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Predicting Guillain-Barre Syndrome: A Machine Learning Approach using Nerve Conduction Study

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***Abstract*— Guillain-Barre Syndrome (GBS) is a rare yet potentially life-threatening neural condition caused by an immune system attack on the peripheral nerve system that quickly causes muscular weakness, numbness and in severe cases it leads to paralysis. So, Timely diagnosis and intervention are crucial for improving patient outcomes. In this study, it aims to develop a model to predict Guillain-Barre Syndrome (GBS) to assist healthcare professionals in early diagnosing GBS by analyzing nerve conduction studies (NCS) data. The model uses key parameters from NCS, such as Latency, Amplitude, and Conduction Velocity, comparing these values against established normative values to assess the likelihood of GBS. The model provides a binary classification indicating whether a patient is GBS positive or negative. Utilizing machine learning algorithm like logistic regression, the project plans to upgrade the precision and efficiency of GBS diagnosis. This enhanced diagnostic capability has the potential to enable earlier detection and more effective treatment, which leads to improved patient outcomes.**

***Index Terms*—GBS Guillain -Barre Syndrome, NCS-Nerve Conduction Study.**

I. INTRODUCTION

Guillain-Barre Syndrome (GBS) is immune related nerve disorder [7] characterized by rapid onset muscle weakness, often triggered by various factors such as zika virus, vaccinations and infection, some surgery. This disorder can affect all age group people. If it gets severe, then it leads to paralysis if not properly diagnosed and treated.

Fig 1 Symptoms of GBS

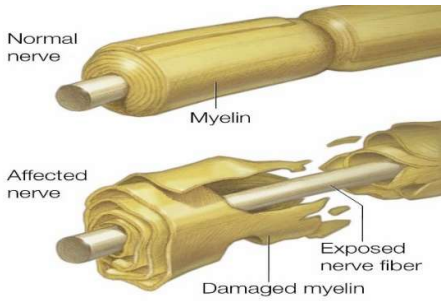

Fig 2 Affected Nerve and Healthy Nerve

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Early diagnosis is crucial for improving patient outcomes, as timely treatment can Considerably lessen the recovery time and prevent from severity of complications. The primary diagnostic tool for GBS involves Nerve Conduction Studies (NCS),[9] which evaluate the function of peripheral nerves by measuring electrical signals. These measurements uncover insights about the nerve damage and the abnormalities that characterize GBS, but manual process of NCS data can be time consuming and leads to human errors.

In this study, we aim to predict the likelihood of GBS in patients using only NCS data. In this dataset, only 18 features are selected for the prediction of Guillain barre syndrome. The features are latency, amplitude and conduction velocity. Latency is time delay in nerve signal transmission, amplitude is strength of the nerve signal. conduction velocity measures the speed at which electrical impulses travel along a nerve. These features are crucial in identifying abnormalities in the nerve functions and understanding their impact on patients.

Slowed conduction velocity and reduced amplitude shows the damage to the nerve fibers or their myelin sheath. For binary classification, the logistic regression model is used, which categorizes patients as either GBS positive or GBS negative based on the features extracted. Logistic regression was selected for its simplicity, reliability and effectiveness in binary classification tasks. This approach presents an opportunity to improve early detection of GBS and aid healthcare professionals in making more informed diagnostic decisions.

II. Literature Survey

The paper [1] which aims to develop a model to predict various subtypes of GBS. The subtypes are Acute Inflammatory Demyelinating Polyneuropathy (AIDP) which is affecting the myelin sheath and causing muscle weakness, usually starting in the legs. Acute Motor Axonal Neuropathy (AMAN) which affecting the myelin sheath and causing muscle weakness, usually starting in the legs. Acute Motor Sensory Axonal Neuropathy (AMSAN) Involves both motor and sensory nerves, causing severe weakness and sensory loss, with slower recovery and Miller-Fisher Syndrome (MF) Rare, affecting eye muscles and causing coordination loss, but typically has a good recovery. In this study they used clinical, serological and nerve conduction data of 129 GBS patient to predict the subtypes of GBS.[1] The data they worked was collected from Instituto Nacional de Neurologia y Neurocirugia located in Mexico City. The collected data was from 1993 through 2002[1]. The dataset consists of 365 features totally, only 16 features were extracted for the prediction process. The machine learning algorithms used in this study are C4.5 decision tree, support vector machine with a gaussian kernel and K Nearest Neighbors (KNN). The accuracy achieved by C4.5 Decision tree was 92.11% and KNN, SVM were achieved nearest to the accuracy of decision tree. The performance was evaluated over 30 runs of 10 folded cross validation.[1]. Electrophysiology is essential for diagnosing Guillain-Barre Syndrome (GBS), which classifying its subtypes, and predicting patient's outcomes [8].

In the paper by S.Sivanandam and colleagues (2023) , a supportive system was introduced to help Hemiplegic patient to fulfil their needs by their gestures and monitor their health . Hemiplegic, is a result of stroke or spinal cord injuries which makes a patient difficult to express their needs. The system uses MPU- 6050 sensor to recognize hand gestures, which allows patients to send messages such as request for water, medicine and restroom assistance to care takers via a GSM module.

This helps both the patient as well as care takers.[2] It also tracks heart rate and oxygen saturation using the MAX-30100 pulse oximeter sensor. The interaction between system and the care takers is managed by microcontroller with WIFI capabilities and the data of the patient were stored in the cloud. This solution provides a cost effective and efficient way to understand the need of the patient and help them immediately after getting the message via GSM module which ensure safety of the patient.

The researcher Sosuke Tanida (2009), who developed an Intelligently Controllable Ankle-Foot Orthosis which utilizes Magneto Rheological fluid brakes to assist patient with ankle dysfunction particularly for those who are affected by Guillain Barre syndrome. The I-AFO offers dynamic control of Ankle torque aiding in gait by preventing drop foot during the swing and stance face. The gait control test helps in the improvement of the patient's ability to maintain foot clearance and forward motion, while also reduces knee instability. This I-AFO demonstrated potential to replace traditional orthotic devices by providing more dynamic control over gait. This results in smoother and safer gait cycle while walking.[3]

In the study by Sergio Albiol-Perez (2013), introduced a virtual motor rehabilitation system called ABAR to improve balance and postural control of patients who are recovering from Guillain Barre Syndrome.[4] The study included two patients who underwent 20 rehabilitation sessions using the ABAR system which has a feature of customizable virtual environments and visual bio feedback. The rehabilitation program included both static and dynamic balance exercises which is performed in sitting and standing positions with difficulty level tailored to each patient. Clinical assessments including the Berg balance scale and Tinetti test shows the

improvements in the patients gait and balance. This system provides a cost-effective solution for supporting motor recovery in Guillain Barre patients.

The study which says that the treatments like Plasmapheresis and immunoglobulin therapy are used to manage the Guillain Barre syndrome. The hematocrit (Ht) value which shows the percentage of red blood cell in the blood and also linked to blood pressure. The hematocrit value was collected from Tokushima university hospital.[5] This study focuses on predicting the hematocrit values at 1 minute,3-minutes and 5- minutes during plasma exchange which can help doctors to manage blood pressure during the procedure. They used a new prediction method to make the predicted Ht values closer to the actual measured Ht values. [5] This happen because the Ht value tend to stay very similar over short time of period, making them easy to predict.

III. Materials and Methods

A. Dataset

The dataset used in this study was manually created by reviewing and analyzing numerous sample reports of nerve conduction study related to Guillain-Barré Syndrome (GBS). A total of 100 patient records were compiled, each containing key attributes relevant to Nerve Conduction Studies (NCS).

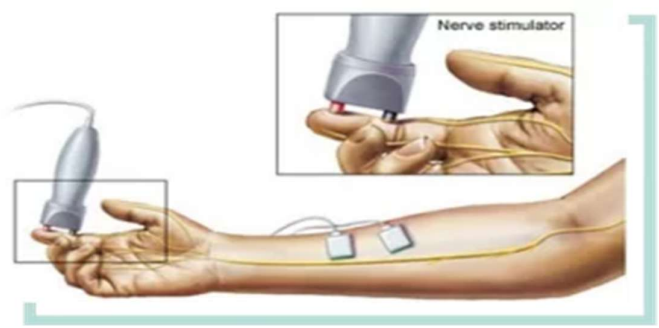


Fig 3 Nerve Conduction study test

The features in the dataset include patient ID, nerve type, nerve name, age, gender, amplitude, latency, and conduction velocity.

For the purpose of building a predictive model, this study focused on a subset of the available features. Specifically, latency, amplitude, and conduction velocity were selected as the primary features for determining the likelihood of GBS. These features were chosen based on their relevance to the electrophysiological characteristics of peripheral nerves, which are often impacted in GBS cases.

TABLE. I EXTRACTED FEATURE

Feature number	Feature name
1	Motor Ulnar Latency (ms)
2	Motor Ulnar Amplitude (mV)
3	Motor Ulnar Conduction Velocity (m/s)
4	Motor Median Latency (ms)
5	Motor Median Amplitude (mV)
6	Motor Median Conduction Velocity (m/s)
7	Sensory Ulnar Latency (ms)
8	Sensory Ulnar Amplitude (mV)
9	Sensory Ulnar Conduction Velocity (m/s)
10	Sensory Median Latency (ms)
11	Sensory Median Amplitude (mV)
12	Sensory Median Conduction Velocity (m/s)
13	Mixed Ulnar Latency (ms)
14	Mixed Ulnar Amplitude (mV)
15	Mixed Ulnar Conduction Velocity (m/s)
16	Mixed Median Latency (ms)
17	Mixed Median Amplitude (mV)
18	Mixed Median Conduction Velocity (m/s)

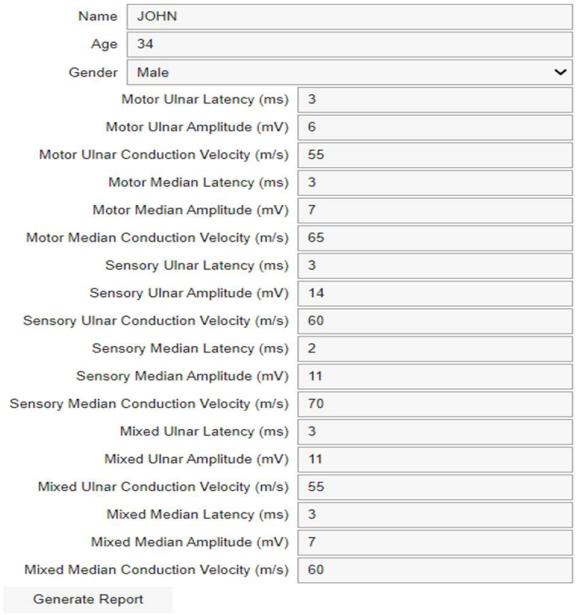


Fig 4 Input Field for Prediction

B. Classification Algorithm

Logistic regression is applied when the outcomes is binary or dichotomous [6]. logistic regression used for binary classification tasks. here, the algorithm models the probability of the class label either GBS positive or GBS negative as a function of an input features. Logistic regression uses a logistic function called the sigmoid function which maps the output to a value of 0 and 1.

The classification decision is based on the threshold value where the predicted class is positive if the probability exceeds the threshold. The threshold value here is set to 0.5. here, applied logistic regression using selected features from nerve conduction study such as latency, amplitude and conduction velocity which is crucial for GBS diagnosis.

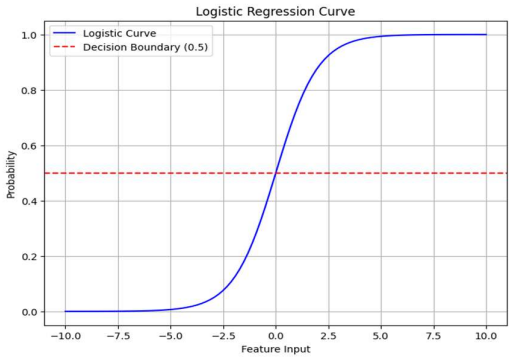


Fig 5 logistic regression Decision curve

The red dashed line in the below graph is the decision threshold for binary classification. If the abnormalities are greater than the threshold value, the model predicts the positive class. If it's less than the threshold value then its negative case.

IV. System Architecture

The architecture for the GBS prediction system integrates the data as input, model processing, and report generation, ensuring that healthcare professionals can efficiently input patient data, obtain predictions, and generate the overall prediction as a report. It provides an interface for healthcare professionals such as the

neurologists; to enter the input of patient details such as name, age, gender and nerve conduction study (NCS) parameters, they are latency, amplitude and conduction velocity.
Input fields were created for entering patient details and entering the nerve conduction parameters for various nerve types (Motor, Sensory) and specific nerves (Ulnar, Median, etc.). A button that initiates the prediction process and generates a report based on the input values. The system detects abnormal values, displays the result either GBS positive or negative, and generates a comprehensive report.
Checks the validity of the input data, ensuring no missing values or incorrect ranges for NCS parameters. Compares the input NCS data with the reference ranges of value for the respective nerves and nerve types to detect abnormalities. The input data is normalized and standardized to match the format used in the machine learning model.
The trained Logistic Regression model is loaded into memory for predictions. This model was pre-trained using historical patient data which consists of the values of amplitude, latency, conduction velocity. The pre-processed features (latency, amplitude, conduction velocity) are fed into the logistic regression model.
The model generates a binary output either GBS positive or GBS negative based on the input values. The system applies a threshold where there is an abnormality more than or equal to 5 then the result will be positive to make the final diagnosis.
Generates a report with the table which showing the patient's nerve conduction study results compared with reference values, marking each parameter as "Normal" or "Abnormal". Displays the overall diagnosis (Positive or Negative for GBS) in the report, where if negative that will be displayed in green color and if it is positive then that will be displayed in red color for the clarity. Once the report is generated, the system resets the input fields for the next patient.

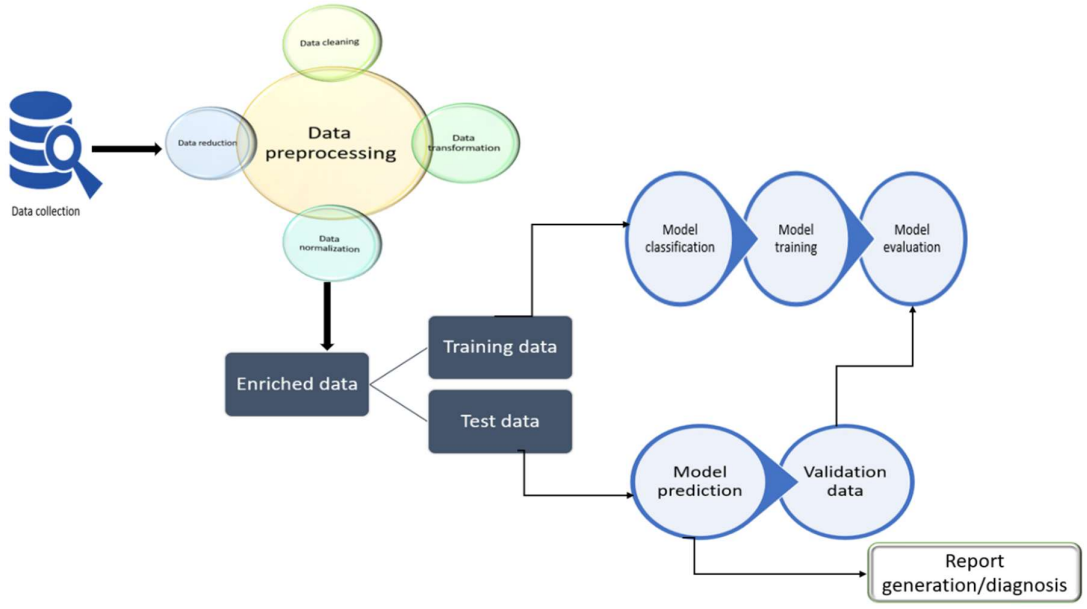


Fig 6. Architecture Diagram

V. MODULES

A. Data Collection

The dataset is created manually that consists of specific data related to Nerve Conduction Study. These data are used to predict GBS at it early stages which reduces the risk factor. The collected dataset consists of records of 100 patients, each containing key attributes of NCS such as latency, amplitude and conduction velocity. Some patient data like patient id, age, gender, nerve type, nerve name was also included. The key attributes are directly used to predict and diagnose GBS. These data are sufficient to predict GBS at its early stage, thus reducing the time taken to detect the disease and improving the patients' health. The dataset consists of more specific information like nerve name, nerve type which helps in accurate predictions. Motor ulnar and motor median was understood from Buschbacher's Manual of Nerve Conduction Studies [10]

B. Preprocessing

The raw data from the dataset is being processed. This includes data cleaning and data organizing, that helps in maintaining the data quality and consistency. Each feature in the dataset contribute equally to the model as the data are normalized. To achieve accuracy and to simplify the model, only the selected features from the dataset is being used. To select those special features, feature extraction process is implemented. In this process only the selected features are given importance due to their clinical significance. The data here are divided into training and testing phase. These are used to assess the model's effectiveness.

C. Model Training

The preprocessed data is used to build a predictive model. These predictive models were trained with the help of Logistic regression. Logistic regression is a machine learning algorithm that is used to predict the likelihood of the patient whether they are GBS positive or GBS negative. Logistic regression is chosen due to its simplicity, ease of understanding and effectiveness in binary classification. The maim motive of model training is to develop a statistical model that can accurately distinguish between GBS positive and GBS negative. For this, logistic regression algorithm places a major role. The model created from this training is selected as final model which are used to compare with the real patient data.

D. Data Labeling

Each feature in the dataset is well labeled and assigned based on the clinical definitions and diagnostic methods for GBS. Specific threshold values are used and assigned for the key features like latency, amplitude and conduction velocity that are used to classify the results. If these values are predefined, the diagnosis process becomes easy and faster. These assigned values are compared with real time data and monitored by healthcare professionals to ensure the accuracy of the labels.

E. Model Evaluation

Model evaluation is a step that helps to assess how well the trained data performs. Each and every step in the process is evaluated. Importance is given to accuracy and precisions to make the model more reliable. Evaluation process involves testing the trained model on unseen data to see its generalizability. A confusion matrix is used that explains the correctly predicted positive and negative cases, incorrectly predicted positive and negative cases conditions and predicts the errors that a model may make.

F. Deployment for Predictions

The models are integrated at user friendly interface where the healthcare professionals can input patient data. Based on the input data, the model processes those data, applies conditions and displays output. As different and unique features are already selected, the healthcare professionals provide the necessary input to view a desire output. For real world scenarios, the model is capable of providing its own and accurate output.

G. Report Generation

Based on the model's prediction and assumptions, the final reports are generated. These reports have patient's details stating whether they are GBS positive or GBS negative. The normal values for the key features are also displayed at the final report, helping in comparing the values and diagnosing the disease. Once the prediction is made the report is ready to view. A detailed report containing all the values are displayed making it easy for both the patient and the healthcare professionals to understand the result.

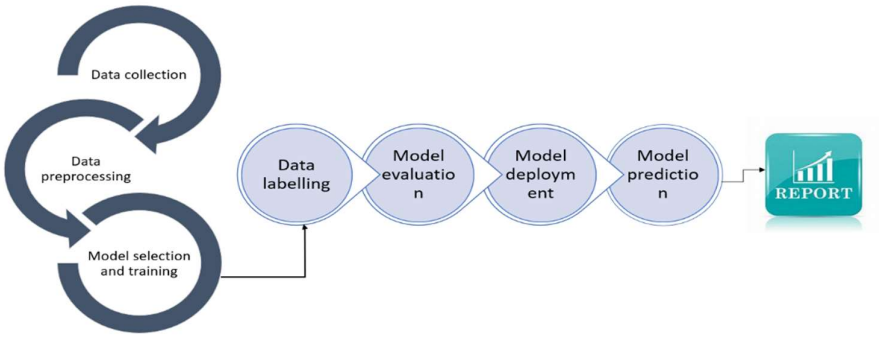


Fig 7. Implementation

VI. CONCLUSION

The developed system leverages logistic regression as a machine learning model to predict Guillain-Barre Syndrome (GBS) using nerve conduction study (NCS) data, specifically analyzing features like latency, amplitude, and conduction velocity to a evaluate GBS likelihood. By automating the comparison of patient data against standard values, the system enhances diagnostic accuracy, minimizes human error, and ensures consistency across different cases. This approach reduces the need for multiple tests, saving time and reducing healthcare costs while enabling earlier diagnosis and faster intervention, which also decreasing hospital stays and improving resource allocation. Early detection facilitated by this system is crucial for preventing severe GBS complications, allowing for timely treatments like intravenous immunoglobulin or plasma exchange, which can mitigate progression and improve recovery outcomes. Additionally, the system's user-friendly interface allows healthcare professionals to input NCS data and receive instant predictions, empowering them to make rapid, data-driven decisions. This accessibility makes it valuable for a wide range of clinical users, from neurologists to diagnostic technicians, contributing to improved patient care and efficiency in medical settings.

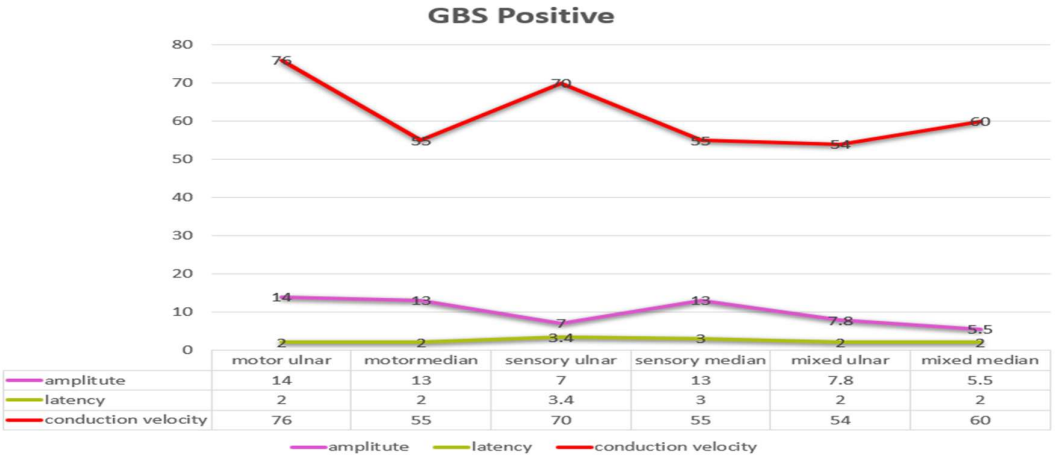


Fig 8 Graph for GBS positive

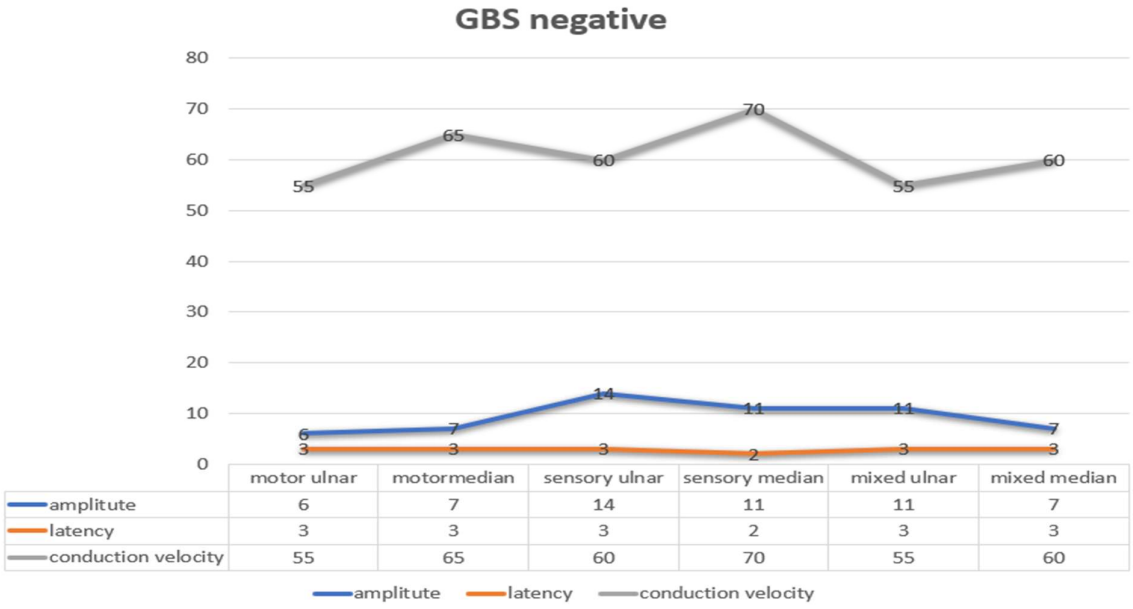
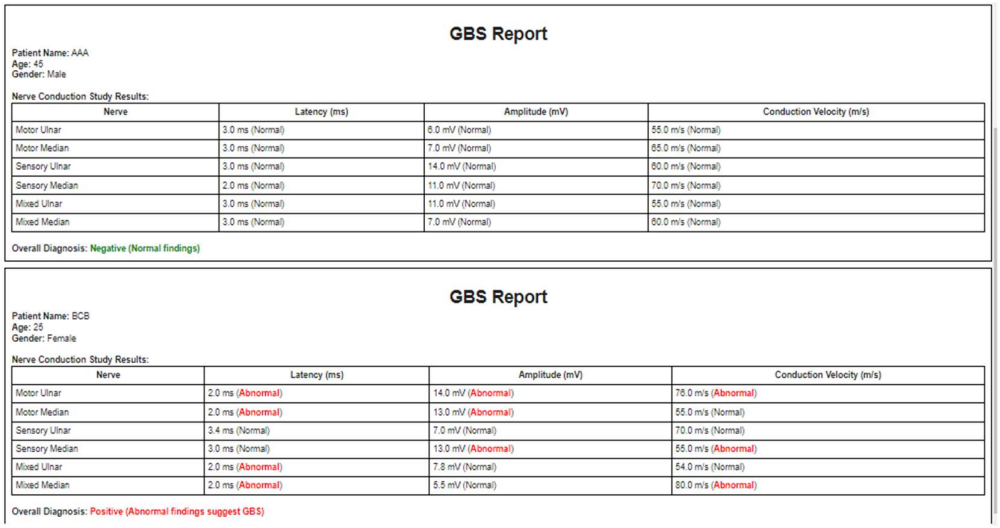


Fig 9 Graph for GBS negative

A. Future Enhancement

By adding more clinical data of the patients such as previous surgery and symptoms with the nerve conduction study data while predicting will improve the accuracy to diagnose Guillain -barre syndrome. Utilizing more advanced machine learning models such as ensemble technique or deep learning will help to increase the overall accuracy of prediction. Enhancing the user interface for health care professionals would make it more user friendly by integrating NLP for voice-based Input.

B. Experimental Output



GBS Report

Patient Name: AAA
Age: 45
Gender: Male

Nerve Conduction Study Results:

Nerve	Latency (ms)	Amplitude (mV)	Conduction Velocity (m/s)
Motor Ulnar	3.0 ms (Normal)	6.0 mV (Normal)	55.0 m/s (Normal)
Motor Median	3.0 ms (Normal)	7.0 mV (Normal)	65.0 m/s (Normal)
Sensory Ulnar	3.0 ms (Normal)	14.0 mV (Normal)	60.0 m/s (Normal)
Sensory Median	2.0 ms (Normal)	11.0 mV (Normal)	70.0 m/s (Normal)
Mixed Ulnar	3.0 ms (Normal)	11.0 mV (Normal)	55.0 m/s (Normal)
Mixed Median	3.0 ms (Normal)	7.0 mV (Normal)	60.0 m/s (Normal)

Overall Diagnosis: Negative (Normal findings)

GBS Report

Patient Name: BCB
Age: 25
Gender: Female

Nerve Conduction Study Results:

Nerve	Latency (ms)	Amplitude (mV)	Conduction Velocity (m/s)
Motor Ulnar	2.0 ms (Abnormal)	14.0 mV (Abnormal)	76.0 m/s (Abnormal)
Motor Median	2.0 ms (Abnormal)	13.0 mV (Abnormal)	55.0 m/s (Normal)
Sensory Ulnar	3.4 ms (Normal)	7.0 mV (Normal)	70.0 m/s (Normal)
Sensory Median	3.0 ms (Normal)	13.0 mV (Abnormal)	55.0 m/s (Abnormal)
Mixed Ulnar	2.0 ms (Abnormal)	7.8 mV (Normal)	54.0 m/s (Normal)
Mixed Median	2.0 ms (Abnormal)	5.5 mV (Normal)	80.0 m/s (Abnormal)

Overall Diagnosis: Positive (Abnormal findings suggest GBS)

Fig 10

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