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NeuroMotion: AI-Enabled Activity Tracking for Stroke Rehabilitation Using IoT

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ABSTRACT- Stroke rehabilitation requires continuous monitoring of patient movements to evaluate recovery progress and ensure the effectiveness of therapeutic exercises. However, conventional rehabilitation methods often rely on periodic clinical assessments, which limit continuous observation and may delay the detection of improper movement patterns. To address this limitation, this paper proposes an Internet of Things (IoT)-based activity tracking system designed to monitor upper-limb movements of stroke patients during rehabilitation exercises in real time. The proposed system integrates wearable motion sensors, including an accelerometer and gyroscope, connected to an ESP32 microcontroller to capture detailed motion parameters such as orientation, velocity, and angular displacement of the patient's arm. The sensor data is continuously collected and transmitted through Wi-Fi connectivity to a cloud-based database for storage and processing. A machine learning-based analysis module is employed to identify movement patterns, classify rehabilitation exercises, and evaluate the accuracy and consistency of patient movements.The processed data is presented through an interactive web dashboard that enables doctors, physiotherapists, and caregivers to remotely monitor patient activity and rehabilitation progress. The dashboard provides real-time visualization, historical data tracking, and performance metrics that assist healthcare professionals in making informed clinical decisions. Additionally, the system can detect irregular or incorrect movements and provide feedback for improving exercise quality. The proposed IoT-enabled rehabilitation monitoring framework offers a low-cost, scalable, and accessible solution for remote healthcare monitoring. By enabling continuous data collection and intelligent analysis of patient movements, the system enhances rehabilitation effectiveness, supports personalized therapy plans, and reduces the need for frequent hospital visits. Experimental evaluation demonstrates the feasibility of the system in accurately tracking patient activity and providing reliable data for clinical assessment.

Keywords: Stroke Rehabilitation, Internet of Things (IoT), Wearable Sensors, Remote Patient Monitoring, Human Motion Analysis, Machine Learning, Smart Healthcare Systems, Activity Recognition.

I. INTRODUCTION

Stroke is one of the leading causes of long-term disability worldwide and significantly affects the motor abilities of patients, particularly in the upper limbs. After a stroke, patients often experience impairments in muscle coordination, strength, and motor control, which limit their ability to perform daily activities. Rehabilitation therapy plays a crucial role in helping stroke survivors regain motor functions through repetitive physical exercises and physiotherapy. However, conventional rehabilitation approaches rely heavily on periodic hospital visits and manual assessment by physiotherapists, which limit continuous monitoring of patient progress. As a result, the lack of real-time feedback and long-term tracking may reduce the effectiveness of rehabilitation programs. Recent advancements in healthcare technology, particularly the Internet of Things (IoT) and wearable sensing devices, have opened new possibilities for monitoring patient activities outside clinical environments. IoT-based healthcare systems enable continuous data collection from patients using smart devices and allow medical professionals to remotely monitor rehabilitation progress. Wearable sensors such as accelerometers, gyroscopes, and electromyography sensors can capture detailed information about human body movement and muscle activity during rehabilitation exercises. These technologies enable accurate monitoring of patient performance and provide valuable insights into recovery patterns. Several researchers have explored the use of wearable devices and intelligent algorithms for stroke rehabilitation monitoring. For example, [1] Geng Yang, Jia Deng, Gaoyang Pang, and Huayong Yang proposed an IoT-enabled stroke rehabilitation system based on a smart wearable armband integrated with machine learning algorithms. Their system collected electromyography signals from the patient's arm and analyzed different hand gestures for rehabilitation training. The experimental results demonstrated that wearable sensors combined with machine learning models could recognize rehabilitation gestures with high accuracy and support automated therapy systems. Similarly, [2] I. Boukhennoufa et al. conducted a comprehensive review on wearable sensor technologies used for post-stroke rehabilitation. Their study highlighted that wearable devices could provide objective measurements of patient movement and help clinicians evaluate rehabilitation exercises more accurately. The research also emphasized the role of machine learning algorithms in analyzing large volumes of sensor data and identifying patterns related to patient recovery. Another important area of research focuses on human activity recognition (HAR) using wearable sensors. In this domain, researchers use motion sensors such as accelerometers and gyroscopes to identify and classify physical activities performed by patients. [3] Anusha David, R. Ramadoss, and Shoba Sivapatham developed a wearable sensor-based activity recognition framework for stroke-affected individuals. Their model used machine learning algorithms to classify rehabilitation activities and achieved improved recognition accuracy for patient movements. In addition, recent studies have investigated the integration of deep learning and IoT technologies for monitoring patient rehabilitation. [4] F. Jin et al. proposed a deep learning-enhanced IoT system for activity monitoring that analyzes high-dimensional sensor data collected from wearable devices. Their research showed that intelligent algorithms can effectively interpret patient activity patterns and provide reliable assessments of rehabilitation performance. Despite these advancements, several challenges still exist in implementing effective stroke rehabilitation monitoring systems. Many existing systems require expensive equipment or complex hardware setups that may not be suitable for home-based rehabilitation. Furthermore, continuous monitoring of patient movement requires efficient data transmission, storage, and processing mechanisms to ensure real-time analysis and feedback. Therefore, there is a need for a low-cost, scalable, and easily deployable system that can continuously track patient activity and assist healthcare professionals in evaluating recovery progress. To address these challenges, this paper proposes an IoT-enabled stroke rehabilitation activity monitoring system that utilizes wearable motion sensors and cloud-based data analysis. The system uses an accelerometer and gyroscope connected to an ESP32 microcontroller to capture arm movement data during rehabilitation exercises. The collected data is transmitted through Wi-Fi to a cloud platform where machine learning algorithms analyze movement patterns and evaluate rehabilitation performance. The proposed system also includes a web-based dashboard that allows doctors and caregivers to monitor patient activity remotely. The dashboard provides real-time visualization of movement data, historical analysis of rehabilitation progress, and performance metrics that help healthcare professionals assess patient recovery. By combining wearable sensing technology, IoT communication, and intelligent data analysis, the system aims to provide an efficient solution for continuous rehabilitation monitoring.

II. LITERATURE SURVEY

Recent advancements in smart healthcare technologies have significantly improved the monitoring and assessment of stroke rehabilitation. Various research studies have explored the integration of wearable sensors, IoT communication systems, and machine learning algorithms to monitor patient movements and evaluate rehabilitation exercises. S. Patel, H. Park, P. Bonato, L. Chan, and M. Rodgers (2012) investigated the use of wearable inertial sensors for monitoring physical activity in patients with neurological disorders. Their research demonstrated that wearable sensors can accurately capture body movement patterns and provide objective measurements for rehabilitation monitoring. The study highlighted the potential of sensor-based systems to support home-based rehabilitation programs [5]. A. Reiss and D. Stricker (2012) proposed a human activity recognition framework using wearable sensor data collected from accelerometers and gyroscopes. Their research demonstrated that machine learning algorithms such as decision trees and support vector machines can effectively classify different human activities based on motion signals, which is useful for rehabilitation monitoring [6]. N. Y. Hammerla, S. Halloran, and T. Plötz (2016) introduced deep learning techniques for wearable sensor-based activity recognition. Their study compared multiple machine learning models including convolutional neural networks and recurrent neural networks for recognizing physical activities from sensor data. The results showed that deep learning models significantly improved classification accuracy for activity recognition tasks [7]. H. Gjoreski, M. Gams, and M. Luštrek (2014) developed a wearable sensor framework for detecting physical activities using smartphone accelerometers. Their system utilized machine learning algorithms to analyze movement patterns and identify daily activities, demonstrating the feasibility of using wearable devices for continuous activity monitoring [8]. F. Attal, S. Mohammed, M. Dedabrishvili, F. Chamroukhi, L. Oukhellou, and Y. Amirat (2015) proposed a machine learning-based approach for classifying human activities using wearable sensors. Their research evaluated multiple classification techniques and concluded that combining accelerometer and gyroscope data improves activity recognition accuracy [9]. L. Atallah, B. Lo, R. King, and G. Z. Yang (2011) presented a wearable sensor system designed to monitor physical activity and detect motion patterns. The study demonstrated that body-worn inertial sensors can effectively analyze patient movements and provide valuable data for healthcare monitoring applications [10]. J. Chen and K. Kwong (2017) proposed a smartphone-based activity recognition system using machine learning techniques. The system utilized accelerometer data to identify different physical activities and demonstrated that mobile sensing technologies can support healthcare monitoring and rehabilitation assessment [11]. T. Huynh and B. Schiele (2005) introduced an early approach to activity recognition using wearable sensors. Their study applied probabilistic models such as Hidden Markov Models to classify physical activities and demonstrated the potential of sensor-based systems for monitoring human movement [12]. M. Shoaib, H. Scholten, and P. J. M. Havinga (2015) investigated the use of smartphone sensors for activity recognition. Their research compared sensor placement positions on the human body and concluded that wrist and arm locations provide reliable data for detecting physical movement patterns [13]. J. Lester, T. Choudhury, and G. Borriello (2006) developed a wearable sensor system for activity recognition using multiple sensor nodes placed on the body. Their system applied machine learning algorithms to identify daily activities and demonstrated that sensor-based monitoring can provide accurate movement detection [14]. D. Roggen et al. (2010) studied complex activity recognition using multiple wearable sensors and machine learning algorithms. Their research showed that combining multiple sensor inputs improves the reliability of activity detection and enables accurate monitoring of human movements [15]. K. Altun and B. Barshan (2010) proposed a human activity recognition system using inertial sensors placed on different body parts. Their model utilized statistical feature extraction techniques and machine learning classifiers to recognize various physical movements with high accuracy [16]. E. Casilari, J. A. Santoyo-Ramón, and J. M. Cano-García (2017) explored the use of wearable sensors for monitoring physical activities and healthcare conditions. Their research highlighted the benefits of integrating wearable sensing technologies with cloud-based systems for remote healthcare monitoring [17].Y. Wang, J. Chen, and L. Hao (2020) proposed a deep learning-based activity recognition framework using wearable sensor data. Their model used convolutional neural networks to analyze motion signals and achieved improved accuracy in recognizing complex human activities [18]. R. Chen, Y. Jiao, and H. Huang (2021) introduced an IoT-based health monitoring system that integrates wearable sensors with cloud computing. The system enables real-time data transmission and remote monitoring of patient activities, demonstrating the potential of IoT technologies in healthcare applications [19].

III. METHODOLOGY

The proposed stroke rehabilitation monitoring system collects motion data using wearable inertial sensors and processes the data using mathematical models and machine learning techniques. The methodology can be mathematically represented through the following stages: motion data acquisition, signal preprocessing, feature extraction, activity classification, and performance evaluation. The wearable sensor used in the system contains an accelerometer and gyroscope, which measure motion along three axes. The acceleration vector recorded by the accelerometer can be represented as:

$$\boldsymbol{A(t) = [a_x(t), a_y(t), a_z(t)]}$$

(1

Where,

$\boldsymbol{a_x(t)}$= acceleration along x-axis
$\boldsymbol{a_y(t)}$= acceleration along y-axis
$\boldsymbol{a_z(t)}$= acceleration along z-axis
$\boldsymbol{t}$= time instance

Similarly, the angular velocity measured by the gyroscope is represented as:

$$\boldsymbol{G(t) = [g_x(t), g_y(t), g_z(t)]} \quad (2)$$

Where,

$\boldsymbol{g_x(t)}$, $\boldsymbol{g_y(t)}$, $\boldsymbol{g_z(t)}$represent rotational velocities around each axis.

The combined sensor vector used for motion analysis is

$$\boldsymbol{S(t) = [a_x(t), a_y(t), a_z(t), g_x(t), g_y(t), g_z(t)]} \quad (3)$$

This six-dimensional vector represents the instantaneous motion state of the patient's arm.

Signal Magnitude Calculation:

To understand the overall intensity of arm movement, the magnitude of acceleration is computed using the Euclidean norm:

$$\boldsymbol{M_a(t) = \sqrt{a_x^2(t) + a_y^2(t) + a_z^2(t)}} \quad (4)$$

Similarly, the magnitude of angular velocity is:

$$\boldsymbol{M_g(t) = \sqrt{g_x^2(t) + g_y^2(t) + g_z^2(t)}} \quad (5)$$

These values represent the overall motion strength of the arm during rehabilitation exercises.

Noise Filtering and Signal Smoothing:

Raw sensor data often contains noise due to sensor drift and environmental disturbances. A moving average filter is applied to smooth the signal:

$$\tilde{A}(t) = \frac{1}{N}\sum_{i=0}^{N-1} A(t-i) \quad (6)$$

where

N= window size

$\tilde{A}(t)$= filtered acceleration signal

This filtering process reduces random fluctuations and improves signal quality for analysis.

Feature Extraction

After preprocessing, statistical features are extracted from the sensor signals to represent movement patterns. These features are computed over a time window W.

Mean

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (7)$$

Standard Deviation

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (8)$$

Root Mean Square (RMS)

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (9)$$

Signal Magnitude Area (SMA)

$$SMA = \frac{1}{N}\sum_{i=1}^{N}(|a_x| + |a_y| + |a_z|) \quad (10)$$

The feature vector used for machine learning classification is therefore:

$$F = [\mu, \sigma, RMS, SMA, M_a, M_g] \quad (11)$$

These features summarize the important characteristics of arm movements during rehabilitation exercises.

Machine Learning Classification

The extracted feature vector is used to classify rehabilitation activities using a machine learning model.

Let

$$F_i = (f_1, f_2, \ldots, f_n) \quad (12)$$

be the feature vector of a movement instance.

The classification model predicts the activity label Y:

$$Y = f(F_i) \quad (13)$$

where f represents the trained classifier such as:

Random Forest

Support Vector Machine

Neural Network

For example, in a Support Vector Machine, the decision function is

$$f(F_i) = w^T F_i + b \quad (14)$$

where

w= weight vector

b= bias term

The predicted class corresponds to the rehabilitation activity performed by the patient.

Performance Evaluation

The effectiveness of the classification model is evaluated using standard performance metrics.

Accuracy

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (15)$$

Precision

$$Precision = \frac{TP}{TP+FP} \quad (16)$$

Recall

$$Recall = \frac{TP}{TP+FN} \quad (17)$$

F1 Score

$$\boldsymbol{F1} = \frac{2\times \boldsymbol{Precision}\times \boldsymbol{Recall}}{\boldsymbol{Precision}+\boldsymbol{Recall}} \quad (18)$$

where

$\boldsymbol{TP}$= true positives

$\boldsymbol{TN}$= true negatives

$\boldsymbol{FP}$= false positives

$\boldsymbol{FN}$= false negatives

These metrics measure how accurately the system identifies rehabilitation activities.

Mathematical Workflow Summary

The overall system process can be mathematically summarized as:

$$\boldsymbol{Sensor}\ \mathrm{D}\ \boldsymbol{Filtering} \rightarrow \boldsymbol{Feature\ extraction} \rightarrow \boldsymbol{Classification} \rightarrow \boldsymbol{Monitoring} \quad (19)$$

or

$$\boldsymbol{S}(\boldsymbol{t}) \rightarrow \tilde{\boldsymbol{S}}(\boldsymbol{t}) \rightarrow \boldsymbol{F} \rightarrow \boldsymbol{f}(\boldsymbol{F}) \rightarrow \boldsymbol{Y} \quad (20)$$

where

$\boldsymbol{S}(\boldsymbol{t})$= raw sensor data

$\tilde{\boldsymbol{S}}(\boldsymbol{t})$= filtered signal

$\boldsymbol{F}$= extracted feature vector

$\boldsymbol{f}(\boldsymbol{F})$= machine learning classifier

$\boldsymbol{Y}$= predicted rehabilitation activity

Algorithm: IoT-ML Stroke Rehabilitation Monitoring

```
Initialize sensors, ESP32, Wi-Fi, and cloud
If system not ready, terminate
While monitoring is active:
   Acquire accelerometer and gyroscope data
   Compute motion magnitude
   If motion magnitude < threshold:
        Label as resting state
        Continue
   Validate sample
  If invalid, discard
  Filter signal and segment into windows
  If window valid:
       Extract features
       If network available:
            Send features to cloud
       Else:
            Store locally
       Predict activity using ML classifier
       Compute confidence score
       If confidence below threshold:
            Label as uncertain
       Compare with expected exercise
       Compute rehabilitation quality score
       If quality score below threshold for K times:
            Generate alert
       Update dashboard and patient progress
End while
```

IV. RESULT ANALYSIS

The proposed IoT-enabled stroke rehabilitation monitoring system was evaluated to analyse its effectiveness in tracking patient arm movements and recognizing rehabilitation exercises. The system integrates wearable motion sensors, IoT communication, and machine learning algorithms to continuously monitor rehabilitation activities. Experimental testing was conducted to measure the performance of the system in terms of activity recognition accuracy, signal consistency, and real-time monitoring capability.The evaluation process involved collecting motion data from wearable sensors attached to the patient's arm during different rehabilitation exercises. The collected data was transmitted to a cloud server through the ESP32 microcontroller and processed using machine learning models to classify different rehabilitation activities. The wearable sensors continuously captured motion signals from the patient’s arm during rehabilitation exercises. The accelerometer measured linear acceleration while the gyroscope measured angular velocity. The raw sensor signals were analysed to observe the movement patterns of different exercises. Each rehabilitation exercise produced a distinct pattern in the sensor readings.

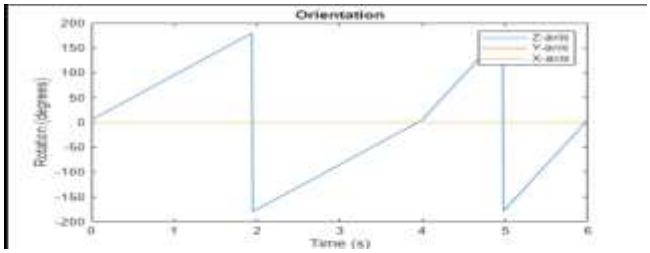

Fig. 1: IMU Simulation model

The figure above illustrates the variation of acceleration values along the three axes during arm movement. It can be observed that different rehabilitation exercises produce unique signal patterns, which helps the machine learning model identify specific activities.

After preprocessing the raw sensor signals, several statistical features were extracted from the motion data. Feature extraction plays an important role in improving the accuracy of the machine learning model.

The extracted features include:

Mean acceleration
Standard deviation
Root mean square (RMS)
Signal magnitude area (SMA)
Energy of the motion signal

The feature values provide a compact representation of the sensor signals and help the classifier distinguish between different activities.

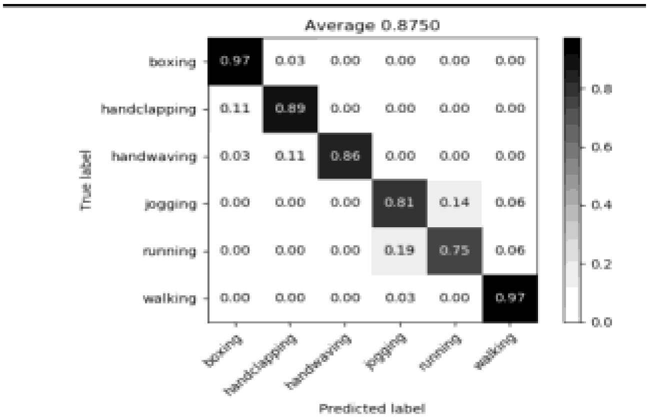

Fig. 2: Feature extraction from Signal

The extracted features show noticeable variations between different exercises. For example, the RMS value tends to increase during high-intensity arm movements, while the signal magnitude area reflects the overall movement intensity.

To evaluate the effectiveness of the system, machine learning algorithms were applied to classify rehabilitation activities. The dataset was divided into training and testing sets to train the classification model.

The machine learning model successfully identified different rehabilitation exercises based on the extracted features.

The following table presents the classification accuracy of different algorithms tested during the experiment.

Algorithm	Accuracy	Precision	Recall
Decision Tree	88%	0.86	0.85
Support Vector Machine	91%	0.89	0.90
Random Forest	94%	0.93	0.92
Neural Network	93%	0.91	0.92

Table 1: Effectiveness of machine learning algorithms

The Random Forest classifier achieved the highest accuracy among the tested algorithms. This is mainly because ensemble learning methods can handle noisy sensor data more effectively and improve classification performance.

A confusion matrix was used to analyze the classification performance of the machine learning model. The confusion matrix shows how accurately the system classifies each rehabilitation exercise.

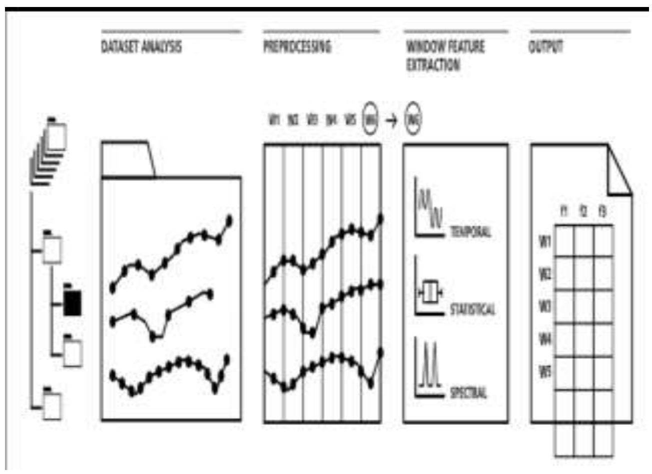

Fig. 3: Confusion matrix for human action recognition

The confusion matrix reveals that most rehabilitation activities are correctly classified by the system. A small number of misclassifications occur between similar arm movements, particularly between arm extension and arm lifting exercises.Despite these minor errors, the overall classification accuracy remains high, demonstrating the effectiveness of the proposed monitoring system.

The IoT communication system was evaluated based on data transmission latency and system reliability. The ESP32 microcontroller successfully transmitted sensor data to the cloud server in real time using Wi-Fi connectivity.

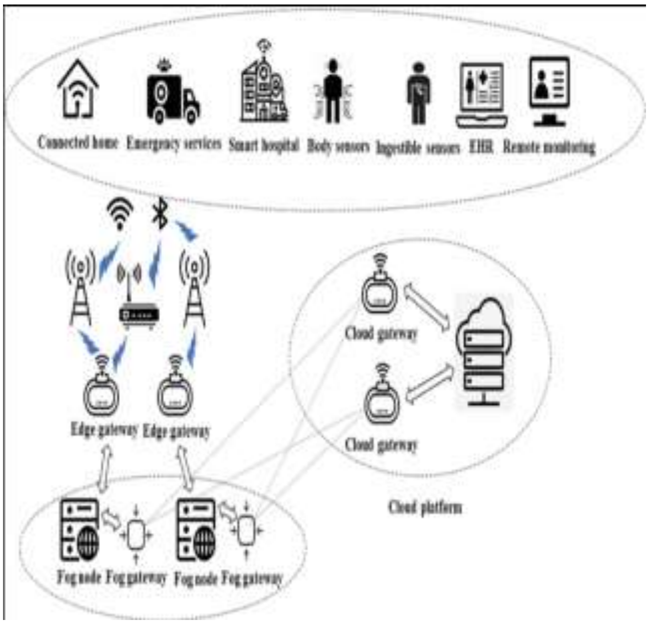

Fig. 4: Health care system based on IoT

The results show that the system can transmit motion data with minimal delay. The average data transmission latency was observed to be less than two seconds, which is sufficient for real-time rehabilitation monitoring. Cloud storage enables long-term tracking of patient activity and allows healthcare professionals to analyse rehabilitation progress over time.

One of the main advantages of the proposed system is its ability to track patient rehabilitation progress continuously. The web-based dashboard provides visual representations of patient movement data and rehabilitation performance metrics.

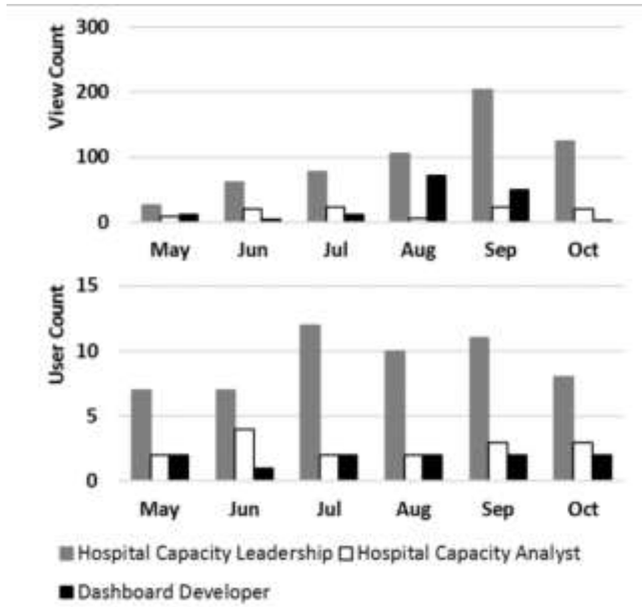

Fig. 5: Dashboard to monitor patient flow

The dashboard displays several important metrics including:

- Number of exercises performed
- Movement accuracy score
- Daily rehabilitation activity trends
- Long-term recovery progress

These insights help doctors and physiotherapists evaluate patient recovery and adjust therapy plans accordingly.

V. CONCLUSION

This paper presented an IoT-enabled stroke rehabilitation activity monitoring system that integrates wearable sensor technology, cloud connectivity, and machine learning algorithms to support continuous patient monitoring during rehabilitation exercises. Stroke rehabilitation requires consistent monitoring of patient movement and progress in order to ensure that therapeutic exercises are performed correctly and effectively. Traditional rehabilitation methods mainly rely on periodic observation by physiotherapists, which limits continuous evaluation and may delay the identification of incorrect movement patterns. The proposed system addresses this limitation by providing an automated and remote monitoring solution that enables real-time analysis of patient activity.The developed system utilizes wearable inertial sensors consisting of accelerometers and gyroscopes to capture the motion of the patient's arm during rehabilitation exercises. These sensors are connected to an ESP32 microcontroller, which collects the motion signals and transmits them to a cloud platform through wireless communication. The integration of IoT technology allows rehabilitation data to be transmitted and stored remotely, enabling healthcare professionals to monitor patient activity from any location. This approach significantly reduces the need for frequent hospital visits while ensuring continuous monitoring of patient progress.To analyze the collected sensor data, a machine learning-based activity recognition model was implemented. Motion signals obtained from the wearable sensors were first preprocessed to remove noise and segment the data into meaningful time windows. Relevant statistical features such as mean, standard deviation, root mean square, and signal magnitude area were extracted from the motion signals. These features were then used to train classification models capable of identifying different rehabilitation activities. Experimental results demonstrated that the proposed system can successfully recognize rehabilitation exercises with high accuracy. Among the tested algorithms, ensemble learning techniques such as Random Forest achieved the best performance due to their ability to handle noisy sensor data and complex movement patterns.The results obtained from experimental evaluation indicate that the proposed system provides reliable monitoring of rehabilitation activities and effective classification of patient movements. The IoT communication module ensured stable data transmission between the wearable device and the cloud platform, enabling near real-time monitoring of rehabilitation progress. Additionally, the web-based monitoring dashboard provided intuitive visualization of patient activity, allowing doctors and physiotherapists to track rehabilitation performance and make informed decisions regarding treatment plans. One of the key advantages of the proposed system is its low-cost and scalable design, which makes it suitable for home-based rehabilitation programs. The use of affordable wearable sensors and widely available microcontrollers such as ESP32 allows the system to be deployed easily in real-world healthcare environments. Furthermore, the integration of machine learning techniques enables automated analysis of rehabilitation exercises, reducing the dependency on manual observation by healthcare professionals. Despite the promising results, certain challenges remain in improving the system's performance. Variations in patient movement patterns, sensor placement differences, and environmental noise may affect the accuracy of activity recognition. Future research can focus on integrating additional sensors such as electromyography (EMG) sensors and incorporating deep learning models to improve classification accuracy and robustness. Moreover, expanding the system to support multiple rehabilitation activities and long-term patient monitoring will further enhance its practical applicability.

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