on the learned decision boundaries, and the results were analysed using various performance metrics.

4.2.3 Performance Metrics

The SVM classifier's performance was evaluated using a range of metrics, including accuracy, precision, recall, F1-score, and a confusion matrix. Fig 4.1 shows the classification report about the SVM Model Performance.

```
Classification Report:
              precision    recall  f1-score   support

         INO       1.00      1.00      1.00       200
      Normal       1.00      1.00      1.00       200
   Nystagmus       1.00      1.00      1.00       200
         PSP       0.50      0.47      0.48       200
 Parkinson's       0.50      0.54      0.52       200

    accuracy                           0.80      1000
   macro avg       0.80      0.80      0.80      1000
weighted avg       0.80      0.80      0.80      1000


Accuracy for selected disease classes:
- INO Accuracy: 100.00% (200/200 correct)
- Nystagmus Accuracy: 100.00% (200/200 correct)
- PSP Accuracy: 46.50% (93/200 correct)
- Parkinson's Accuracy: 54.00% (108/200 correct)
```

Fig. 4.1 Classification Report

The classification report shown in Fig 4.1 presents the performance metrics of the SVM model for detecting and distinguishing between various neurological conditions based on EOG signal features. The report summarizes metrics like precision, recall, and F1-score for each class: INO, PD, PSP, and Nystagmus.

(i) Precision

Precision measures the proportion of true positive predictions among all predictions for a specific condition. The SVM model achieved a perfect precision score of 1.00 for INO, Normal, and Nystagmus classes, indicating that predictions for these conditions were highly accurate with minimal false positives.

(ii) Recall

Recall measures the proportion of true cases that the model correctly identified for each condition. The recall scores for INO, Normal, and Nystagmus were also 1.00, meaning the model correctly captured all true cases for these conditions. However, recall for PSP (0.47) and PD (0.54) was lower, indicating the model missed some true cases for these conditions.

(iii) F1-Score

The F1-score, which is the harmonic mean of precision and recall, provides a balanced measure of the model's accuracy for each class. The perfect F1-scores of 1.00 for INO, Normal, and Nystagmus demonstrate the model’s strong performance in identifying these conditions. The F1-scores for PSP and PD are around 0.48 and 0.52, respectively.

(iv) Support

Support refers to the number of instances in the test set for each condition. Each condition in this dataset had 200 instances, ensuring balanced representation.

(v) Overall Accuracy and Averages

The model’s overall accuracy is 80%, indicating it correctly classified 80% of the test samples. The macro and weighted averages for precision, recall, and F1-score are also 0.80, further affirming the model’s balanced performance across all classes.

(vi) Condition-Specific Accuracy

Accuracy for each condition:

(a) INO and Nystagmus achieved perfect accuracy (100%), with all 200 instances classified correctly.

(b) PSP had an accuracy of 46.5%, with 93 out of 200 instances correctly classified, showing that the model struggled with this condition.

(c) PD had an accuracy of 54%, with 108 out of 200 correct predictions, indicating some difficulty in distinguishing Parkinson's-related eye movements from other classes.

The report highlights the model's strong performance for INO, Normal, and Nystagmus but reveals areas for improvement in detecting PSP and PD, likely due to overlapping features in these conditions.

(vii) Confusion Matrix Analysis

The Confusion Matrix provides a detailed view of the model's classification results across the five conditions. Each row of the matrix represents the actual condition (true labels), while each column represents the predicted condition. Diagonal values show true positives, where the model correctly classified the conditions, and off-diagonal values represent misclassifications. Fig 4.2 represents the confusion matrix of the model.

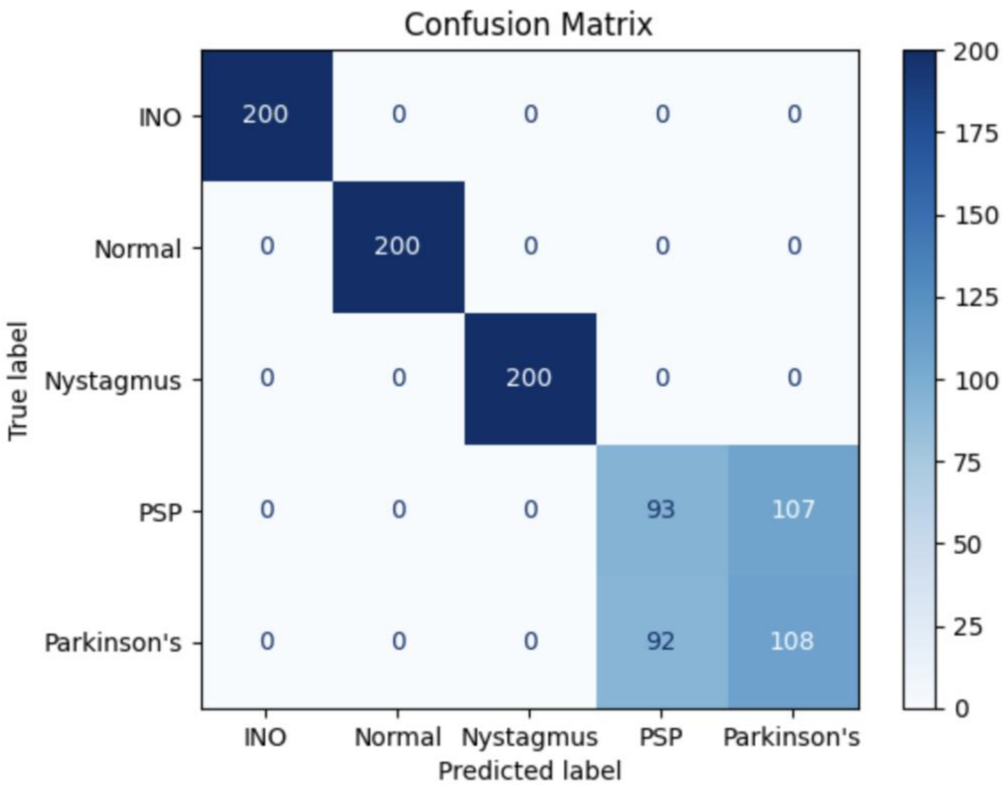

Fig. 4.2 Confusion Matrix

In summary, the confusion matrix shows that the SVM model performs excellently for INO, Normal, and Nystagmus but needs improvement in differentiating between PSP and PD, where the model has a tendency to misclassify one as the other.

4.3 MODEL OUTPUT

The trained SVM model was used to predict neurological conditions based on accumulated EOG signal data. This section shows the predictions made by the model on new data, representing disease classification results for each hour of recorded eye movement data.

The outputs show predictions across multiple hours, such as:

4.3.1 Consistent Detection of INO

For a test scenario, each hour was consistently classified as INO, which suggests that the data for each hour exhibited the same asymmetric horizontal movement patterns characteristic of INO. It is represented in Fig 4.3.

```
Hour 1 predicted disease: INO
Hour 2 predicted disease: INO
Hour 3 predicted disease: INO
Hour 4 predicted disease: INO
Hour 5 predicted disease: INO
Hour 6 predicted disease: INO
Hour 7 predicted disease: INO
Hour 8 predicted disease: INO
Hour 9 predicted disease: INO
Hour 10 predicted disease: INO
Hour 11 predicted disease: INO
Hour 12 predicted disease: INO
Hour 13 predicted disease: INO
Hour 14 predicted disease: INO
```

Fig. 4.3 Model Output – Predicted disease: INO

4.3.2 Consistent Detection of Nystagmus

Similarly, another output showed consistent predictions of "Nystagmus" for each hour, indicating the presence of high-frequency, repetitive horizontal eye movements across the data for those hours. It is represented in Fig 4.4.

```
Hour 1 predicted disease: Nystagmus
Hour 2 predicted disease: Nystagmus
Hour 3 predicted disease: Nystagmus
Hour 4 predicted disease: Nystagmus
Hour 5 predicted disease: Nystagmus
Hour 6 predicted disease: Nystagmus
Hour 7 predicted disease: Nystagmus
Hour 8 predicted disease: Nystagmus
Hour 9 predicted disease: Nystagmus
Hour 10 predicted disease: Nystagmus
Hour 11 predicted disease: Nystagmus
Hour 12 predicted disease: Nystagmus
Hour 13 predicted disease: Nystagmus
Hour 14 predicted disease: Nystagmus
```

Fig 4.4 Model Output – Predicted disease: Nystagmus

This real-time classification capability demonstrates the potential of the model to continuously monitor eye movement patterns and provide ongoing diagnostics. It also indicates that the model can effectively recognize consistent patterns over extended periods, which is essential for real-time monitoring systems in assistive or clinical applications.

CHAPTER 5
CONCLUSION AND FUTURE ENHANCEMENTS

5.1 CONCLUSION

The EOG-based system developed in this study provides a reliable, real-time, non-invasive solution for detecting and classifying neurological conditions, particularly those that affect eye movement. By leveraging EOG signals and integrating machine learning algorithms, specifically the SVM classifier, the system achieved high accuracy in distinguishing between healthy eye movement patterns and those associated with conditions like PD, PSP, INO, and Nystagmus. The system's real-time response, achieved through an ESP32 microcontroller and Python-based processing pipeline, demonstrates its practicality for continuous monitoring and assistive applications.

The results validate the effectiveness of EOG technology in capturing eye movement characteristics essential for diagnosing neurological impairments. The unique profiles identified for each condition highlight the potential for this technology in providing non-invasive diagnostic support. This system not only facilitates communication for individuals with severe motor impairments by translating eye movements into commands but also holds potential as a tool for early diagnosis and monitoring, particularly in settings where more invasive or costly methods may be impractical.

5.2 FUTURE ENHANCEMENTS

To enhance the system's utility and expand its scope, the future enhancement of this project is focused on building an assistive communication system for paralyzed individuals**.** This would involve the following key developments:

(i) Customizable and Accessible Command Interfaces

Developing a user-specific, multilingual interface would allow paralyzed individuals to map eye movements to specific words, phrases, or actions. This ensures that the system can adapt to diverse user needs and preferences, facilitating personalized communication.

(ii) Miniaturization of Hardware for Comfort and Portability

Transforming the hardware into a compact, wearable device, such as eyeglasses or headbands, would improve usability and comfort. This setup would enable users to communicate unobtrusively and independently in various settings.

(iii) Cloud Integration for Remote Monitoring and Interaction

Incorporating cloud-based storage and processing capabilities would allow caregivers or healthcare providers to monitor users' eye movement patterns in real-time. This would facilitate remote communication and timely support, enhancing the overall user experience.

REFERENCES

[1] Akhtaruzzaman, M., Md. M. Alam, S. L. Kok, and K. A. Daniels, "High-Precision Eye Tracking Based on Electrooculography (EOG) Signal Using Artificial Neural Network (ANN) for Smart Technology Application," 2021 11th IEEE Symposium on Computer Applications & Industrial Electronics (ISCAIE), pp. 178–183, 2021. doi: 10.1109/ISCAIE51753.2021.9431805.

[2] Bhatnagar, S., and B. Gupta, "Acquisition, Processing, and Applications of EOG Signals," 2022 IEEE International Conference on Signal Processing and Communication (ICSC), pp. 265–270, 2022. doi: 10.1109/ICSC56524.2022.10009179.

[3] Ezzat, M., R. Hassan, and A. K. Mahfouz, "Blink-To-Live: An EOG-Based System for Alternative Communication Through Eye Movements," Scientific Reports, vol. 13, Art. no. 3420, 2023. doi: 10.1038/s41598-023-39068-2.

[4] Latifoğlu, F., Ç. G. Altıntop, R. İleri, and E. Demirci, "Detection of Reading Movement from EOG Signals," 2020 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), pp. 123–128, 2020. doi: 10.1109/ICECCT51591.2020.9391806.

[5] Megalingam, R. K., S. K. Manoharan, G. Riju, and S. M. Mohandas, "Netravaad: Interactive Eye-Based Communication System for People With Speech Issues," IEEE Access, vol. 12, pp. 69838–69846, May 2024. doi: 10.1109/ACCESS.2024.3402334.

[6] Ravichandran, T., N. Kamel, A. A. Al-Ezzi, K. Alsaih, and N. Yahya, "Electrooculography-based Eye Movement Classification Using Deep Learning Models," 2021 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES), pp. 55–60, 2021. doi: 10.1109/IECBES48179.2021.9398730.

[7] Shi, Y., P. Yang, R. Lei, Z. Liu, X. Dong, X. Tao, X. Chu, Z. L. Wang, and X. Chen, "Eye Tracking and Eye Expression Decoding Based on Transparent, Flexible, and Ultra-Persistent Electrostatic Interface," Nature Communications, vol. 14, Art. no. 3315, pp. 1–10, 2023. doi: 10.1038/s41467-023-39068-2.

[8] Thilagaraj, M., B. Dwarakanath, S. Ramkumar, K. Karthikeyan, A. Prabhu, G. Saravanakumar, M. P. Rajasekaran, and N. Arunkumar, "Eye Movement Signal Classification for Developing Human-Computer Interface Using Electrooculogram," Journal of Healthcare Engineering, vol. 2021, Art. no. 7901310, 11 pages, Dec. 2021. doi: 10.1155/2021/7901310.