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Development of A Mobility Assistive Limb Integrated with Health Monitoring

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Abstract
This paper proposes a mobility limb that is integrated with health status monitoring, which has been designed to assist people with mobility impairments or those undergoing rehabilitation, including post-surgical recovery, partial paralysis, and lower-limb loss. The Arduino Uno microcontroller is used to take real-time sensor data and process it. A gyroscope and a MEMS sensor are used to measure the joint angles of the healthy limb that are used to regulate the servo motors on the affected limb. Physiological data, including heart rate and body temperature, is shown on the LCD and transmits the data to a backend system upon request, which then uses a machine learning-based method to evaluate the patient condition with high accuracy. The model shows the potential of combining motion assistance and physiological monitoring in a cost-effective rehabilitation-oriented model.
Keywords: *Smart mobility, limb motion replication, rehabilitation systems, health monitoring, sensor-based control*

1. Introduction

The mobility impairments and post-injury rehabilitation frequently entail the necessity of constant monitoring, specific movement correction, and live health surveillance. Traditional rehabilitation approaches typically have a narrow focus on repeated physiotherapy sessions, which in most cases may fail to ensure any form of ongoing monitoring or steady improvement when the client is not under a clinical setting. These are the shortcomings that reveal that an intelligent, automated rehabilitation aid is required that can help the affected patients with the recovery process [1]. The problems outlined above are solved by the creation of a smart mobility limb system that incorporates health-monitoring functions. The system uses motion-sensing technology to dynamically record the motion patterns of a healthy limb of the patient depending on the joint angle, movement velocity, and orientation [2], [3]. The analysis involves such movement patterns and replicates them on the wounded or damaged limb using motorized actuators and support structures [4], [5]. Coordinated bilateral movements are anticipated to facilitate gait equity, equilibrium, and overall coordination during the rehabilitation period [6], [7]. In addition to the mobility support, the proposed system shows values of the key physiological parameters such as the heart rate, body temperature, and limb motion activity as per the angles of the knee and ankle joints. In its turn, it helps increase the level of patient safety, as the mechanical assistance is combined with physiological surveillance allowing assessing the presence of abnormal conditions in time during the course of therapy [8]. The integrated solution is aimed at improving the effectiveness of rehabilitation and minimizing the use of constant manual supervision. It is made to assist patients in achieving rehabilitation following orthopedic surgery, physical trauma, neurological disorders as a result of stroke, and associated partial paralysis. The given solution allows tailored therapy through providing real-time motion tracking, coordinated limb support, and constant health management, thereby offering a cost-efficient, automated, and combined platform of rehabilitation [9], [10]. Hospitals, physiotherapy centers, rehabilitation clinics, and home-based care environments are some of the target areas of this application. Overall, the

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proposed system will help with the rehabilitation process, providing assistance with posture and gait correction and safer rehabilitation due to the use of motion guidance and nonstop monitoring of health indicators.

2. Literature Review

Majority of the academic research has focused on gait tracking, limb surveillance, and health-integrated mobility. Another option frequently proposed in 2024 was to use multimodal sensing on smart prosthetic legs, particularly EEG and fNIRS, which demonstrated that they were capable of providing superior integration of neural signals, particularly in rehabilitative situations. The obtained brain-derived information also improves the recognition of user intention and provides more effective health indicators, including cognitive load and fatigue levels. This type of design idea can also be applied to the rapidly expanding field of neuro-adaptive prosthetics, centered around perceiving the intent of the user in a more natural manner [11]. The complexities of both fNIRS and EEG make the system more complex and less adaptable to real-time ambulatory use, as it faces latency and complexity problems, particularly when patients are required to use rehabilitation support that is portable and easily transportable. Another important addition to the given field of research is a 2023 study which examines portable IMU-based gait monitoring systems and adaptive prosthetic control strategies. This paper illustrates the way several inertial sensors may be used to continuously record limb dynamics and provide feedback in real time, which can be used to enable closed-loop control of responsive and adaptive prosthetic systems. The main strong attributes of IMU-based methods are connected with cost-effectiveness, portability, and appropriateness for long-term gait analysis, the problems of which establish the premises for their implementation in rehabilitation and biomechanical studies. In comparison to the motion analysis systems available in labs, IMU-based systems have a number of significant limitations including sensor drift, sensitivity to sensor location and accuracy changes [2]. These pose several issues concerning improved sensor fusion, calibration plans, and adding additional sensing modalities in order to bring further success to gait analysis over the long term [12]. In 2024, it was further developed by conducting a study based on digital insoles and machine learning in the diagnosis of knee arthroplasties. These systems are dependent on direct forefoot pressure to give clinically accredited data, e.g., the identification of asymmetry or the onset of osteoarthritis. Continuous monitoring in real-life conditions is suitable with digital insoles, so nearly real-time detection of gait abnormalities can be realized. However, even with the benefits, they can only sense data of the feet and forefoot and can give very minimal information about joint-level kinematics [13]. Moreover, durability issues, sensor calibration, and variation in day-to-day use conditions are among the hindrances to the broader clinical use of digital insoles in multimodal rehabilitation facilities. In another research, the EMG-based algorithms were studied in 2024 in order to define how the data on the muscle motions can be applied to understand the actual motor intentions. In contrast to traditional machine-learning processes, deep learning offers more precise classification of complicated classes of movements and, therefore, contributes greatly to increased precision of control in assistive devices [14]. Multimodal sensor inputs can also be employed in such systems to increase the validity of interpretation of neuromuscular patterns. Nevertheless, the successful training of EMG-based methods needs very large annotated datasets, whereas the issue of placing electrodes, differences among users, and generalization across different populations is still significant. These factors make the application of EMG-controlled mechanisms in a normal rehabilitation setting difficult.

3. Existing System

The existing form of rehabilitation is highly manual in nature, as clinicians are required to assist the patient in their daily rehabilitation of leg movements. This dependence on continuous human engagement may lead to certain inconsistencies, overburdened activity of clinicians, and the inability to capture accurate movement data [15]. Without real-time

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monitoring of any type, it is difficult to find out the progress of patients. On the other hand, most existing traditional wearable devices are only capable of basic motion tracking, such as counting steps or a limb-position sensor, but not of active assistance. None of them offers matching motion input with adaptive feedback that would assist a weakened or impaired leg, which would be useful in a narrower scope of rehabilitation. Thus, they are not able to offer intelligent mirroring or any significant active support that may be needed for successful motor recovery.

3.1.Existing System Disadvantages

There are some significant flaws in the current rehabilitation systems in the form of the absence of automated support and coordinated movement. Most current solutions cannot achieve intelligent coordination between the sound and diseased limbs, which leads to a longer recovery time and more physical effort among patients with unilateral impairments [16], [5]. Another limitation is the high dependency on the supervision of physiotherapists, which makes regularity and efficiency hard to achieve in therapy sessions. Despite the fact that neuro-adaptive prosthetics employing EEG and fNIRS have been investigated, their high system complexity makes them impractical due to large latency time and difficulty in ambulatory daily use [11]. Similarly, while EMG-based control has the ability to provide high intent recognition, user variability, electrode placement sensitivity, and related issues are important impediments to broad applicability [14]. Classic configurations do not have health-monitoring functions as well. Without real-time monitoring of vital signs and movement information, medical intervention is difficult to perform at the right time, particularly in cases of patients who require constant attention [8]. This also limits the potential of proper rehabilitation in home-care or distant locations, thereby minimizing the overall adaptability and availability of the rehabilitation process. Figure 1 Shows Smart Mobility Limb System Overview, Figure 2 Shows Health Monitoring Framework

4. Proposed System

The proposed method is based on an intelligent leg-movement synchronization architecture as a means of enhancing the rehabilitation process among people with lower-limb disabilities. It has motion sensors in the healthy leg to record real-time movement procedures that are replicated in the affected limb through a motorized support unit. This automatic reflection of gait behavior facilitates the maintenance of correct walking posture, muscular re-education, and reduces the necessity of constant manual intervention of physiotherapists. Moreover, the device is equipped with a real time health monitoring aspect which constantly measures important physiological parameters such as heart rate, temperature, and movement efficiency. The measures are visualized in a local interface where caregivers and therapists can track the progress, identify anomalies, and also make timely changes to the therapy plan. The proposed methodology will provide a more consistent and efficient rehabilitation experience that is individual oriented through merging intelligent motion replication and continuous health data collection Figure 3 Shows System Architecture

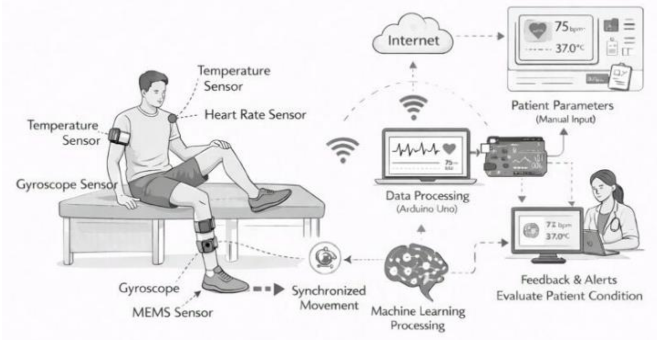

Figure 1 **Smart Mobility Limb System Overview**

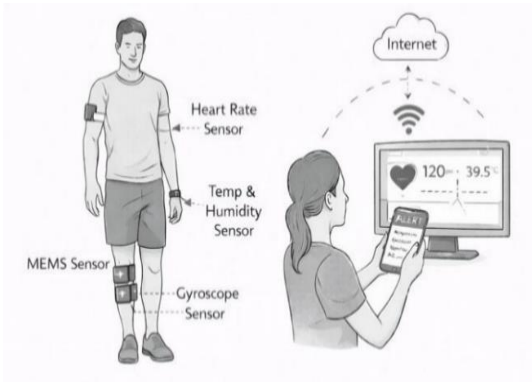

Figure 2 **Health Monitoring Framework**

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4.1. Proposed System Advantages

The suggested rehabilitation system is able to support the affected leg by sensing the motion of the healthy leg and recreating the same movement with the assistance of motorized support. These coordinated movements assist patients in adapting a correct walking pattern as well as improving their balance and posture in rehabilitation. Repeated guided motion enhances relearning of the muscles and it promotes functional recovery at a faster rate. Since the system automates the entire treatment process, the need to have physiotherapists present all the time is reduced, thus making the course of treatment less demanding but more efficient. Besides the motion support, the system continuously monitors vital parameters like the heart rate, the body temperature and the movement efficiency. These values are recorded in real-time and can be displayed to therapists and caregivers so as to check the progress of patients hence assisting in early identification of abnormal changes. This current feedback enables the therapy to be adapted based on the requirements of the individual patient and makes the system applicable to both hospital and home-based rehabilitation. Figure 4 Shows Block Diagram

Table 1 Comparison of Existing and Proposed Systems

Existing System	Proposed System
Depends on manual therapy and manual human intervention.	Intelligent motor-assisted leg synchronization.
Needs constant attendance of physiotherapists.	Eliminates reliance on physiotherapists.
Manual motions are not always consistent.	Gives accurate and reliable movements.
No smart reflecting of healthy leg intensification.	Automatically imitates movements of healthy legs to the injured leg.
No or limited real-time data collection.	Supports real-time data collection.
Tracking of progress is challenging.	Allows proper tracking of progress.
Movement is just monitored using wearable devices.	Proactively supports and helps with movement of legs.
Slow rehabilitation process.	Quick and effective rehabilitation.

5. System Architecture and Methodology

5.1.System Architecture

The smart mobility platform employs modular architecture which integrates actuation and processing as well as sensing. The system mounts MEMS sensor and a gyroscope on the healthy leg to measure data regarding motion. One of the devices is a health monitoring unit, which measures body temperature and heart rate and shows the information on an LCD. Other physiological information is hand typed using a web-based interface. The sensors transmit their data to the Arduino uno which is the central processing controller. The Arduino works with the input signals and produces appropriate control signals. Then it transmits these commands to servo motors which imitate the motion on the affected limb. This architecture is used to ensure that there is a specified flow of information between the input, processing, and output phases. The block diagram shows that the sensors are used to collect data that is converted to control the movement of the limbs. As the design is based on a modular design, the system can be easily expanded by adding new sensors or components without having to alter the fundamental design. The various activities in this system are simply organized. The motion and health data of the user are collected using the sensors. The controller then uses this data to create appropriate signals to be given to the motors which assist in replicating the motion on the affected limb. The health-related values may be also directed to an external system upon demand where necessary. With the separation of these functions, the general arrangement becomes more easier to adjust without altering the primary

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principle of work.

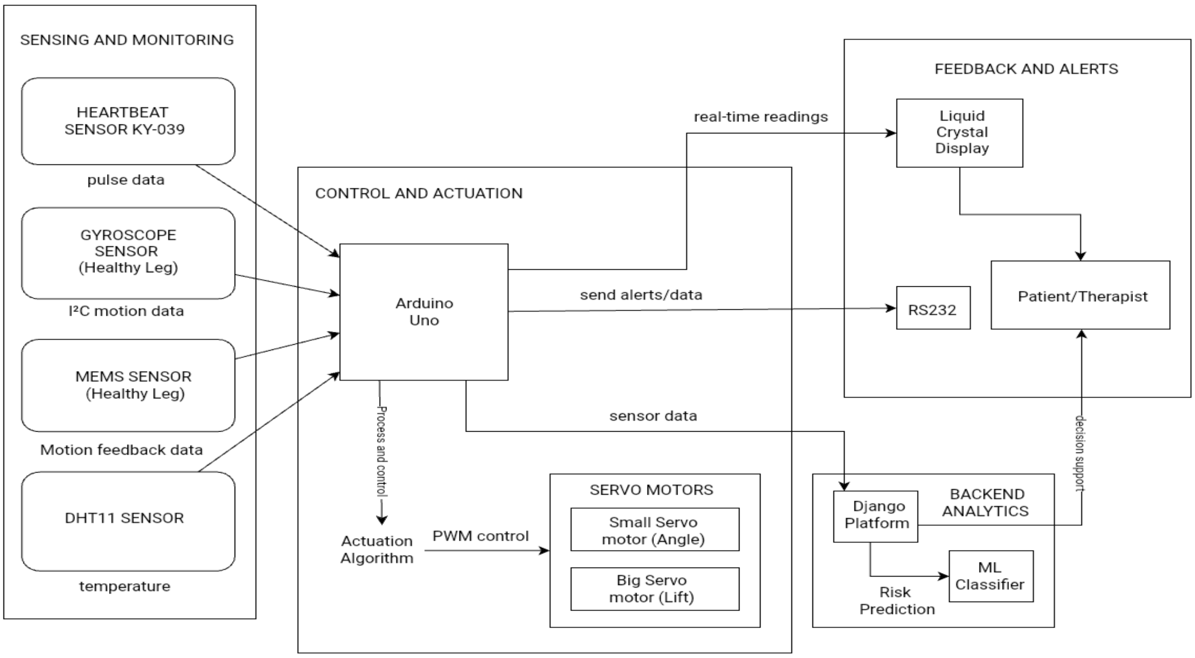

Figure 3 System Architecture

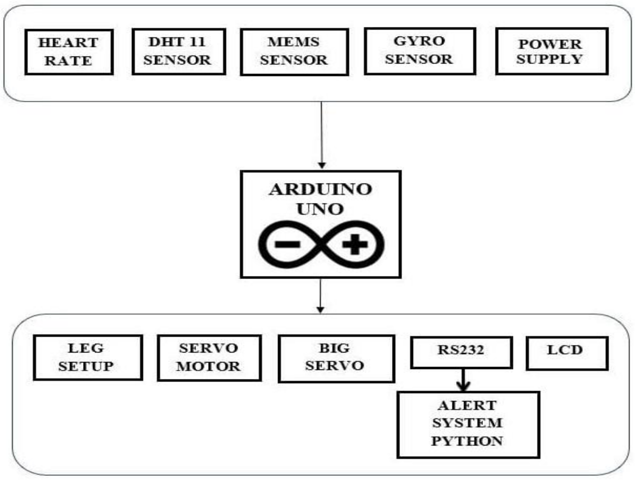

Figure 4 Block Diagram

5.2.Methodology

The Smart Limb Movement Replication with Health Insights is a multistage system that is meant to combine motion sensing, data collection, movement replication, basic health monitoring, and calibration. The general purpose of the system is to make sure that limb movements on the healthy limb are monitored and replicated perfectly on the damaged limb and that rehabilitation practice can be performed safely and controlled. The developed methodology will guarantee simultaneous motion replication, and constant physiological observation to facilitate harmless rehabilitation procedures. Fig. 5 depicts the general working flow of the proposed system, which consists of the following processes in a sequence: system start, sensor data collection, decision-based data processing, adaptive actuation, and constant monitoring.

Data Acquisition by Using Sensors: - The initial step is the real-time motion data acquisition of the healthy limb of the patient by the MEMS and gyroscope sensors. Foot mounted pressure sensors are used to measure the load distribution and ground contact when walking. The changes in acceleration and joint angle are observed to describe the movement of the limbs. Besides the motion data, simple physiological rates like heart rate and temperature are monitored so as to check the condition of the patient under rehabilitation. All sensors are attached to a microcontroller which samples the data with a fixed rate.

Adaptive Actuation Through Motion Replication:

-The motion data obtained on the healthy limb are then used to activate an actuation mechanism that is a motor to which the affected limb is connected. The controller uses the data that is received on the sensor and produces the correct control signals to reproduce the motion that is observed in a well-coordinated fashion. The system modulates the torque, the range of movement and position of the limb in order to reduce sudden and painful movements. This is a mirroring-based method that helps in regular gait training and balance preservation during the rehabilitation training.

Surveillance and Safety Appraisals: - There is recording and analysis of physiological and motion data through the use of a laptop-based interface. The obtained values are compared with the set threshold ranges to determine whether the patient is normal or abnormal. The analyzed status is represented on the laptop interface and an LCD module. RS232 is also used to establish communication between the microcontroller and the laptop, when necessary.

The process facilitates constant safety monitoring through the detection of deviant physiological or movement patterns within the rehabilitation process. The existing prototype has a basic monitoring performed by comparing the physiological parameters to the predetermined threshold ranges to identify the abnormal conditions. In case abnormal values are found, they can be shown in the form of alerts on the monitoring interface. More sophisticated safety measures like emergency stop measures, torque restraint and protective hardware protection are to be introduced in upcoming models of the device.

Fine-tuning and Individualization: - Calibration is also done before the system is operationalized so as to make sure that the system is tuned to specific rehabilitation requirements. Sensor sensitivity settings are changed, actuation limits are configured and motion replication parameters are adjusted depending on the physical state of the user. These modifications are optimized by the application of trial-and-error methods, to obtain comfortable movement and reliable monitoring of conditions like partial limb paralysis or post-operative movement restriction.

Performance Evaluation and Validation: -The consistency of motion replication, response behavior, coordination between sensing and actuation, and monitoring of basic physiological parameters are controlled testing system performance. Based on these observations, the system can be deployed in controlled rehabilitation settings, such as those in healthcare settings and monitored in-home rehabilitation settings. Figure 5 Shows Workflow Diagram

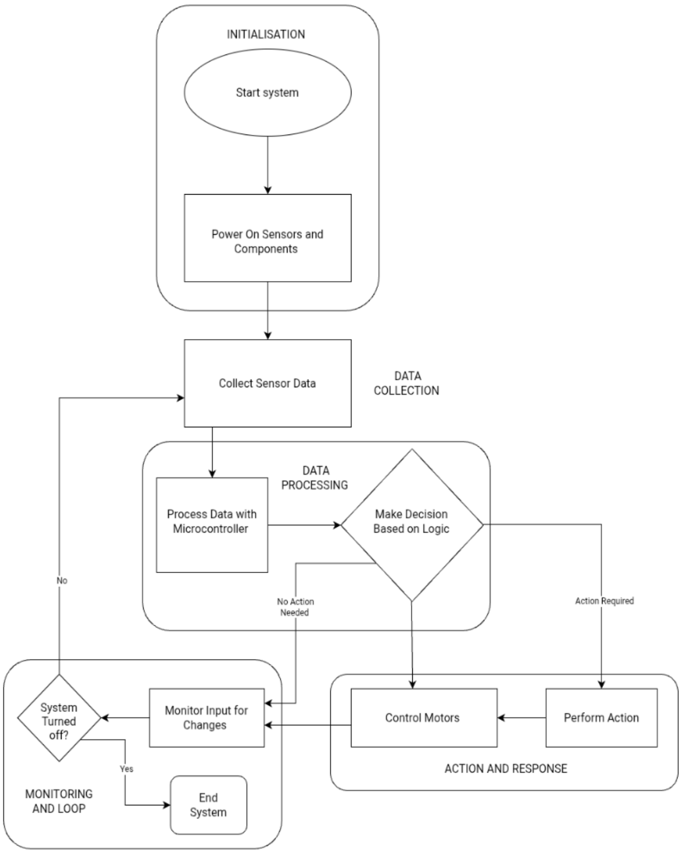

Figure 5 **Workflow Diagram**

6. System Implementation

6.1.Hardware Components

Arduino Uno: - The main control unit of the Proposed smart mobility limb system is Arduino Uno. It also constantly takes the motion information provided by the sensor on the gyroscope attached to the healthy leg, and computes it to reproduce what would have been done by the healthy limb. With the processed data on the angle, the Arduino Uno then

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produces the PWM value to complete the servo motors with subsequent smooth and coordinated movement. The Arduino Uno is programmed in Embedded C and the Arduino IDE, offering real-time control that can be trusted and also coordinates the sensors and actuators of the system in a very effective manner.

Heartbeat Sensor: - The heartbeat sensor checks the pulse rate of the patient during rehabilitation. The sensor measures the heart rate of the patient through optical sensing methods and also offers real time physiological data. The sensor transmits real-time data of heart rate to the Arduino Uno, which is stored and used to show in the system interface. This provides constant physiological surveillance of the patient. The supported limb movements are carried out simultaneously, helping caregivers monitor the condition of the patient during the treatment process.

Servo Motor: - The angular position of the assisted limb is controlled by the servo motor in replicating the movement of the healthy leg. The Arduino Uno provides position commands to it depending on the readings of the gyroscope and MEMS sensor. A high torque and a fine control of the angle have ensured the servo motor gives a smooth and precise movement of the limbs and hence, can carry out rehabilitation exercises simultaneously. This renders it applicable to guided physiotherapy where controlled and repeatable movements are necessary to recovery that is safe.

Gyroscope Sensor: - The gyroscope sensor is used in this project to enable the capture of rotational movement and orientation of the healthy leg of the patient, which is necessary so as to properly reflect the movement onto the assisted limb. It identifies the angular velocity on the basis of Coriolis effect and provides the real time rotational data constantly to the Arduino Uno to be processed. Its high level of responsiveness and reliability allows it to trace the slightest changes in leg movement, which helps to promote smooth and concerted movement of rehabilitation in the suggested mobility limb system.

MEMS Sensor: - The MEMS sensor is attached to the healthy leg and it measures the changes in linear acceleration and movement during rehabilitation exercises. It is used together with a gyroscope sensor to transmit motion data to the Arduino Uno to process it. The data of the sensor of the servo motors on the assisted limb are then combined to form the appropriate control signals that make the movement of the limb replica smooth and synchronized. This facilitates the even gait patterns and successful recovery.

DHT11 Sensor: - The system uses the DHT11 sensor to check the body temperature of the patient during the rehabilitation process. It has a digital temperature reading which is processed by the Arduino Uno as a continuous response in order to monitor health. Since the project aims at measuring temperature, the parameter to be measured is temperature only. The DHT11 sensor is used as it guarantees easy integration and good real time tracking. This assists in monitoring any abnormal change in body temperature while the assisted limb follows the guided movements.

Liquid Crystal Display: - Information on the real time system is displayed on the LCD module that might include sensor readings. It communicates with the Arduino Uno to give both the user and the caregivers real time and easy to read feedback of the vital parameters when performing rehabilitation. The display makes it easier to use and to monitor the current health monitoring process.

6.2.Software Description

The proposed software architecture of the smart mobility limb system gives it a support of continuous supervision of the system, monitoring health parameters as necessary, and real-time synchronization of the motion of the system. Here, back-end data processing and embedded control programming are the joint result of the entire software stack which will achieve efficient and safe support of rehabilitation. The control application is written and built on the Arduino Integrated Development Environment and coded in Embedded C. A gyroscope sensor and MEMS sensor on the healthy leg continually supply motion information to the Arduino Uno that then compares the angular readings to read through the patterns of movement. The processed values are translated into the

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appropriate control signals that can be used to drive the servomotors attached to the affected limb and recreate the natural gait dynamics. The incremental position updates with known scaling is used by the control algorithm to ensure the safety and smooth movement to prevent the unstable or jerky movement during the rehabilitation sessions. It performs physiological surveillance by sampling body temperature, heart rate and other vital parameters in the process of rehabilitation. The sensor data are sent out in a serial manner to an external processing unit. Status indicators are placed in the system following the acquisition and processing of the data so that the patient safety can be aware in time. In the LCD panel, real-time feedback is shown. The Empirical Validation will be undertaken with the help of backend scripts written in Python as a means of processing and evaluation of the system performance. A Random Forest classifier and health data analysis as well as risk condition detection are performed through machine learning. The model offered was created with the help of a publicly accessible medical dataset that is provided by Kaggle. This dataset has 1177 cases and 30 clinical variables such as demographic data, vital signs, and laboratory data. The target variable is a three-class classification problem since it involves three categories of risk, that is, high, low, and medium. In order to balance the classes used to train the model, resampling methods were used, and the dataset was evenly distributed with 1587 samples. The 80 and 20 stratified split was used to separate the dataset into training and testing sets to ensure that all the three classes were represented proportionately in model development and testing. This will enhance the system to become smarter in order to make data-inspired decisions and performance measurement.

6.3.Implementation

The intelligent mobility system comprises of motion-sensing devices, health information devices as well as an electromechanical actuation on a microcontroller-based design. The Arduino uno is the controller of the system. It takes sensor data, control logic and general system operation. The healthy limb has a gyroscope sensor and MEMS sensor to record details of the movement. Angular velocity and orientation are determined by the gyroscope by communicating via I^2C and MEMS sensor gives feedback regarding limb movement and load conditions. The system involves the raw sensor values which are then processed with trigonometric and mapping computations to generate constant values of joint angles which are used to replicate motion. The rehabilitation technique involves the use of the movement patterns of the healthy limb to create the same movement patterns on the affected limb in real time. There are two servo motors in the actuation unit. The knee joint contains a high-torque servo motor that offers flexion and extension and the ankle joint contains a low-torque servo motor that makes the angular adjustment fine. The high-torque and the low-torque servo are driven using the feedback of MEMS sensor and the angle values of the gyroscope, respectively. The Arduino uno produces the PWM signals to make the two motors work. The system operates by using the servo motors to mimic the movement of the healthy limb on the affected limb depending on the sensor data that is processed under the Arduino controller. The motors will give the desired angular movement which can be used in rehabilitation exercises. This study did not, however, experimentally confirm the torque capacity, load limits and safety margins and will be investigated in future hardware optimization. A closed-loop system is a better approach to control, leading to a more balanced movement of the limbs and increased comfort during the rehabilitation exercise. The system is designed to track physiological parameters in the therapy in order to enhance patient safety. KY-039 heart rate sensor is a sensor which measures pulse changes by detecting infrared light absorption, and DHT11 is a sensor which measures body temperature based on a single-wire digital sensor. The LCD displays the heart rate, body temperature, gyroscope and MEMS sensor angle value, such that one can view the performance of the system at any given time. Once the monitoring interface asks the data over RS-232, the Arduino transmits the values of the physiological sensors to the system and the values are automatically representing in the monitoring fields, with other values being added by hand. As a system, it uses a

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backend platform that was created using the Django framework. The module is a random forest-based machine learning model, which interprets physiological data and displays insightful information in the form of a web interface. The backend will then compare the values that it receives with the threshold limits that are set in advance to determine the normal or abnormal conditions and the results will be displayed on the LCD and the monitoring interface to assist in providing the timely clinical response. The prototype was tested to confirm its fundamental workings. The system offers preliminary assistance of motion and is trusted to provide reliable monitoring of physiological parameters.

Results and Discussion

7.1. Results

The prototype that has been developed demonstrates that the proposed smart mobility limb system is feasible. In initial observations, the sensors were stable and capable of making consistent motions. The servo motors reacted to control inputs and they provided controlled limb movement. The delay-based control method makes the system realize motion mimicking with motion controllable synchrony, and adheres to the principles of torque-controllable design AiDIN-IV system [15]. The health monitoring module was found to be reliable in the course of experimental analysis. The system architecture is very clear and it involves the use of sensors, Arduino processing and servo actuation to induce healthy limb movement on the affected limb. The prototype presented is able to replicate motion so far but quantitative measures like angular replication error or motion accuracy in degrees were not quantified in this study. The next step to do is elaborate experimental analysis to ascertain angular deviation and accuracy of synchronization between the healthy and the affected limb. The performance measured is in accordance with previous literature regarding wearable sensors-based health-monitoring and rehabilitation systems [8]. The health monitoring module takes the heart rate through a heartbeat sensor and the body temperature through DHT11 sensor and the readings are shown on the LCD and transmitted to be analyzed. This prototype stage did not involve comparing the module with medical-grade devices despite the fact that the module is able to offer real-time monitoring. The future study will entail comparison to clinical monitoring instruments to establish the accuracy of measurements. The system is based on a Django framework and a random forest classifier as its background analysis, and introduces an intelligent processing element that adheres to current research tendencies of adaptive gait generation and hierarchical structure of systems [16]-[18]. Class 0 represents low risk, Class 1 represents medium risk and Class 2 represents high risk patient conditions. To deal with the class imbalance in the dataset, RandomOverSampler from the imbalanced-learn library was used. The accuracy of the software-based health monitoring module was tested using a Random Forest classifier which was able to attain an accuracy of 99.37 percent, as shown by the confusion matrix and accuracy score. This indicates that the suggested software architecture can be used to categorize the health status with great effectiveness, which improves the overall reliability of the whole system. The classification report and confusion matrix show a good performance of all three risk categories with almost equal values of precision, recall, and F1-score of 0.99.

Table 2 Performance Evaluation of Random Forest Classifier

Metric	Value
Accuracy	99.37%
Precision	0.99
Recall	0.99
F1-Score	0.99
Cross Validation Accuracy	97.48% - 99.68%

As the confusion matrix below in the results section shows, the classifier can accurately detect three categories of health-risks including low, medium and high-risk. The classification report indicates a high precision, recall and F1-scores of about 0.99, meaning that the model performs equally on all the classes. The revisions will be made in the future with

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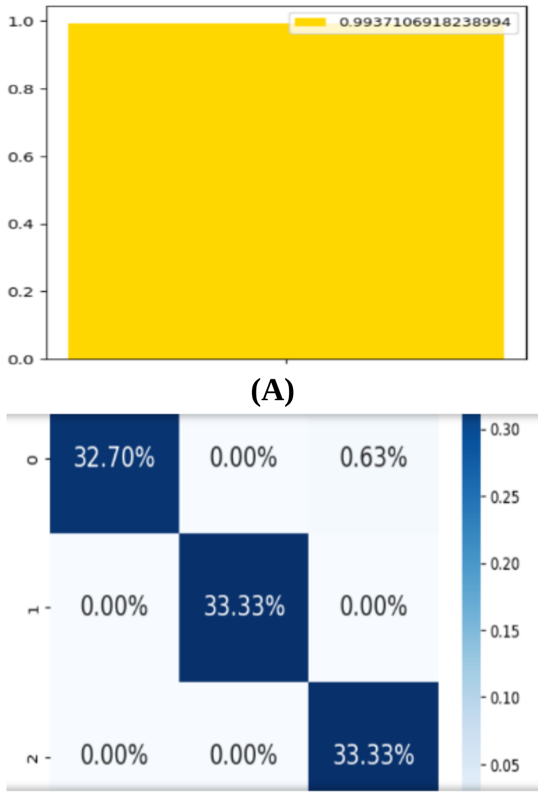
more clear class labels and other statistical interpretations like sensitivity and specificity. The prototype will be aimed at illustrating synchronized motion repetition between the healthy and affected limbs with sensor data and servo actuation. Though delay-based control method allows replicating the motion in almost real time, no precise measurements of the latency between the actuation and sensing measurements were made. The next step in work will involve timing analysis as a way of measuring system delay and optimizing real-time gait synchronization. To further confirm the strength of the model, five-fold cross validation was conducted, and the findings revealed strong consistency in the accuracy of the model between 97.47 percent and 99.68 percent. The fact that cross validation scores and test accuracy were very similar also indicates that there was no strong overfitting observed as the results indicated that the model can be generalized. Such consistency implies that the classifier is exhibiting a consistent performance with varying datasets. Figure 6 Shows Evaluation of Health Monitoring Module (A) Accuracy Score. (B) Confusion Matrix.



(A)

(B)

Figure 6 **Evaluation of Health Monitoring Module (A) Accuracy Score. (B) Confusion Matrix.**

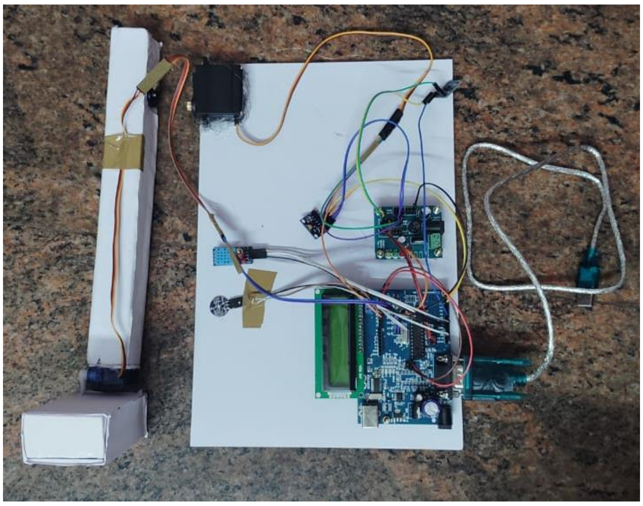


Figure 7 **Developed Smart Mobility Limb Prototype**

7.2. Discussion

Overall, the experimental results show that the developed prototype realizes real-time motion assistance and reliable physiological monitoring, conceptually paralleling gait coordination strategies so far described for advanced multi-legged robotic systems [19], [20]. Preliminary experimental studies were able to verify constant sensor functionality, constant motion replication, and dependable physiological surveillance. Nevertheless, the current study did not provide statistical confidence intervals and repeatability analysis. The further work will include numerous experimental trials and statistical analysis to demonstrate the reliability and consistency of the system. Figure 7 Shows Developed Smart Mobility Limb Prototype

Conclusion and Future Scope

The fact that a smart mobility limb, which has inbuilt health-monitoring features is developed represents an effective rehabilitation approach that integrates motion support and physiological monitoring on the same system. In this case, the proposed method uses an Arduino Uno as the main controller to send the real-time motion data of the gyroscopic and MEMS sensors and recreates the actions of the healthy limb on the affected limb through coordinated actuation. The motion mirroring mechanism assists in other patients with post-surgical disorders, partial paralysis or nerve diseases in regaining gait coordination, posture and balance. Constant measuring of the vital parameters, including the heart rate and body temperature, will be more patient-safety-assuring because it will be possible to identify the abnormal physiological conditions early and create information on time. The low price, compactness, and easy-to-use design also expand the scope of practical use in the hospital, rehabilitation centres, and private care. The created prototype proves the adequacy of smart mobility limb system as the motion assistant and physiological monitoring system. Nonetheless, no formal clinical trials or user studies have been carried out on assessing the effectiveness of rehabilitation or comfort of a patient. The next clinical study to be conducted will focus on patients in the rehabilitation to determine the practical usability and therapeutic results. The system is a control mechanism where sensor-based motion detection is utilized to actuate servo motors to mirror the movement of the healthy limb. The arduino controller takes sensor signals and sends out the PWM signals to control the motors. Even though the implementation of the concept itself is successful, the further mathematical modeling, including the use of kinematic equations or even the PID-based control analysis, will be investigated in the future. The prototype mainly aims at exhibiting the reenactment of motion and health tracking devices. Although the design is supposed to help with portable rehabilitation, power consumption and battery life were not thoroughly considered during the implementation. The future work is going to examine the energy needs and optimize the management of power to operate longer portables. Further studies can focus on the internationalization of the system by the introduction of machine learning algorithms into the system to make it smarter and more flexible. It will make it possible to provide customized rehabilitation according to personal movement and progress of the patient. Remote monitoring, wireless sensor networks and cloud-based data management could be used in improving mobility, remote monitoring and long-term analysis. The presented system can be expanded to be applicable to a wider spectrum of rehabilitation applications, and hence ensure the future of the intelligent assistive rehabilitation technologies, should the further optimization of the hardware and clinical validation.

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