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Smart Rehabilitation Glove Based On AI And IOT Technology For Brain Stroke Patients

Heena Dhiman[1], Rajneesh Kumar[2]
[1]Assistant Professor, Department of Computer Science and Engineering, MM Engineering College, Maharishi Markandeshwar (Deemed to be) University, Mullana, Ambala, Haryana-133207
[2]Professor, Department of Computer Science and Engineering, MM Engineering College, Maharishi Markandeshwar (Deemed to be) University, Mullana, Ambala, Haryana-133207
[1]er.heenadhiman11@gmail.com and [2]drrajneeshgujral@mmumullana.org

Abstract: *Rehabilitation is a crucial part of the recovery process for people with disabilities, even if it can be more difficult in case of limbs disorder after brain stroke. Which is important for everyday tasks and longer processes to recover than other body parts of body. In this study, smart rehabilitation glove for brain stroke patients is proposed which includes Internet-of-Things (IoT) based sensors flexi-force, flex, Max30100 to monitor bending angle and gripping strength of fingers in real-time. The ThingsBoard cloud keeps track of the real-time data produced by the sensors for future analysis. Machine learning (ML) models such as Random Forest Regressor and XGBoost Regressor, used to predict recovery scores. To classify patient progress of rehabilitation various ML classifiers were used, out of which Neural Network outperforms with 98.1% accuracy. The proposed smart glove system provides both healthcare providers and patients instant feedback and helps them improve stroke recovery processes.*
Keywords: *smart glove, post stroke recovery, machine learning, internet of things, brain stroke rehabilitation, recovery score prediction, patient progress, artificial intelligence.*

1. INTRODUCTION

An abrupt localized lesion in the central nervous system can result in brain stroke, a type of neurological injury. Despite the symptom, it can lead to permanent brain or spinal cord injury or vascular dysfunction that results in the death of cells in the retina. There are three primary types of brain stroke: hemorrhage, ischemic stroke, and transient ischemic attacks (TIAs). An ischemic stroke occurs when blood flow to a specific area of the brain is interrupted by clogged arteries. This makes it so that neurons don't get enough oxygen, which causes ischemia and death [1]. Depending on the location and amount of the damage, signs of a brain stroke may pertain to abrupt muscular paralysis, trouble speaking, loss of sensory function, and changes in the face or way of walking. Dysphagia makes it hard to swallow; hemiparesis or hemiplegia makes single side of body paralyzed or weak; and difficulties with both speaking and writing. After a stroke, cognitive issues including dementia and memory loss can significantly affect a patient's quality of life. The severity of these problems depends on where and the severity of brain damage, highlighting the importance of early diagnosis, rehabilitation, and promoting health. Due to their distance from the central nervous system and the longer time it takes for nerve impulses to repair, strokes are particularly slow to impair motor function in the hands and feet [2]. Conventional rehabilitation techniques are time-intensive and costly since they call for a lot of medical visits and occasionally depend on subjective opinion. In addition, the employment of complicated, bulky, and difficult-to-transport therapeutic equipment makes the rehabilitation process expensive and labour-intensive. The traditional method of measurement, which makes use of standard medical equipment like a dynameter and goniometer, has limitations including the requirement for manual operation, manual assessment recording, assessment of misalignment competence, total endurance of grip, etc. According to research study reports [3], goniometers may make a 5° error when evaluating ROM and the accuracy of readings from wearable technology.

The development of a smart rehabilitation glove for brain stroke is the analysis's proposed approach for these kinds of problems. The emerging technologies of Artificial Intelligence (AI) and the Internet of Things (IoT) provide a variety of opportunities for remote therapy and real time tracking. Precise mobility and physiological data may be recorded by smart glove that are integrated with IoT-based sensors. This makes it possible to provide personalized treatment and constant observation apart from hospitals [4]. By forecasting recovery growth, categorizing rehabilitation phases, and identifying unusual recovery patterns, combining these systems with AI techniques enables more effective and flexible rehabilitation techniques. With a specific goal of assisting in the rehabilitation of hand motor abilities following a stroke, this study proposes an AI and IoT-enabled smart rehabilitation glove for brain stroke patients. Five Flex sensors

assess the bending angles of fingers, five Flexi-Force sensors evaluate grip strength, and a MAX30100 sensor measures heart rate and blood oxygen saturation (SpO_2).The glove sends data digitally to the ThingsBoard cloud platform for storage and analysis with the help of an ESP32 microcontroller and an OLED display. The real-time data is processed by machine learning models that use Random Forest Regressor and XGBoost to forecast a continuous recovery score. Support Vector Machine, Decision Tree, and Neural Network classifiers are used to divide rehabilitation stages into early, mid, and final phases.
The rest of the work is organized as follows. The relevant work in relation to smart gloves based on the Internet of Things is discussed in Section 2. While Section 3 provides an overview of the method and materials used. Section 4 described the artificial intelligence based analytics for recovery score and stage classification. The final result and analysis covered in Section 5. Section 6 concludes by outlining the work's key findings and future directions. The smart rehabilitation glove that has been proposed aims to make rehabilitation after a stroke easier to get to, more effective, and more personalized by offering accurate real-time monitoring and predictive analytics. This will help healthcare systems do their duties better and improve patient outcomes.

2. LITERATURE REVIEW

Numerous research has investigated the design and development of smart rehabilitation gloves for brain stroke patients utilizing Internet of Things (IoT) and Artificial Intelligence technologies. The studies conducted by various authors on smart rehabilitation gloves examined as follows. A study by Sarwat et al. [5] demonstrated how to build a smart glove that has a hosted on the web for checking how well a treatment is working, the convenience of a smartphone app for sending and receiving information, and a real-time database. To keep track of hand movement, the data glove had a 6-axis Inertial Measurement Unit, flex sensors and force-resistive sensors (FSRs). For each finger joint, force-resistive sensors (FSRs) and flex sensors recorded the angle and binding force, respectively. After getting data from the sensors, the Arduino processor handled it and sent it to a mobile app via Bluetooth. The patient was directed to start exercising using the smartphone app. With a remarkable degree of precision (0.1°), Jha et. al. [6] presented a glove that simultaneously tracks the access to all ten joints in the finger four medial interphalangeal, five hypochondral, five metacarpophalangeal, and one phalangeal joint. Each of the 10 of the glove's sensors are checked for accuracy and repeatability using a sensor for inertial measurement units (IMUs) that has been pre-calibrated. A Virtual Reality (VR) platform was designed that links the smart glove to custom virtual reality games were utilized on an Android smartphone through a Raspberry Pi-based module. This demonstrates how useful the glove is in the real world.
In addition to the monitoring of five finger movement and grasping, the researchers also investigated the monitoring of key health indicators. Zakri et al. [7] developed a glove with five flexible sensors, it was easy for nurses to figure out what the five fingers were trying to say. Furthermore, this device can follow the vital signs of persons who have suffered stroke in real-time utilizing DS18B20 temperature and pulse sensors. For the purpose of to assess the temperature sensors, flex sensor glove prototype and pulse and were employed to collect heart rate and temperature. Users may observe and receive data sent by the DFPlayer small gadget on the LCD as well as via the microphone on the device. By comparing the DS18B20 temperature sensor with an Avico digital thermometer, which has an average error of 0.1%, it has been demonstrated to be sufficient for measuring the internal temperature of the body. An examination was performed between the findings of a heart rate test obtained with the pulse sensor and heart rate correctly. Adittya et al. [8] produced a smart glove prototype using 3D printing technology. The glove had flex sensors, RF modules, and an Arduino micro controller for processing. A radio frequency (RF) transmitter and a radio frequency (RF) receiver were utilized in order to make wireless communication between the two-microcontroller accessible. A machine that can test the prototype automatically and observe how accurate it is in different settings, such as at different speeds and distances. Han et al. [9] presented a small and easily carried and ergonomic designed to measure grip strength in individuals with neurologic hand diseases. The smart glove utilizes an ESP32 microprocessor, affixed to a glove including pressure sensors embedded in the dactyls. A rehabilitation glove was demonstrated by Chang et al. [10] to remotely test and monitor patients' finger elasticity. The glove further captures flexibility for later analysis used for monitoring and assessing therapy sessions. With the Raspberry Pi microprocessor, the data was handled and sent to a mobile device. The readings for all five fingers were recorded in Comma-Separated Values format, accompanied with the timestamps of the observations.
Robotic gloves were programmed for the recovery following cerebral stroke victims, and Arivarasi et al.[11]

presented them sensor data is gathered. by the ESP32 microcontroller unit and sent to the doctor via the Amazon Web Services (AWS) cloud for analytics using the Message Queuing Telemetry Transport (MQTT) protocol. The external communication layer comprises patterned gloves made of cotton for enhanced control, microprocessor, power by pneumatic ligaments that convergence or lengthen by atmospheric pressure, a flexible sensor for strain detection, in addition to an array of control valves. The virtual layer that enables the patient and physician to evaluate the data, one must examine the user interface/application and the AWS cloud services.. Iqbal et al. [12] introduced a portable machine designed to monitor many critical signs, including arterial pressure, surrounding temperature, body temperature, blood concentrations, moisture, and movement. A simple link makes it easy to use, and power control and an energy-efficient design make the battery last longer. Zakri et al. [13] introduced a rehab glove designed to assist cerebral infarction survivors in regaining motor coordination and manual dexterity with a mechanical controller capable of an angle deflection angle of 260A piece of information pressure in air of 0.25 MPa generates a measured pressure of 5.1 Newtons. The maximum variation in the bending angle measures 5.1°.

3. MATERIALS AND METHODS

3.1 System Architecture

- **Flex sensor:**

A resistive sensor that detects surface bending is called a flex sensor. The smart glove's flex sensor keeps track of the bending angle to measure how much the finger bends. When performing functional activities, the finger joints must be able to deflect within a certain proportion of their whole range of motion. The sensor provides fluctuating resistance readings based on its deflection angle while maintaining a constant resistance value while in a neutral position (vertical orientation). Since the sensor's electric properties have altered due to motion, its resistance increases as the deflection angle approaches 45 degrees [14]. It becomes much harder to bend when the angle of bending reaches 90 degrees. This completely demonstrates the correlation between bending and resistance. Carbon-resistive conductive ink is printed on a thin, bendable base to make the flex sensor. In its straight form, this conductive ink is about 25k resistors, but it can bend in 45-to-90-degree angles. The sensor produces a resistance signal that is directly proportional to the substrate's bending radius. Since the deflection angle is higher, the flex sensor's resistance goes down, as seen in Table 1.

Table 1. Bending angle measurement using flex sensor resistance [15]

Sr. no.	Variable resistance value (kilo ohm)	Deflection angle (degree)
1.	25	0
2.	62.5	45
3.	100	90

The output voltage is the voltage fall through the pull-down resistor. To ascertain the voltage output, use the following equation (Eq. 1) and method (method 1) for converting the flex sensor's result into the deflection angle:

$$V_o = V_{cc}\frac{R}{R+R_{flex}} \qquad \text{..} \ (1)$$

Where, V_o represents output voltage that measures over the constant resistor over the constant resistor, Vcc is the power supply or the voltage divider circuit is input voltage, R is fixed resistor or constant resistance value, Rflex is flex sensor resistance which change its value based on bending angle.

- **Flexi-Force Sensor:**

A resistive-based sensor, the Flexi-Force can detect the amount of force or pressure acting on a surface. As additional carbon components come into contact with the sensor, its resistance decreases due to its numerous thin, flexible layers and conductive lines. In proportion to the decrease in the detecting range, the sensor's sensitivity rises. The sensor cannot measure pressure over its maximum range, which may damage it. [16]. The Flexi-Force sensor, a crucial part of the proposed smart rehabilitation glove for brain stroke patients, measures the user's gripping strength and physical exertion. The vibrating circular surface of the flexi-force sensor was forced to yield the analog raw data. The x voltage value, which is approximately 0.5 volts, is converted to the analog data, which is approximately 1023 volts, which is collected from the sensors. Four levels of grip strength are mapped: affirm, minimal, mild, and strong.

The 10kΩ Resistors are interconnected to create a voltage divider circuit. The A0 ADC input of the ESP32 is linked to the ADC converter pins A0 through A3, which are connected to the pull-down resistor.

Table 2: Gripping strength measurement using flexi-force sensor readings [15]

Sr. no.	Range (sensor reading)	Gripping strength
1.	0-9	Affirm
2.	10-199	Minimal
3.	200-499	Mild
4.	499-1023	Strong

The Equation 2 Illustrate a voltage divider circuit for a flexi-force sensor and its mapping. conversion of the flexi-force sensor's value into gripping strength.

$V_O = V_{CC} \frac{R}{R+FSR}$ .... (2)

Vo represents the output voltage measured across the fixed resistor R, functioning as the output signal; Vcc denotes the supply voltage or input voltage provided to the circuit; R is a resistor with a constant resistance; FSR refers to a Force Sensitive Resistor, a variable resistor whose resistance fluctuates according to the applied force.

- **Max30100 sensor:**

Max30100 sensor is capable of measuring pulse rate and saturated oxygen level. A photodetector measures the amount of reflected light from the MAX30100, moment the finger or earlobe reflects light (or where the skin isn't too bulky for lights to penetrate the tissue easily). Photoplethysmogram is the name of this technique used to identify pulses employing light. [17]. The MAX30100 is powered by a 1.8V voltage along with another additional source of 3.3V voltage for the internal light emitting diodes.

- **ESP32 microcontroller board:**

The Esp32 (Espressif Systems number 32) is a system-on-chip (SoC) that is high-performance, low-power, and comes with a microprocessor that is built in with Wi-Fi and Bluetooth. It is ideal for creating gadgets that need wireless communication and real-time data capture because of these qualities. The proposed smart rehabilitation glove for brain stroke patients uses this microcontroller as its main processing device. Information from many sensors, including the MAX30100 sensor and the flex sensor and flexi-force sensor, are processed by the microcontroller that controls them. After interpreting the sensor data, it transmits it straight to the ThingsBoard cloud platform for real-time viewing and analysis. With its quick Analog-to-Digital Converter (ADC) and dual-core CPU, it ensures precise and quick data transmission [18].

- **OLED display:**

▪ OLED (Organic Light-Emitting Diode) is an LED with a chemical sheet called the emissive electroluminescent layer that emits illumination when powered. In this type of display technology, two layers of energized conductors are sandwiched by a single layer of sheets made of carbon that is organic. A power source consists of two parts: an opaque anode, which is frequently composed of an opaque material, and a metallic electrode [19].

▪ **Lipo battery:**

It consists of a lithium-ion battery that can be charged again and again. It uses a polymer electrolyte instead of a liquid cell. This solution is made up of highly conductive semisolid (gel) polymers [20]. Compared to other types of lithium batteries, these batteries offer more concentrated energy. The standard voltage of batteries based on lithium metal oxide is 3.6 or 3.7 volts. Lipo batteries have strong charging and discharge properties and can be recharged.

▪ **3D printed case:**

For the purpose of mounting the Max30100 sensor on an arm and display, a compact plastic display casing which is rectangular in shape is custom-designed and manufactured. The Max30100 was put on the base of the case, and the display screen was put on top. In addition to having enough internal room for hardware components, the case assembly doesn't require screws to close. Black PLA (Polylactic Acid) material was used to print the intended casing. The band strip is utilized on the ends of the casing to provide the impression that the system is a wearable band.

- **Arduino IDE:**

The open-source integrated development environment (IDE) Arduino is used to program the proposed smart rehabilitation glove for brain stroke patients. The Arduino IDE possesses tools that make it easier to connect the device to the computer, connect sensors, connect to Wi-Fi and Bluetooth, and more. The ESP32 microcontroller is used to develop and upload code that collects real-time data from the sensors [21]. After processing, the microcontroller wirelessly transmits the information to the cloud platform,

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enabling remote monitoring and analysis. Furthermore, debugging features are made possible by the IDE's serial monitor, which helps you visualize data generated by sensor and system performance.

• **ThingsBoard cloud:**

The open-source platform ThingsBoard Cloud enables Internet of Things applications to gather data generated incautiously, present it, and monitor objects from a distance. ThingsBoard Cloud served as the main platform for the analysis and processing of sensor data in the proposed Internet of Things (IoT) enabled smart rehabilitation glove for brain stroke patients. Using the MQTT (Message Queuing Telemetry Transport) protocol, the data is electronically sent to ThingsBoard, which saves every value it gets and offers a dashboard for displaying real-time sensor data, such as grip strength and finger deflection angles. Dashboards such as these allow medical professionals to monitor patients' rehabilitation progress in real time from a distance. In addition to data logging [22]. Its adaptability, design, and analytics make it an effective tool for patient monitoring from a distance.

3.2 Proposed Model

The smart glove for brain stroke rehabilitation system that has been developed incorporates a number of sensors into a glove in order to monitor a patient's finger movement, grip strength, oxygen level, and pulse rate. The data collected by the glove is then sent to the cloud so that medical professionals may view it remotely as shown in Figure 1. It makes it easier to track how the patient reacts to various activities and prescription drugs.

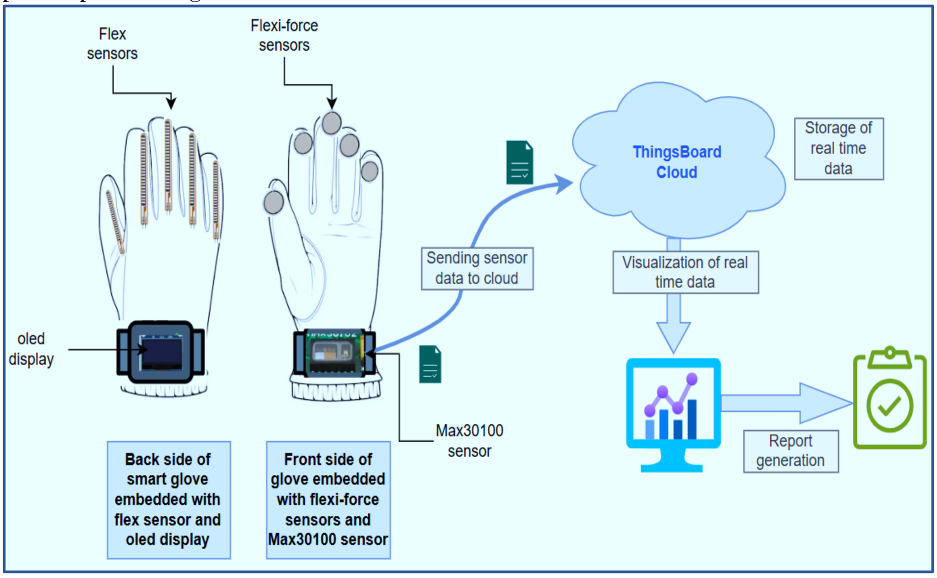

Figure 1: Proposed model of smart rehabilitation glove for brain stroke patient

The smart rehabilitation glove can gather data in simultaneous and transmit it to the cloud using internet of things-based sensors and components like five activate sensors, five flexi-force sensors, Max30100 sensor, microcontroller board, and battery etc. All incoming data is processed and analysed by the Things Board cloud, which then makes it available on a dashboard for viewing and monitoring. Since this data can be accessed remotely, healthcare providers may track patients' improvement over time. Furthermore, the system can generate data in CSV and Excel sheet formats, which makes it easier to track rehabilitation efforts and assess patient health.

• **Data Collection:**

The smart glove's integrated sensors capture data on bending angle and gripping strength as it occurs during any activity performed by patient. To ensure consistency, created raw information has to be timestamped, saved, and matched with data from various sources [22]. An ESP32 microcontroller receives unverified information through its analog-to-digital converter (ADC) pins and transforms them into digital signals. An ESP32 microprocessor board and sensors send real-time data to the smart rehabilitation glove for brain stroke patients that is being considered. It functions as the processing unit that manages the data, translating the analog impedance readings from the sensors into useful data like gripping strength and bending angles. This architecture is well suited for the ESP32 microcontroller because of its fast-processing speed, low energy consumption, and built-in wireless connectivity to the internet. Through its wireless connection, the ESP32 subsequently communicates with the ThingsBoard cloud.

• **Cloud Integration:**

Data created instantly may be accumulated, presented graphically, and recorded thanks to the cloud

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platform. The ThingsBoard is a cloud platform which offers a strong platform for gathering, storing, and visualizing IoT data in addition to additional features like real-time dashboards and alerts. The proposed smart rehabilitation glove for brain stroke patients help in recovering from a brain stroke works with MQTT protocols to send attribute and sensor data from the ESP32 microprocessor to the ThingsBoard cloud, where it can be stored and processed [23]. Dashboards in real time provide data, alerts may be set up, and historical data can be reviewed to help in making decisions. ESP32 micro-controller board running Arduino development environment software collects and sends sensor data to the ThingsBoard IoT server with help of installing library MQTTClient Library. Systems with resource limits, such as insufficient connectivity, limited computational voltage, limited storage space, and energy limitations, can be supported via MQTT, a protocol for communication between machine and data transmission [21]. MQTT may be implemented on a variety of networks, including both wireless and wired networks, and it functions on TCP/IP connections. On the ThingsBoard Cloud screen, important metrics like muscle stiffness and grip strength, as well as muscle spasticity, can be seen in real time due to the smart glove system. The volage and resistance are shown on the former and secondary sections of the dashboard, which are separated into three sections. As seen in Figure 2, the different bending angles of finger are displayed in instantaneous on the dashboard's bottom side.

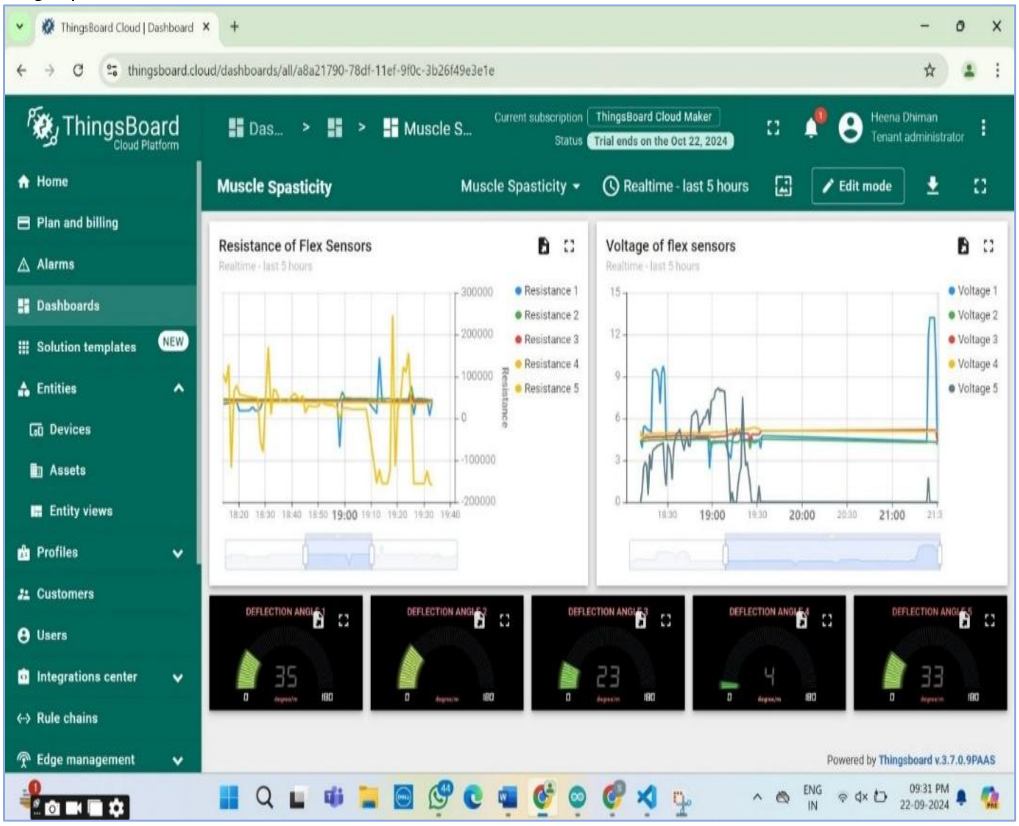

Figure 2. Screenshot of ThingsBoard cloud dashboard for real time data of flex sensor.

Flexi-force sensors in the glove obtain the amount of pressure each finger is putting on it at the same time. The dashboard records data screenshot on grip strength, allowing patients and medical practitioners to monitor grasping abilities in real-time depicted in Figure 3. The ThingsBoardcloud dashboard is separated into two sections: the one of the side displays the Flexi-Force sensor's real-time data, while another side displays each finger's grip strength in real time.

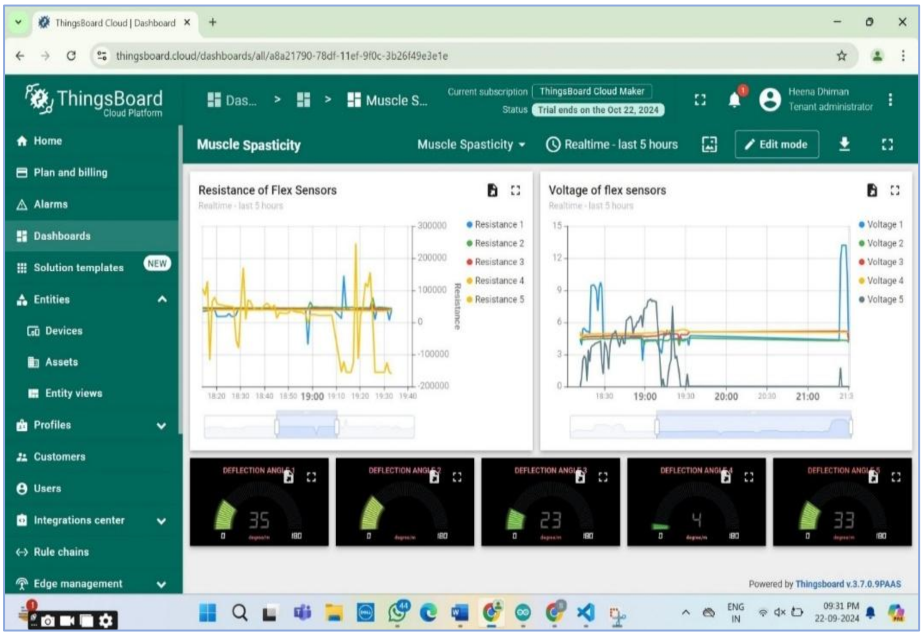

Figure 3: Screenshot of ThingsBoard cloud dashboard for real time data of flexi force sensor.

- **Prototype:**

The prototype, shown in Figure 4, gives an in-depth description of the different steps of the smart glove. A complicated connectivity structure is necessary for the designing and building of a smart rehabilitation glove that integrates several sensors and other electronic components. The one flex sensor for each finger is carefully attached to the inside surface of the glove, corresponding to the natural curve of each finger. The smart rehabilitation glove can also monitor the pressure exerted thanks to five flexi-force sensors that are mounted at the fingers. In order to keep things balanced and comfortable, the flexible conductive jumper wire links all the sensors to a central ESP32 computing. device. A low-power communication technique, like I2C or SPI, is used to connect the OLED display and keep the battery from running out while keeping the data update rates smooth for easy reading.


Figure 4: Prototype of smart rehabilitaion glove for brain stroke patients

Furthermore, a MAX30100 sensor is positioned close to the wrist to guarantee ideal skin contact and accurate readings, and it is connected to monitor vital indicators such as heart rate and saturation oxygen levels.

4. AI-BASED ANALYTICS

4.1 Recovery Score Prediction (Regression)

This study demonstrates that anticipating recovery scores is crucial for determining a patient's rate of brain stroke recovery. Regression models are created using machine learning techniques like Random Forest and XGBoost to do this. These versions utilize real-time sensor data from smart rehabilitation gloves, including heart rate, SpO_2 levels, finger flexion angles, grip strength, and session length. Predicting a recovery score within 0 and 100 is the goal; higher scores indicate a stronger recovery of motor skills; each data point corresponds to a session of therapy. The Random Forest and XGBoost regressors were trained and evaluated using standard metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). The regression-based recovery score model offers a reliable and unbiased means of tracking patient progress, allowing for personalized care and timely adjustments to rehabilitation programs. The proposed smart rehabilitation glove aims to provide quantifiable data on stroke victims' recovery progress.

• **Classification Models:**

In order to anticipate a continuous recovery score, XGBoost and Random Forest Regressors were trained using the sensor characteristics. These models evaluate the patient's success in rehabilitation using flex angles, grip strength, heart rate, SpO2, and session duration.

• **Random Forest Regressor:**

The Random Forest Regressor, often known as RFR, is a valuable tool for analyzing data that does not exhibit regular patterns and exhibits unpredictability. To improve prediction accuracy and reduce overfitting, it builds a large number of trees and averages their output. Throughout training, this ensemble learning approach generates a large number of decision trees and outputs the mean prediction of each tree to improve accuracy and reduce excessive fitting. The Random Forest method is particularly good at handling complex, multivariate sensor data, such as that utilized in stroke treatment [22]. Examples of this type of data include heart rate (HR), SpO_2, grip strength, finger flexion angles, and session duration. Every decision tree is trained with a different set of data that was picked at random by employing bootstrapping, which is also known as randomization with substitution. A subset of attributes is randomly selected for each tree in order to determine the best divisions at each node. This prevents the trees from fitting excessively by separating them. Regression tasks are designed to determine a continuous output, in this case the recovery score. In a canopy of trees, each tree makes a prediction, and the end result is the mean of all those projections.

▪ The feature set for n sensor observations is represented by X = [X1, X2, ..., Xn], where each feature is associated with a sensor value (e.g., heart rate, SpO_2, flex sensor readings, force sensor data, etc.).

▪ Let the target, which stands for the recovery score, be represented as $\hat{y}$.

The prediction for each individual tree T_k is $y_k = f(X)$, where $f(X)$ is the tree's decision function derived from the feature splits. The random forest model's final prediction $\hat{y}$ is as follows in equation 3:

$$\hat{y} = \frac{1}{K}\sum_{k=1}^{K} y_k \quad (3)$$

Where:

▪ $\hat{y}$ is the Random Forest model's expected recovery score.

▪ The forest's total tree count is denoted by K.

▪ The expected recovery score from the k-th tree is denoted by y_k.

The final prediction is an average (in regression tasks) of all decision tree outputs depending on the data set it was trained on. The continuous recovery score derived from these sensor readings will be the intended output, and each observation in the dataset will include the corresponding values.

X= [F1, F2, F3, F4, F5, G1, G2, G3, G4, G5, HR, SpO2, Duration]

Where:

▪ **F1–F5:** Finger flexion values

▪ **G1–G5**: Grip strength values

▪ **HR**: Heart rate

▪ **SpO_2**: Oxygen saturation

▪ **Duration**: Session duration in minutes

A number of decision trees will be utilized in order for the Random Forest Regressor to acquire the knowledge necessary to map the characteristics **X** to the recovery score y. The ensemble's trees will offer distinct insights into how these sensor data affect the recovery score. A final, reliable forecast is produced by adding together all of the predictions made by each tree. The Random Forest Regressor model makes use of the statistical significance of numerous decision trees in order to anticipate the recovery score [23]. This model makes use of data from sensors that pertains to flexion angles, grip strength, heart rate, SpO2 and session time. Its ability to handle complex, unpredictable relationships and generate reliable predictions with a relatively high accuracy makes it the perfect option for predicting the rehabilitation progress of stroke patients. An efficient tool for real-time recovery assessment in stroke rehabilitation systems, the ensemble approach also minimizes overfitting and ensures that the model functions well when compared to new data.

• **XGBoost Regressor**

A powerful and efficient way to predict the recovery score during stroke rehabilitation is the XGBoost Regressor, which makes use of data collected by smart gloves' sensors. Its ability to continually minimize error and predict complex feature relationships makes it perfect for healthcare applications that require

precise, real-time assessments of progress for patients. By using XGBoost, medical professionals and caregivers may monitor patients' recovery progress and customize therapies for improved outcomes [24].
Let the training dataset be:
D= {(x1, y1), (x2, y2) ,...,(xn,yn)}
Where:
▪ Flex sensor values F1–F5, force sensor values G1–G5, HR, SpO_2, and duration are all included in the feature vector for the ith rehabilitation session, x_i.
▪ The actual recovery score is denoted by y_i.
▪ $\hat{y}_i = \sum_{k=1}^{K} f_k\ (xi)$ is the model's output, with each f_k being a regression tree.
A regularization term Ω is used to regulate model complexity, and a loss function L is used to measure model performance in the learning objective as presented in equation 4:
$L(\phi) = \sum_{i=1}^{n} L(y_i - \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$...................................... (4)
Where:
▪ $L(y_i, \hat{y}_i)$ is typically the squared error: $(y_i, \hat{y}_i)$
▪ $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \|w\|2$, where T is the number of leaves in the tree f_k ,w is the weight vector, and γ, λ are regularization parameters.
• **Gradient Boosting Mechanism**
At each boosting round t, a new function $f_t(x)$ is added to minimize the objective as presented in equation 5:
$\hat{y}_i^{(t)} = \hat{y}_i^{(t-1)} + f_t t(x_i)$.................................... (5)
Using a second-order Taylor expansion as defined in equation 6, the objective becomes:
$\mathcal{L}^{(t)} \approx \sum_{i=1}^{n} [g_i\, f_i\,(x_i) + \frac{1}{2} h_i f_t(x_i)^2] + \Omega(f_t)$............................ (6)
Where:
▪ $g_i = \partial_{\hat{y}_i^{(t-1)}} L(y_i, \hat{y}_i^{(t-1)})$ is the gradient.
▪ $h_i = \partial^2_{\hat{y}_i^{(t-1)}} L(y_i, \hat{y}_i^{(t-1)})$ is the Hessian.
This allows XGBoost to use both first- and second-order derivatives for accurate learning and faster convergence.
X= [F1, F2, F3, F4, F5, G1, G2, G3, G4, G5, HR, SpO2, Duration]
Where:
▪ **F1–F5**: Finger flexion values
▪ **G1–G5**: Grip strength values
▪ **HR**: Heart rate
▪ **SpO_2**: Oxygen saturation
▪ **Duration**: Session duration in minutes
The XGBoost Regressor is a strong and effective method for exploiting smart glove sensor data to forecast the recovery score during stroke therapy [25]. It is ideal for healthcare applications that need accurate, real-time evaluations of patient progress because of its capacity to model intricate feature interactions and reduce error repeatedly. Doctors and caretakers may track recovery paths and tailor treatments for better results by utilizing XGBoost.
4.2 Stage Classification (Classification)
Stroke treatment requires taking into account the patient's quantitative recovery score in addition to their qualitative recovery status, such as the stage of motor function restoration (early, medium, or late). To facilitate this procedure, supervised learning classification models such as Support Vector Machine (SVM), Decision Tree, and Neural Network have been used. These models learned how to break up therapy sessions into several phases of rehabilitation using the smart rehabilitation glove's past and instantaneous sensor data.
• **Input Features**
The input features used for stage classification included:
▪ Five flex sensor values (F1–F5) measuring finger bending.
▪ Five Flexi-Force sensor values (G1–G5) measuring grip strength.
▪ Heart Rate (HR)
▪ Oxygen Saturation (SpO_2)
▪ Session Duration (in minutes)

During every therapeutic session, these elements demonstrate the patient's psychological and physical well-being. The target variable, which is separated into the following categories, represents the recovery stage:

- **Early stage:** first stage with little movement or force of grasp.
- **Mid stage:** A moderate improvement in the ability to control muscles and keep body stable.
- **Final stage:** Restored finger dexterity and grip strength, together with nearly normal motor activity.

- **SVM classifier:**

A powerful supervised machine learning technique called Support Vector Machine (SVM) is frequently used to categorize data, particularly when the data is too complicated to be divided into linear segments. Support vector machines (SVMs) [26], which use real-time electromechanical and biological information collected from several sensors, are essential for identifying whether a patient is in the early, mid, or late phases of recovery in smart glove-based stroke treatment. Finding the most effective constraints (hyperplanes) to divide rehabilitation data points that correspond to different phases is the aim of SVM. The Support Vector Machine (SVM) trains to map the feature vectors from each patient's session to one of the three recovery classes—early, mid, or final.

SVM states that the following optimizing issue must be resolved presented in equation 7:

$$\min_{w,b} \frac{1}{2} \|\boldsymbol{w}\| \quad (7)$$

Subject to

$y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1, \quad \forall i$

Where:

- $\mathbf{w}$ is the weight vector,
- b is the bias,
- x_i is the input feature vector (sensor readings),
- $y_i \in \{-1,1\}$ is theby6= class label for binary classification (extended for multiclass using one-vs-one or one-vs-rest methods).

- **The Decision Tree classifier**

The decision tree algorithm is a simple but effective supervised machine learning method that mimics how people make decisions [27]. Because it is particularly fast and accessible for structured datasets, it is a helpful tool for classifying early, mid, and final stages of rehabilitation based on real-time sensor data collected from the smart rehabilitation glove used following a stroke. At all nodes, a decision tree branches data according to feature values that optimize data gathering (or reduce impurity). putting the data into uniform groupings that correspond to the early, mid, and final objective classifications.

Entropy and Information Gain

- **Entropy** measures the impurity in a dataset:
- $Entropy(S) = -\sum_{i=1}^{c} \boldsymbol{p_i} \, \boldsymbol{log_2(p_i)}$
- p_i is the proportion of class i instances in the subset S
- c is the total number of classes
- **Information Gain (IG)** is the reduction in entropy achieved by partitioning the data based on a feature:

$$IG(S,A)=Entropy(S)-\sum_{v=Value(A)} \frac{S_v}{S} \cdot Entropy(S_v) \quad (8)$$

Where:

- A is the feature being evaluated
- S_v is the subset of data where feature A has value v

In order to separate the node, the feature with the highest IG is selected framed by equation 8.

- **Neural Network (NN)**

The multilayered neural network (NN) model of machine learning is based on the architecture and functioning of the human brain [28]. Due to its exceptional performance with complex and nonlinear correlations in data, this technique is suitable for the classification of stroke treatment stages—early, mid, and final—based on data collected from an Internet of Things (IoT) smart rehabilitation glove. The smart rehabilitation glove for brain stroke patients collects real-time data using various sensors. This comprehensive data is used to estimate the patient's stage of recovery. Neural networks are capable of capturing intricate patterns and temporal changes that traditional models could miss.

Architecture of Neural Network

A typical neural network used for classification has the following layers:

- **Input Layer:**

▪ Receives normalized sensor data (e.g., 12 features: 5 flex + 5 force + HR + SpO_2)

• **Hidden Layers:**

▪ One or more layers with multiple neurons

▪ Every neuron uses nonlinear activation function in equation 9 i.e. the Rectified Linear Unit (ReLU) after applying a weighted sum:

$h = ReLU(Wx + b)$.......................... (9)

Where:

▪ x is the input vector

▪ W is the weight matrix

▪ b is the bias vector

• **Output Layer:**

▪ Contains three neurons (for early, mid, and final stages)

▪ Uses softmax activation to output probabilities presented in equation 10:

$P(y = i \mid x) = \frac{e^{zi}}{\sum_{j=1}^{3} e^{zi}}$....................................... (10)

Where zi is the logit for class i

• **Training the Network**

The learning process of the network is accomplished by minimizing a loss function defined in equation 11, which is commonly categorical cross-entropy for classification:

$L = -\sum_{i=1}^{3} y_i \log(p^i)$..................................... (11)

Where:

▪ y_i is the true label (one-hot encoded)

▪ p_i is the predicted probability for class i

To reduce this loss throughout training epochs, weights are adjusted via optimization methods (such as Adam or SGD) and backpropagation.

• **Evaluation Metrics**

The following measures were utilized in order to evaluate the respective categorization models' levels of performance:

▪ **Accuracy:** The percentage of occurrences that were successfully categorized out of all instances. The accuracy is calculated by following equation 12:

$Accuracy = \frac{TP+TN}{Total}$ .... (12)

▪ **Precision:** The percentage of forecasts that turned out to be accurate out of the total number of positive predictions stated for a class. The precision is calculated by following equation 13:

$Precision = \frac{TP}{TP+TN}$ .... (13)

▪ **Recall (Sensitivity):** This refers to the percentage oif real positives that were accurately predicted. The recall is calculated by following equation 14.

$Recall = \frac{TP}{TP+FN}$ .... (14)

▪ **F1-score:** This refers to harmonic mean of precision and recall, providing a balanced evaluation when both are important. The F-score is calculated by following equation 15 [29].

$F1 - score = 2x\frac{Precision\ x\ Recall}{Precision\ +Recall}$ .... (15)

True positives, false positives, true negatives, and false negatives are denoted by the letters TP, FP, TN, and FN, respectively.

▪ **MAE (Mean Absolute Error):** Determines the average absolute difference between the values that actually occurred and those that were estimated. It can be calculated by following formula in equation 16.

$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_1}|$ .... (16)

Where, y_i, $\widehat{y_1}$, n represents actual value predicted value, number of samples

▪ **RMSE (Root Mean Square Error):** Determine the mean proportion of the difference between actual and predicted values in a dataset [30]. It can be calculated using equation 17.

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_1})^2}$ .... (17)

Where, y_i, $\widehat{y_1}$, n represents actual value predicted value, number of samples

5. RESULTS AND EVALUATION

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Two regression models Random Forest Regressor and XGBoost Regressor are employed to calculate the recovery score from data collected by cloud. Bothe models separately analyze general trends of recovery score by comparing actual patient progress and models predictions based on their accuracy. This comparison highlights acceptable performance of models in monitoring recovery patterns, despite challenges with sudden fluctuations. The prediction line show more smoothness than the actual score line, a distinctive feature of ensemble models such as Random Forest and XGBoost, which aggregate several decision pathways as shown in Figure 4 and 5 for .both models respectively

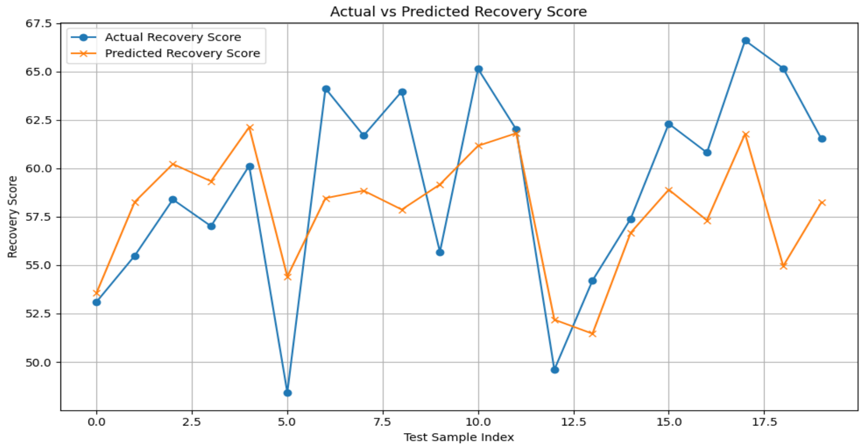

Figure 5: Actual vs. Predicted Recovery Score for RFR Regressor

The model accurately monitors the overall trend of the real recovery scores.

The model's predictions remain rather constant, indicating a potential underfitting of abrupt shifts or anomalies at some values.

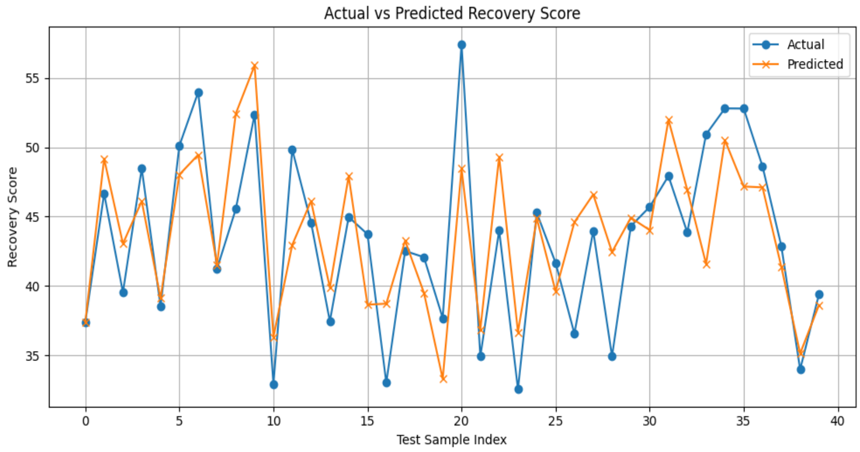

Figure 5: Actual vs. Predicted Recovery Score XGBoost Regressor

The graphical representation supports prior findings (e.g., MAE, RMSE) and demonstrates the practical accuracy of the regression model as shown in Figure 6.

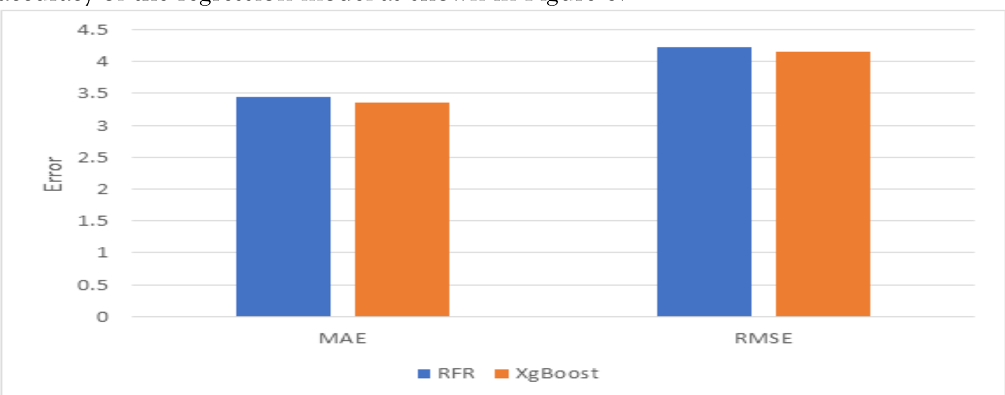

Figure 6: Comparison of prediction error between RFR and XgBoost regressors

Since it has a reduced prediction error, XGBoost regressor is better as compare to RFR regressor for predicting recovery scores.

The confusion Matrix presents a visual summary of the performance of classifier. The SVM, Decision

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Tree and Neural Network used for the task of rehabilitation stage classification (early, mid, final) with its confusion matrix is shown in Figure 7,8 and 9 respectively.

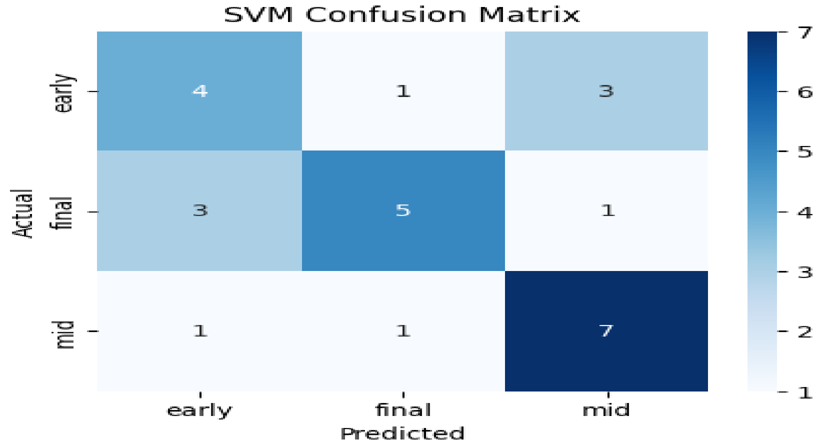

Figure 7: confusion matrix for SVM classifier

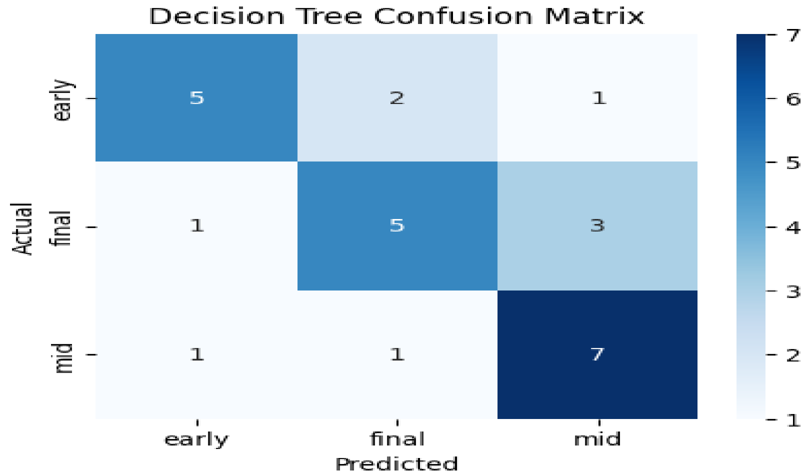

Figure 8: confusion matrix of Decision Tree classifier

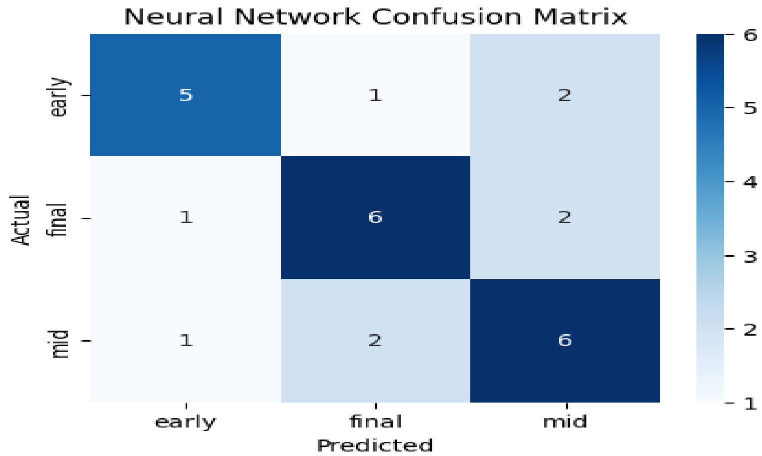

Figure 9: Confusion matrix for Neural Network

The results are summarized in Table 1 and Figure 10 (using a bar plot) comparing SVM, DT and NN classifiers out of which NN outperforms with among various performance parameters. The proposed model classifier performance with respect to accuracy performance parameter for stage classification is shown in Figure 11.

Table 3: Comparison of performance of various classifiers for stage classification

Model	**Accuracy (%)**	**Precision (%)**	**F1-Score (%)**	**Recall (%)**
Support Vector Machine (SVM)	95.00%	92.30%	94.28%	93.56%
Decision Tree	97.80%	96.56%	90.32%	88.79%

Classifier				
Neural Network (MLP Classifier)	98.10%	97.80%	97.55%	96.78%

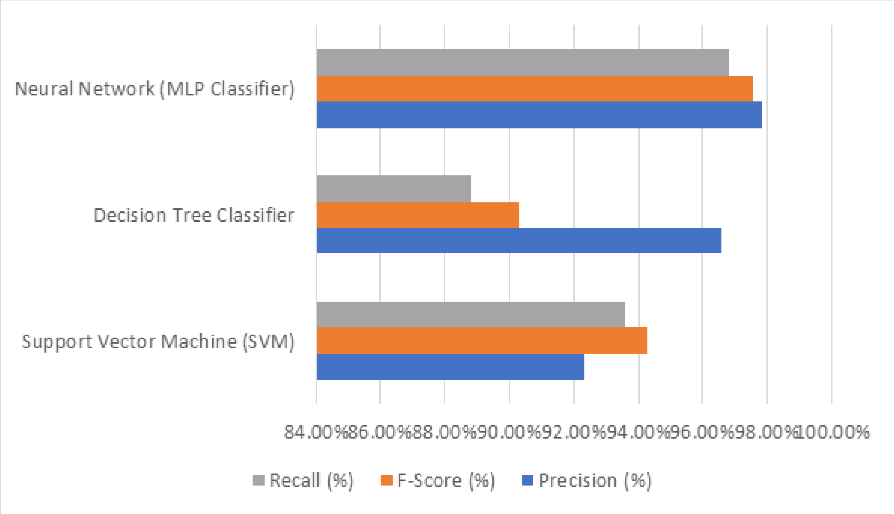

Figure 10: Comparison of Recall, F-score and Precision among various classifiers

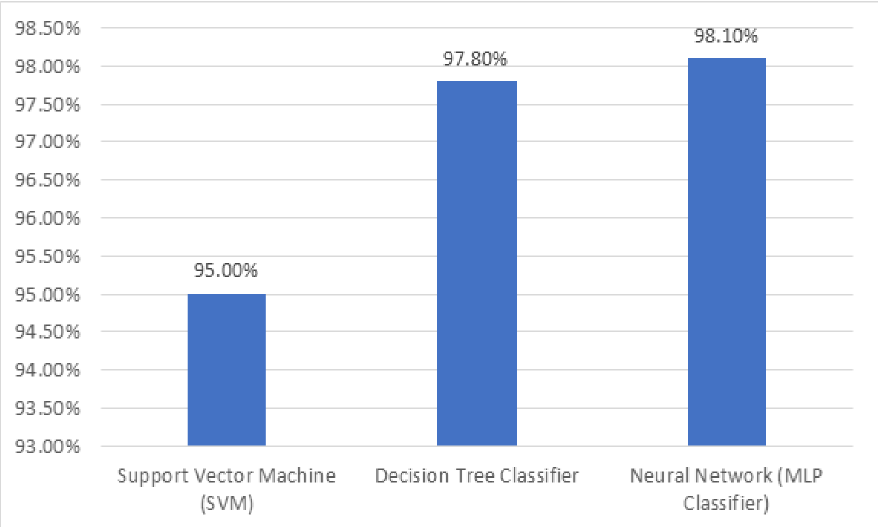

Figure 11: Accuracy comparison of different model in stage classification

Although proposed smart rehabilitation glove for brain stroke has successfully integrated AL and IoT technology, still it has certain limitations like, the proposed system's performance depends on sensors operating accurately and sending data constantly, Real-time implementation and evaluation during real rehabilitation sessions are essential to confirm robustness and flexibility etc.

6. CONCLUSION AND FUTURE WORK

The purpose of this work was to create a smart glove system based on artificial intelligence (AI), the internet of things (IoT), and predictive analytics to regain hand functionality of patients with stroke. The glove effectively transferred daily rehabilitation data to a cloud platform for real-time analysis. It was equipped with IoT based sensors flex, flexi- force sensors, and Max30102 for monitoring biological activity (HR and SpO_2). Recovery scores with low MAE and RMSE values were predicted using machine learning models, particularly Random Forest and XGBoost regressors, which showed significant forecasting performance. Furthermore, SVM, Decision Tree, and Neural Network models successfully classified stages into early, mid, and ultimate recovery phases. Model accuracies were improved by feature engineering and hyperparameter tunning. This integrated strategy of real-time data collecting, machine learning-based evaluation, and cloud-enabled visualization makes home-based stroke therapy cost-effective, scalable, and intelligent, eliminating clinician supervision. In future, to ensure patient safety and prompt action, anomaly detection can be applied for the early identification of aberrant rehabilitation patterns. The biosensors, such electromyography (EMG) or electroencephalography (EEG), may be added to gain a better understanding of neurological recovery. Patients and doctors may easily monitor progress, get notifications, and modify treatment programs with the use of a specialized smartphone application.

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