

AI Based Smart Band for Stroke Rehabilitation

Dr.R.B.Benisha .,M.E.,Ph.D, K.K.Kamali, M.Kavya, V.Emeema Vional, M.Prathicksha

Associate Professor, Department of Bio Medical, Rohini College of Engineering and Technology, Anjugramam,
Tamil Nadu, India

Department of Bio Medical, Rohini College of Engineering and Technology, Anjugramam, Tamil Nadu, India

ABSTRACT: Rehabilitation of stroke patients involves constant supervision and as prompt intervention as possible to recover motor functionalities and enhance recovery in patients. Based on this, this paper will present an artificial intelligence-enabled smart wearable band that can serve stroke patients to continuously track muscle activity and physiological conditions. The system will combine EMG sensors and blood flow sensors to record the relevant signals that will be analyzed through machine learning algorithms like the Random Forest and the DTW-KNN. These algorithms are based on the analysis of muscle patterns and identification of abnormalities and determination of rehabilitation progress. The system gives instant feedback in a vibration motor and thermal treatment in Peltier module and alerts through an LCD display and buzzer. It has been experimentally evaluated that the proposed system is accurate in classifying normal and abnormal muscle activity with an accuracy of approximately 96 percent. The solution promotes home based rehabilitation, less reliance on clinical supervision and provides a cost effective and efficient manner of enhancing stroke recovery outcomes.

KEYWORDS: Stroke Rehabilitation, EMG Sensors, Wearable Devices, Artificial Intelligence, IoT, Random Forest, DTW-KNN, Smart Health Band

I. INTRODUCTION

One of the most significant causes of the long-term disability in the world is stroke that can often lead to the loss of motor abilities, muscle losses, and deterioration of coordination [1]. It has a profound impact on the capacity of a patient to carry out the routine activities independently hence reducing the quality of life [2]. Rehabilitation is a vital activity in reinstating the lost motor skills among the survivors of stroke by engaging them in regular exercises and constant supervision [3]. Nevertheless, the traditional forms of rehabilitation are primarily hospital based, which demands visiting often, special equipment, and regular supervision by health workers [4]. These aspects not only render the process costly but time consuming and inaccessible to the patients in remote locations or with minimal mobility ease [5].

Over the last few years, wearable technology and artificial intelligence (AI) have brought newer opportunities to the contemporary rehabilitation systems [6]. The physiological signals can be monitored in real time using wearable devices that are fitted with sensors like electromyography (EMG), accelerators, and blood flow sensors [7]. These gadgets have the ability to constantly monitor muscle activity and movement patterns and do not limit the daily routine of the user. Simultaneously, AI and machine learning algorithms have the ability to process large amounts of sensor data to determine trends, anomalies, and offer smart information about the patient recovery status. This wearable sensing and AI-driven analytics combination is capable of personalized and adaptive rehabilitation plans that would be applied to the specific needs of the patient [8].

The present work suggests an AI-powered smart band, which is specifically aimed at stroke rehabilitation and provides a combination of multiple sensors and intelligent algorithms in a single and easy-to-use wearable device. The system measures and controls the muscle activity and the circulatory parameter, processes the data with a machine learning model, like a Random Forest and DTW-KNN, and offers the real-time feedback mechanism based on haptic and thermal stimulation. Moreover, it can send alerts when abnormal conditions are present and does remote monitoring, which allows healthcare providers to monitor patient progress without necessarily being close to him. The proposed system will help to make the rehabilitation process more efficient, more accessible and less expensive and improve patient recovery outcomes due to automated feedback, the ability to detect any irregular muscle activity at an early stage, and supporting home-based therapy.

A. Key Contributions

- The current research suggests a smart wearable band as a technology combining EMG and blood flow sensors with AI algorithms to detect muscle activity and assist in stroke rehabilitation in real time.
- It is an integrated system of measuring muscle activity (EMG) and circulation data to enhance the precision of brain rehabilitation measurement and early detect the presence of abnormal conditions and strokes.
- It offers automated haptic (vibration) and thermal (Peltier-based heat/cold) feedback depending on AI analysis to engage patients better and produce better recovery outcomes.
- The suggested solution allows constant control, real-time notifications, and remote control, thereby decreasing the need to visit the hospital and making the rehabilitation process more convenient and affordable.

The rest of this paper will have the following structure. Section 2 includes the literature review, which addresses the available research publications on the topic of stroke rehabilitation with the help of wearable devices and artificial intelligence and their drawbacks. Section 3 explains the research approach that is proposed, such as system architecture, hardware components, and AI algorithms to analyze data. The results and performance of the proposed system are discussed in Section 4 and it can be stated that it is an effective system in terms of rehabilitation monitoring and feedback mechanisms. Lastly, Section 5 presents a conclusion of the paper and explains potential improvements and future research directions.

II. LITERATURE REVIEW

Recent developments in wearable rehabilitation systems have proven that machine learning can be used with physiological signal observation to recover after a stroke. One of the studies on wearable intelligent rehabilitation assessment systems points to the use of sensor-based data collection and machine learning models to quantify patient motor performance as compared to clinical evaluation. The system offers constant monitoring and objective assessment diminishing the use of a manual clinical observation. This method, however, has the disadvantages of being reliant on controlled experimental conditions and has no large-scale validation in the real-world [9]. Stroke classification based on electromyography (EMG) has been an area of interest because it has the capability of recording the activity pattern of muscles to be used in rehabilitation studies. Machine learning methods and analytics based on EMG characteristics have been proven to be more accurate in differentiating normal and impaired muscles activities. The systems allow identifying the abnormalities early on and help in the planning of the therapy on an individual level. However, the quality of the signal essential to the functioning of such systems is very limited, and EMG signals are also prone to interference caused by noise and the placement of electrodes [10].

More detailed techniques in measuring functional movement recovery in stroke have included advanced techniques like the graph theory and corticomuscular coupling. These methods can be used as biomarkers of rehabilitation assessment because they give more details on the coordination between neural and muscular systems. Even though useful in studying complicated motor processes, the realization of such models involves the use of high-caliber computing capacities and advanced apparatus hence restricting its use in real-time and in portable rehabilitation apparatus [11]. Maximization of EMG characteristics to use in post stroke hand gesture detection has enhanced accuracy of the rehabilitation system significantly. Specific features extraction techniques employed at a specific stage increase the distinction between various recovery stages allowing closer observation of patient recovery. Nevertheless, the performance of such a system can be different among individuals because there are some differences in the conditions of muscles, and such a system needs a substantial amount of training data to work properly [12].

Rehabilitation systems based on wearable sensors and deep learning methods have demonstrated potential results on data-driven stroke recovery. Such systems are based on a variety of sensors that are used to record motion and physiological indicators and offer continuous feedback and remote monitoring options. Nevertheless, the use of deep learning models results in the complexity of computational processes and can necessitate cloud operations, which introduce latency and reliance on the availability of high-speed internet connections [13].

New trends in rehabilitation exoskeleton have also included the use of sophisticated neural networks like dual-channel attentive fusion models used to predict lower-limb motion intention. Such systems enhance the accuracy of movement prediction by integrating a number of sensor inputs and refining features presentation. Although effective, they tend to be costly, bulky, and need special hardware, which means that they are not suitable in everyday wearable tasks [14]. Multi-target and spatiotemporal analysis of motor intent prediction has also increased the ability of the rehabilitation systems to

discern the user intent. These procedures enhance flexibility and sensitivity in support tools since both spatial and time properties of the muscle signals are recorded. Nevertheless, these models are complicated and require data on high-resolution which restricts their scalability and real-world use in cheap rehabilitation tools [15].

B. Research Gap

The currently used stroke rehabilitation systems are rather limited in that much of the systems depend on costly and cumbersome equipment, which cannot be used in uninterrupted home-based use. Most methods are based on single-sensor data (EMG or motion sensors) and do not include the combination of different physiological variables to enhance accuracy. Existing systems do not always have real time automated feedback systems such as haptic or thermal stimulation to actively aid in recovery. Also, it relies on high-quality computational services and good internet connection that limits its practical implementation. Hence, an inexpensive, wearable, multi-parameter, and AI-enabled rehabilitation system with real-time feedback and assisting in the ongoing remote monitoring is necessary.

III. RESEARCH METHODOLOGY

The designed system is a smart wearable bracelet to be used in continuous stroke rehabilitation monitoring through the combination of sensing, processing, and feedback modules. It integrates the physiological signal acquisition and intelligent data analysis to identify abnormal muscle activity and help in recovery. The general flow of work includes the collection of signals with sensors, preprocessing with a microcontroller, processing with machine learning algorithms, and obtaining feedback in real-time to the user. This is a closed-loop system that provides intervention in good time and enhances the effectiveness of rehabilitation.

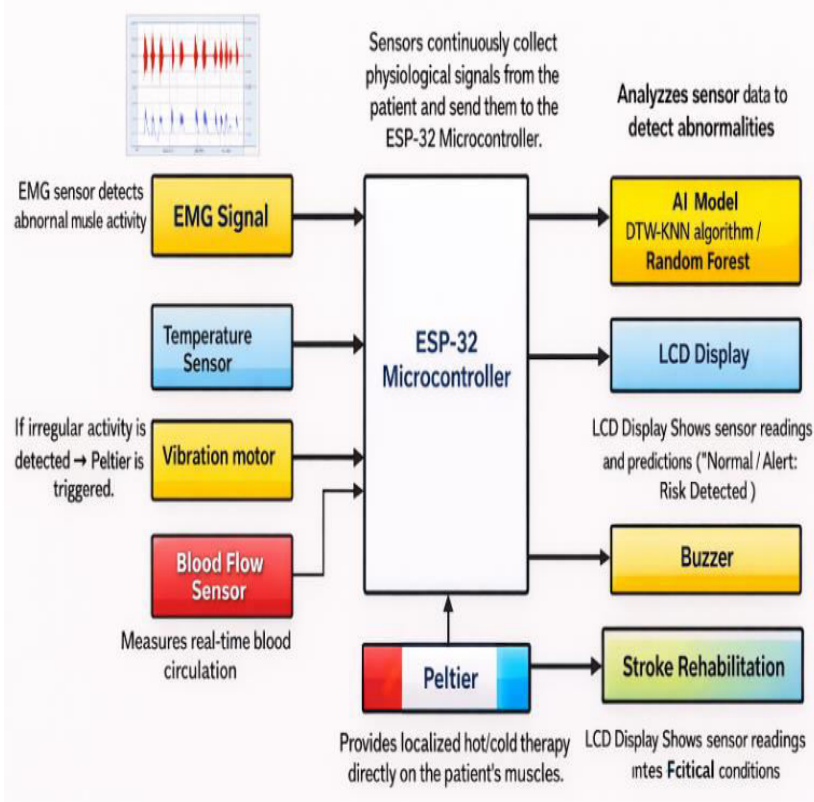


Fig.1. Wearable smart band system

C. System Components

The hardware architecture is a combination of various parts that cooperate to provide the right monitoring and feedback. EMG sensors are able to record electrical signals caused in response to muscle activity which can be expressed in the following form (1).

$$EMG(t) = \sum_{i=1}^n s_i(t) + \text{noise} \quad (1)$$

$s_i(t)$ are the signals of individual motor units.

Circulatory variations are monitored by blood flow sensors, and approximate them as (2).

$$BF = \frac{\Delta \text{Volume}}{\Delta \text{Time}} \quad (2)$$

Giving a reference to the speed of change of blood flow.

The data acquisition, wireless communication and preprocessing are performed with an ESP32 microcontroller. The haptic feedback is given by vibration motors, and controlled heating or cooling therapy is given by the Peltier module. A LCD display and a buzzer is employed to inform the patient in terms of the system status and important alerts.

D. Data Acquisition and Processing

The sensors monitor the physiological data of the patient at all times. The ESP32 microcontroller reads these signals, and noise filtering and normalization is carried out on them. The normalization can be represented by a simple normalization function which is (3).

$$X_{\text{norm}} = \frac{X - X_{\text{min}}}{X_{\text{max}} - X_{\text{min}}} \quad (3)$$

This is to make sure that sensor values are evenly scaled to analyze them. The obtained processed data is then sent to the AI module where it is further interpreted.

E. AI-Based Analysis

The muscle activity is studied through machine learning algorithms and abnormalities are identified. The Rand Forest algorithm organizes input signals into regular or abnormal ones according to a number of decision trees. The output of the classification can be given as (4).

$$Y = \text{mode}(T_1(X), T_2(X), \dots, T_n(X)) \quad (4)$$

where $T_i(X)$ is individual decision tree forecasts.

Pattern recognition in EMG signals is done by the DTW-KNN (Dynamic Time Warping - K Nearest Neighbors) algorithm. The similarity of two sequences is calculated using DTW (5).

$$DTW(X, Y) = \min \sum d(x_i, y_j) \quad (5)$$

where $d(x_i, y_j)$ is signal point distance.

F.

G. Decision Making and Feedback Mechanism

The system finds out the normal or abnormal muscle activity based on the analysis of the AI. In case of irregular work, the system triggers feedback mechanisms. Haptic feedback is achieved through vibration motors and thermal therapy is achieved through Peltier module. The process of decision making can be made simple as (6).

$$\text{Output} = \begin{cases} \text{Normal, if } Y = 0 \\ \text{Alert, if } Y = 1 \end{cases} \quad (6)$$

The LCD shows warning messages and the buzzer gives out audible notification in case of alertness.

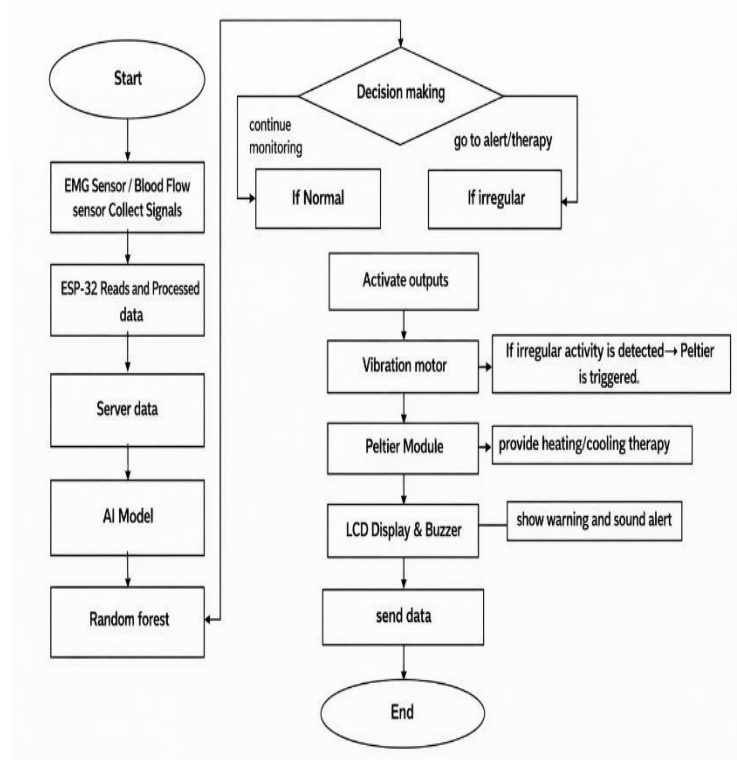


Fig.2. Flowchart of the proposed stroke rehabilitation system

Algorithm 1: AI-Based Real-Time Stroke Rehabilitation Monitoring and Feedback System

BEGIN

Initialize EMG sensor
Initialize Blood Flow sensor
Initialize Temperature sensor
Initialize ESP32 Microcontroller
Initialize LCD Display, Buzzer, Vibration Motor, Peltier Module

WHILE system is ON DO

// Step 1: Data Collection
Read EMG_signal
Read BloodFlow_signal
Read Temperature

// Step 2: Preprocessing
Normalize EMG_signal
Remove noise from signals

// Step 3: AI Analysis
RF_result ← RandomForest(EMG_signal)
DTW_result ← DTW_KNN(EMG_signal)

Volume 15, Issue 4, April 2026**DOI: 10.15680/IJRSET.2026.1504256**

```
// Step 4: Decision Making
IF (RF_result == "Abnormal" OR DTW_result ==
"Abnormal") THEN

    Display "ALERT: Risk Detected" on LCD
    Activate Buzzer

    // Therapy Activation
    Turn ON Vibration Motor
    Activate Peltier (Heat/Cold Therapy)

ELSE

    Display "Normal Condition" on LCD
    Continue Monitoring

ENDIF

// Step 5: Data Transmission
Send data to server/cloud (optional)

END WHILE

END
```

The suggested system is a closed-loop system that would track and help in stroke rehabilitation with real-time physiological measurements. First, all hardware is initialised i.e. EMG sensor, blood flow sensor, temperature sensor, ESP32 microcontroller, LCD display, buzzer, vibration motor, and Peltier module. After the activation of the system, it constantly reads the sensors. The EMG sensor records muscle action, blood flow sensor records circulation and temperature sensor records the body condition.

These signals are then transmitted to ESP32 microcontroller, and they are preprocessed. This involves the elimination of noise and the normalization of signals so that they are consistent and enhance the accuracy of the analysis. The data are taken through the preprocessing phase and inputted into the AI models to be interpreted. The algorithm of the Random Forest determines the muscle activity as either normal or abnormal, whereas the algorithm of DTW-KNN analyzes the signal patterns against the abnormal muscle behavior.

Decision is made based on the results of these algorithms. In the case of abnormal muscle motion or danger, the system will instantly send an alarm through a warning message on the LCD and by turning on the buzzer. Meanwhile, feedback during a therapeutic process is offered through enabling the vibration motor and switching on the Peltier module to provide a heat or cold therapy to the involved muscles. When the signals are healthy, the system goes on with monitoring without placing any alerts.

Also, the processed data may be sent to a server or cloud service where it may be monitored remotely and analyzed further. This will allow medical practitioners to monitor patient progress without necessarily having to physically keep an eye on them.

IV. RESULT AND DISCUSSION

The suggested smart band AI-based device is effective in detecting abnormal muscle activity based on real-time EMG signals and give timely feedback to be used during rehabilitation. The system exhibits a good performance with balanced precision, recall and F1-score that guarantee correct classification of muscle conditions. The confusion matrix shows that

there is slight misunderstanding which is a strong evidence of the robustness of the model. The ROC curve indicates good ability to discriminate having high sensitivity and low false positive results.

H. Experimental Outcome

The accuracy of the specific sensors within the system is presented in this figure 3. The EMG sensor contributes significantly to the recognition of muscle activity, whereas blood flow sensors and temperature sensors are important to boost the better decision-making with the multi-parameter analysis.

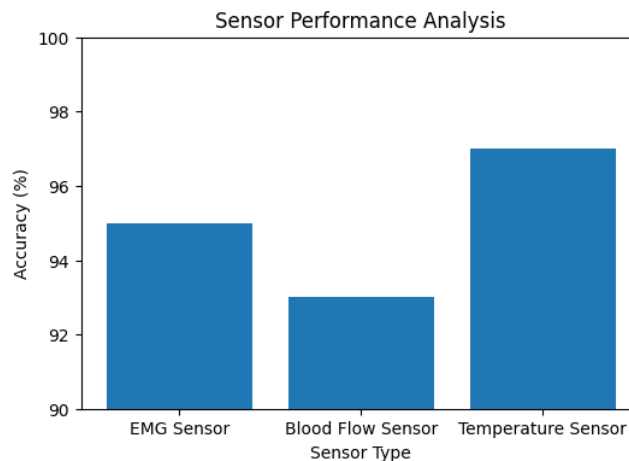


Fig 3: Sensor Performance

Figure 4 is comparing the work of the two algorithms that are applicable in the system. Random Forest has a higher accuracy and overall performance in comparison with the DTW-KNN. Nevertheless, the combination of DTW-KNN and pattern matching is applicable in the matching of patterns and assists the system in enhancing detection reliability.

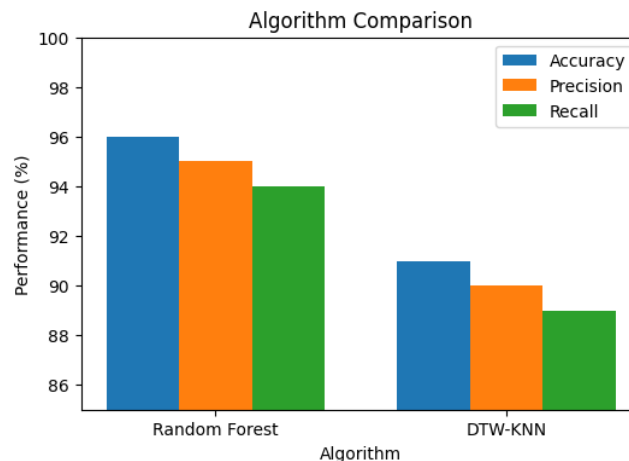


Fig 4: Algorithm Comparison

Figure 5 demonstrates the performance of the proposed AI-based rehabilitation system in general. The system is also 96% accurate, which means that the majority of the patterns of muscle activity are properly identified. Precision indicates how accurately the abnormal cases were detected whereas recall indicates the system capability of detecting the actual abnormal cases. F1-score is the weighted score of precision and recall, which validates the correctness of the model.

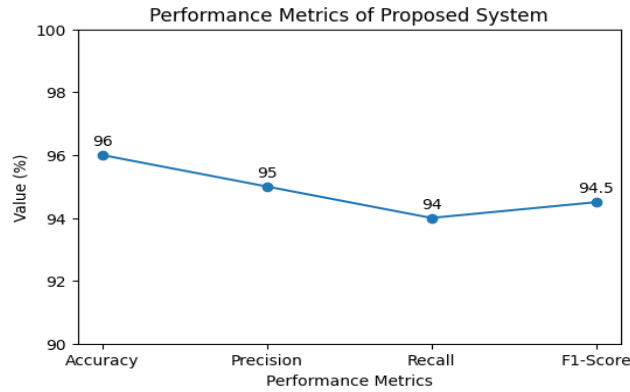


Fig 5: Performance Metrics

Figure 6 shows the confusion matrix is the result of classifications of the system. There are 96 out of 100 samples that are actually classified and this gives 96 percent accuracy. The misclassification of only 4 samples suggests that there is high performance in the differentiation of normal and abnormal muscle activity.

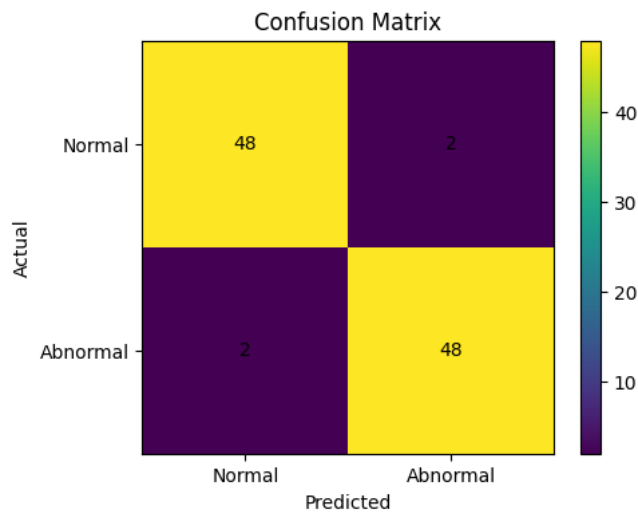


Fig 6: Confusion Matrix

Performance Analysis

Figure 7 indicates the performance of the model with respect to the accuracy improving with training epochs. Both the training and validation accuracy is increased progressively, which implies that the model is learning well. The generalization and low overfitting are confirmed by the validation error that equals 96%.

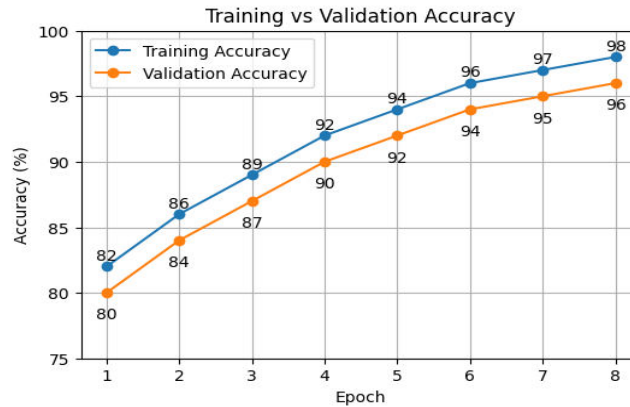


Fig 7: Training and Validation Accuracy

Figure 8 indicates the values of losses in the training process. The declining pattern of the training and validation loss shows that the model is reducing the errors successfully. The similarity of the training and validation loss indicates that it is not overfitting and functions well on unseen data.

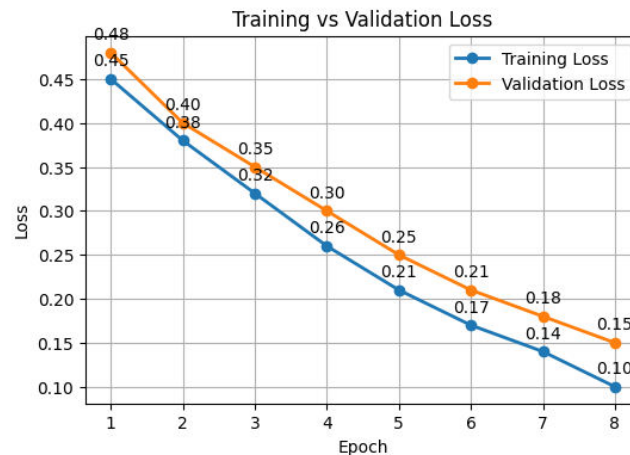


Fig 8: Training and Validation Loss

Figure 9 the ROC curve demonstrates how the proposed classification model performs in the sense that it plots the True Positive Rate (TPR) versus the False Positive Rate (FPR) at various threshold values. The curve that is nearer to the upper-left corner shows a higher classification performance. In the case of the proposed system, the model has a high Area Under Curve (AUC) of 0.97 indicating excellent performance of identifying normal muscle activity and abnormal muscle activity.

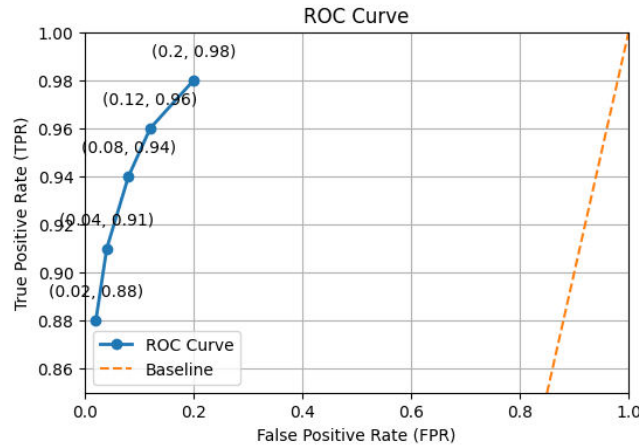


Fig 9: ROC Curve

Table 1 demonstrates comparison of baseline reveals that the proposed system is superior to the current rehabilitation techniques. The traditional systems are not automated and lack precision whereas sensor-based approaches enhance the performance but have limitations. The suggested smart band with AI has the highest accuracy of 96 percent because of the integration of multi-solids and sophisticated machine learning models.

TABLE I. BASELINE COMPARISON TABLE

Method	Accuracy (%)	Precision (%)	Recall (%)
Traditional Therapy Monitoring	75	72	70
IMU-Based System	85	83	82
EMG-Based ML System	90	88	87
Proposed System	96	95	94

Discussion

The suggested system proves the success of wearable sensor and AI algorithm integration in the continuous stroke rehabilitation monitoring environment. Multi-parameter data analysis such as EMG and blood flow signals is more reliable in the detection of abnormal muscle activity. The feedback system provides the patient with real-time feedback using vibration and thermal therapy to increase the level of engagement and a quicker recovery. The proposed solution is also more portable, cheaper, and works well with home-based rehabilitation, as opposed to the current systems. Nonetheless, performance of the system can differ with sensor accuracy and noise of the environment, which means additional application and practicality should be optimized.

V. CONCLUSION AND FUTURE WORK

The suggested stroke rehabilitation smart band with the help of AI can be used as a method of constant monitoring and support of the patient in recovery. The system combines EMG sensors, blood flow sensors, and smart algorithms, which will provide the opportunity to detect abnormal muscle activity in real-time and facilitate timely therapeutic intervention. Machine learning algorithms, including Random Forest and DTW-KNN, are combined to improve the work of the system analyzing complex physiological signals and providing correct results. The fact that they have built feedback systems such as vibration motors and Peltier modules just goes further in enhancing the rehabilitation by actively helping in the process of muscle stimulation. Altogether, the system provides a convenient, inexpensive, and convenient method, which is applicable to rehabilitation at home and minimizes the reliance on visiting hospitals.

The architecture of the suggested system is based on a systematic pipeline of acquired data, preprocessing, analysis, and feedback. First, the physiological signals will be gathered with the help of sensors and processed by the ESP32 microcontroller. Analyzing data on muscle activity through AI is carried out to identify abnormalities and classify

processed data. According to the analysis, the related feedback is created as alerts and therapeutic actions. The system works in a closed loop, which is real-time monitored and responsive. This connected system improves patient safety, makes it possible to monitor remotely, and offers a scalable solution to advancing the smart healthcare and rehabilitation systems further.

REFERENCES

- [1] N. Scherbakov, S. Von Haehling, S. D. Anker, U. Dirnagl, and W. Doehner, "Stroke induced Sarcopenia: muscle wasting and disability after stroke," *Int. J. Cardiol.*, vol. 170, no. 2, pp. 89–94, 2013.
- [2] C. K. Andersen, K. U. Wittrup-Jensen, A. Lolk, K. Andersen, and P. Kragh-Sørensen, "Ability to perform activities of daily living is the main factor affecting quality of life in patients with dementia," *Health Qual. Life Outcomes*, vol. 2, no. 1, p. 52, 2004.
- [3] X. Li, Y. He, D. Wang, and M. J. Rezaei, "Stroke rehabilitation: from diagnosis to therapy," *Front. Neurol.*, vol. 15, p. 1402729, 2024.
- [4] L. Märit, "Person-centered collaboration in the sick leave and rehabilitation process-in a primary care context," 2024.
- [5] J. Barjis, G. Kolfschoten, and J. Maritz, "A sustainable and affordable support system for rural healthcare delivery," *Decis. Support Syst.*, vol. 56, pp. 223–233, 2013.
- [6] U. B. Khalid, M. Naeem, F. Stasolla, M. H. Syed, M. Abbas, and A. Coronato, "Impact of AI-powered solutions in rehabilitation process: Recent improvements and future trends," *Int. J. Gen. Med.*, pp. 943–969, 2024.
- [7] J.-W. Jeong, W. Lee, and Y.-J. Kim, "A real-time wearable physiological monitoring system for home-based healthcare applications," *Sensors*, vol. 22, no. 1, p. 104, 2021.
- [8] B. R. Devi, V. Neela, A. Ashwitha, C. S. K. Reddy, P. Balaji, and M. Sudhakara, "AI-Driven Predictive Models for Personalized Rehabilitation and Assistive Systems," in *Predictive Algorithms for Rehabilitation and Assistive Systems*, IGI Global Scientific Publishing, 2025, pp. 87–114.
- [9] L. Guo et al., "Wearable Intelligent Machine Learning Rehabilitation Assessment for Stroke Patients Compared with Clinician Assessment," *J. Clin. Med.*, vol. 11, no. 24, p. 7467, Dec. 2022, doi: 10.3390/jcm11247467.
- [10] J. Lee, Y. Kim, and E. Kim, "Data-Driven Stroke Classification Utilizing Electromyographic Muscle Features and Machine Learning Techniques," *Appl. Sci.*, vol. 14, no. 18, p. 8430, Sep. 2024, doi: 10.3390/app14188430.
- [11] X. Hua et al., "Evaluation of movement functional rehabilitation after stroke: A study via graph theory and corticomuscular coupling as potential biomarker," *Math. Biosci. Eng.*, vol. 20, no. 6, pp. 10530–10551, 2023, doi: 10.3934/mbe.2023465.
- [12] O. Mansour, H. Sarwat, Z. Ullah, X. Song, J. Jia, and P. B. Shull, "Stage-specific EMG feature optimization for enhanced post-stroke hand gesture recognition," *J. NeuroEngineering Rehabil.*, vol. 23, no. 1, p. 13, Dec. 2025, doi: 10.1186/s12984-025-01807-5.
- [13] A. Kaku, A. Parnandi, A. Venkatesan, N. Pandit, H. Schambra, and C. Fernandez-Granda, "Towards data-driven stroke rehabilitation via wearable sensors and deep learning," 2020, arXiv. doi: 10.48550/ARXIV.2004.08297.
- [14] L. Zhang et al., "DCAF-Net: Dual-Channel Attentive Fusion Network for Lower Limb Motion Intention Prediction in Stroke Rehabilitation Exoskeletons," 2025, arXiv. doi: 10.48550/ARXIV.2512.12184.
- [15] M. D. Schmidt and I. Iossifidis, "The Spatial and Temporal Resolution of Motor Intention in Multi-Target Prediction," 2026, arXiv. doi: 10.48550/ARXIV.2603.05418.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details