Physical Rehabilitation and Classification of Motor Impairments Using Wireless Sensor Technology and Machine Learning Algorithms

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***Abstract* – Disability statistics are on the rise due to ageing, population growth and medical shortcomings. The most common type of disability being mobility, places a huge burden on individuals and the society. The total loss of motor function of the limbs due to accidents, muscle weakness, or even paralysis could be rehabilitated using physiotherapy approaches. However, traditional exercises and technological approaches in rehabilitation are either too expensive or difficult for physiotherapists to objectively track, measure and monitor patients' progress and recovery status. Wearable technology has now created an avenue to reliably test and monitor patients both inside and outside of clinical settings, allowing for a more complete diagnosis of impairment and individualization of rehabilitation therapies. This paper aims to develop a cost-effective physical rehabilitation and classification system for motor impaired patients to self-diagnose their impairment using high accuracy, complex machine learning classification algorithms, by performing the recommended exercises corresponding to the exact motor impairment to regain motor functions. The paper employs the use of wireless sensor technologies and machine learning algorithms to achieve this. The proposed system acquires data using Arduino Nano and Arduino Pro-Mini microcontrollers with ADC connected to the analogue measurement channels. The flex sensors, force resisting sensors and IMUs were embedded on wearables to extract motor function parameters. A Bluetooth module was used for wireless communication. Four ML classification algorithms were utilized to determine the model with the highest performance metrics. They were deployed on a desktop app using the Python Kivy library. The acquired data are stored and processed on a database, which will help patients' track and evaluate their rehabilitation performance. The results show that the system tracks rehabilitation sessions effectively and measures the recovery level of patients correctly. Thus, it provides a cheaper rehabilitation solution for patients with motor impairments to improve their motor function, thereby reducing recovery timeframes.**

Keywords – Physical Rehabilitation, Motor Impairments, Wireless Sensor Networks, Smart Wearables, Physiotherapy, Machine Learning.

I. INTRODUCTION

The loss of motor function can substantially impact a person's quality of life by making them partially or completely reliant on others. Owing to different reasons, whether due to birth difficulties, work-related accidents, or aging, people are increasingly being diagnosed of physical or motor disabilities. In specialized clinics, physiotherapy techniques are necessary to assist people partially or totally regain lost motor or physical abilities. Through the individualized physical therapy exercises, limitations that would ordinarily preclude a physically active and healthy life can be reduced [1].

This wide range of applications for the measurement of human body parameters is responsible for their increased popularity in recent years. Advances in recent years have become an incredibly important area of focus for scientists, researchers, and technologists alike. For several years, the changes in the healthcare industry have been one of the most transformational. Technology has become a third-party member of an industry that was previously exclusive to doctors and patients [2]. Although information and communication technology (ICT) has always played a role in medicine and its operations, it is now a fundamental aspect of and dominates patient care. Wearable technology is now able to achieve the goals of tailored, interactive training with increased patient motivation. While new technological advancements, such as cloud computing, artificial intelligence, and big data are making their impact in healthcare, continuous advances in treatment delivery play a critical role in protecting individuals from illnesses or their consequences, given one's medical history, their environment, and other factors [3].

When combined with disruptive technology such as wearable healthcare devices, mobile healthcare apps are becoming a vital element of users' home screens. These technologies have a vast potential to revolutionize how the health ecosystem interacts with the public, becoming more prevalent in the healthcare industry. As a computation platform, mobile apps and devices serve as a communication platform and a Graphical User Interface for patients and clinical workers. Human subject data is rapidly accumulating, and machine learning is already beginning to be utilized as a tool for correlating these datasets with medical predictions [4]. Individuals with chronic illnesses, including older adults with asthma, chronic pulmonary or cardiovascular disease, as well as people with diabetes, benefit greatly from these wearables. Using sensors that can collect diverse data sets at the same time allows for more accurate medical assessments when they are located remotely, encouraging the use of remote prescriptions, and cutting down on the number of face-to-face consultations [5].

Severe physical disabilities cause deficiencies that result in a lack of ability to carry out everyday activities. A variety of complications prevents people from executing their physical capabilities; among them are musculoskeletal issues, surgeries, and diseases of the degenerative nature, heart illness, and even age. Neurological and orthopedic dysfunctions, such as poor posture, can lead to mobility issues [6]. Rehabilitation is vital for keeping movement, or perhaps restoring function, if it has been lost. Its purpose is to restore all functions that were affected by the impairment. While it is not conceivable, moving the upper and lower limbs that help in locomotion is made easier. In order to better their motor skills, patients must engage in physical activity. In physical therapy clinics and at home, exercises are suggested to help patients better their psychological conditions, as well as minimize recovery timeframes.

Furthermore, current research suggests that early and thorough therapy can help people regain their motor function capacity. At the present time, many people experience various kinds of physical or motor restrictions as a result of various causes, requiring them to seek out rehabilitation sessions in this era of rapid technological and economic growth. Researchers are using the latest breakthroughs in computer science to try to prevent and treat various bodily problems, and also to find ways to make it easier for persons who will need long-term care. In the health and physical rehabilitation setting, machine learning has been used to engage patients who suffer from motor impairment. This has included the use of machine learning in different settings like health, entertainment, military, education, and physical rehabilitation to evaluate, diagnose, and train patients with respect to prescribed exercise programs.

Additionally, there has been an exponential increase in the number of different sensors for measuring the body available as wearable devices, with each offering a different level of functionality [7], which gives users the ability to design and build monitoring applications ranging from a simple heart rate to limb movement data. This sensor system generates datasets such as varied feedback data in real-time. Healthcare applications have benefited greatly from advances in measurement sensor and networking technologies. We can already see the effects of Wireless Sensor Healthcare Solutions on a global scale. To help modernize and improve healthcare, new IoT-enabled devices are being employed in place of traditional medical equipment [8]. Wearables solutions can revolutionize healthcare services by monitoring physiological and motor data to give customized healthcare based on physical activity, behaviour, health condition and other factors that affect everyday life quality.

The idea of wearable technology has the ability to serve as a solution to the challenge of monitoring movement quality in homes and communities. The wearable technology that we have seen in the previous decade is providing new ways to monitor many illnesses, including neurological and cardiovascular diseases. Unfortunately, there is still a long way to go before methodologies are developed to derive clinically useful information from wearable sensor data in the context of motor disability rehabilitation.

Thus, this paper presents an approach to evaluate the quality of limb movements in persons suffering from motor impairments based on the analysis of flexion, force and accelerometer data widely used as part of wearable systems. Precisely by using data obtained from wireless body-worn sensors, the mobility status of individuals can be estimated, and physical rehabilitation progress statistics can be analyzed using machine learning algorithms.

Section II presents the theoretical background of the study and review of related works that are available in literature. Section III explains the methodology adopted in this research work which covers the materials and methods of system design, model development process, model performance evaluation, and the total system integration. Results obtained from the four developed ML classification models, implementation and testing of the system are presented in Section IV. Also, reasons for picking the SVM classification model is highlighted. Section V presents the summary of the research study, recommendations, and contributions to scientific knowledge.

II. LITERATURE REVIEW

A. Background

Pharmacological interventions have long been directed primarily at motor impairments [9]. Motor disability is defined by the partial or complete loss of function of a body part, most commonly the limbs. It frequently manifests as low stamina, muscle weakness, lack of muscle control, or total paralysis. Motor impairment is a significant cause of physical disability, affecting how individuals carry out their daily activities. Some examples of motor disability conditions include Parkinson’s disease, Cerebral Palsy, Stroke, etc. Physical and motor rehabilitation on the other hand, is a fundamental part of patients' recovery regardless of whether the limitation is the result of an accident, an illness or the advancing in age [10]. Physiotherapists practice their profession through the physical rehabilitation of patients with physical disability. Rehabilitation is a procedure in which specialists assist patients in improving their quality of life by recovering or enhancing their physical condition while regaining their autonomy and independence in order to return to an active social and working life with economic independence.

Wireless Sensor Technologies has changed people's lives and the way things are done around the world. It is making a significant difference in the healthcare business by leveraging its full potential for impact. The focus on bringing such technologies into medical devices allows for continual monitoring of elderly patients and those with chronic motor problems. More lately, wearable devices have been widely available because they are capable of detecting, transmitting, and analysing relevant data [11]. Smart wearables have the potential to transform the healthcare industry by providing individuals with simple sensor devices that collect data about the vital parameters of the body in order to provide personalized health and wellness data. This information can then be used to influence day-to-day activities and overall well-being. This range of health care technologies was created to help the physiotherapist communicate more effectively with the patient, to improve care, and to assist with remote patient monitoring when a patient chooses to live independently. The likelihood of getting positive clinical outcomes, increased levels of patient satisfaction, valid informed consent, and compliance with rehabilitation programs increases with effective therapeutic communication [12].

Artificial intelligence has recently played a significant part in technological growth. Machine learning which is a vital component of artificial intelligence, provides a plethora of models that can be employed to improve system's training and prediction. Today's AI technology can take many forms, including software programs and hardware interfaces, to create systems that can learn from their own datasets. Artificial intelligence techniques are being used in a variety of settings, including health care and research. In health care, AI beat cardiovascular risk algorithms and detected skin cancer better than a dermatologist. In the field of rehabilitation, artificial intelligence (AI) offers a variety of uses. It is utilized to identify posture and subsequently analyze patients data [13]. ML is being utilized in rehabilitation for symbiotic neuroprosthetics and myoelectric control, brain computer interface technologies, perioperative medicine, and other applications. In musculoskeletal medicine, machine learning approaches have been applied in diagnostic imaging, patient data assessment, and clinical decision support [14].

The increase in research in the field of physical rehabilitation is justified by the need for objective analysis of patients' evolution in the absence of physiotherapy professionals and the high cost of physiotherapy sessions. These patient-centric systems perform real-time monitoring of the patient's physical condition, allowing the sessions to be carried out in person or remotely. These systems also enable interoperability between the patient and the health professional, the automatic diagnosis, efficiently and not obstructive, allowing the physical rehabilitation session to flow naturally, progressive and non-stop. Real-time monitoring, interoperability between patients and physiotherapists, and the possibility of correcting the execution of exercises immediately, improve patient-physiotherapist communication [15].

Articles report the development of smart appliances like smart walkers, smart crutches, wearables, force platforms or spheres to carry out rehabilitation of patients. These devices use IMU, accelerometers, magnetometers or gyroscopes, pressure sensors, force sensors or motion sensors and doppler radars. With these sensors, they intend to determine the balance, gait, position, guidance or forces applied by the patient. Some of these systems developed also include mobile applications where the collected data is registered and made available for physiotherapy sessions [16]. There are still other articles that reveal the application of interactive technologies such as virtual reality and systems such as Kinect from Microsoft, which perform remote motion detection with optical technology, for extract the biometric data of patients in a playful way [17].

B. Review of Related Works

The following papers highlighted below made use of similar methods and techniques as related to Machine Learning and Wireless Sensor Technologies in achieving a physical rehabilitation system or a classification system. The related works have been summarized in tabular form, showing the approaches adopted, cost implications, and the gap(s) peculiar to each of the systems.

Table 2.1 Summary of related works

Title of Work	Approach	Gap(s)	IoT	ML	Cost
Classification of Ischemic Stroke using Machine Learning Algorithms (2016) [18]	Machine Learning, Used self-reported data, CT & MRI scans.	Model can only classify types of Ischemic Stroke Does not aide rehabilitation	No	Yes	Moderate
SoPhy: A Wearable Technology for Lower Limb Assessment in Video Consultations of Physiotherapy (2017) [19]	Embedded sensors, Real-time assessment of weight distribution, foot movement & orientation over web interface.	Focused only on lower limb assessment Rehabilitation progress cannot be ascertained. For use only for video consultations.	Yes	No	Moderate

Physical rehabilitation based on smart wearable and virtual reality serious game (2019) [1]	IoT. Virtual Reality, Serious Games.	Focused only on upper limb rehabilitation	Yes	No	Expensive
Real time monitoring system for upper arms rehabilitation exercise (2015) [15]	Embedded Sensors, Real time assistance from physiotherapists.	Focused only on upper limb assessment Physio-therapist assistance required	Yes	No	Moderate
Design of Smart Portable Rehabilitation Exoskeletal Device for Upper Limb (2016) [20]	Robotic Device, Assists range of movements of the upper limbs during rehabilitation exercises.	Focused only on upper limb assessment Mechanical devices are quite heavy. Poor speed control can lead to complications.	Yes	No	Expensive
Machine Learning algorithms activity recognition in ambulant children and adolescents with cerebral palsy (2018) [21]	IoT, ML algorithm to classify type of activity performed.	Only accounted for the type of activity, Rehabilitation was not performed.	Yes	Yes	Moderate
Smart Crutches: Towards Instrumented Crutches for Rehabilitation and Exoskeletons-Assisted Walking (2018) [22]	IoT device to detect presence of weight Activity detection	Only accounted for the lower limbs	Yes	No	Expensive
A Smart Solution for Proprioceptive Rehabilitation through M-IMU Sensors (2020) [23]	Made use of IMU sensors for tracking in VR games. Feedback from VR games sent to physiotherapists	Still heavily relies on Physiotherapists.	Yes	No	Expensive
Recent machine learning advancements in sensor-based mobility analysis: Deep learning for Parkinson's disease assessment (2016) [24]	The authors used measuring devices to collate data from ten unique individuals with idiopathic Parkinson's disease. Multiple motor tasks were labeled and categorized for detecting bradykinesia.	Focused only on Parkinson Disease. No Rehabilitation performed	Yes	Yes	Expensive
Machine Learning Algorithm for Stroke Disease Classification (2020) [25]	Used ML algorithms to classify pictures of patients into the two types of stroke: hemorrhage stroke and ischemic stroke, eight algorithms were used in this paper	Focused only on Stroke No Rehabilitation performed	No	Yes	Cheap
Enabling stroke rehabilitation in home and community settings: A wearable sensor-based approach for upper-limb motor training (2018) [26]	It can detect movements for the upper limbs while also performing ADL, it can also assess and analyze the quality of in-house rehabilitation exercises.	Focused only on upper limbs	Yes	No	Moderate
Wearable and IoT Technologies Application for Physical Rehabilitation (2018) [27]	Use of a pair of smart gloves to engage with serious games for rehabilitation of the upper limbs.	Focused only on upper limbs	Yes	No	Moderate
Flex Force Smart Glove Prototype for Physical Therapy Rehabilitation (2018) [28]	Ultilized a smart glove, embedded with Flex Force sensors, it enables collation and processing of data received from the hand of the individual in a simple and concise manner.	Focused only on upper limbs	Yes	No	Moderate
An IoT-Enabled Stroke Rehabilitation System Based on Smart Wearable Armband and Machine	Used a wearable armband, machine learning algorithms, and a 3-dimensional printed robot hand were utilized to show	Focused only on the upper limbs	Yes	Yes	Expensive

Learning (2018) [29]	a stroke rehab system that was enabled by IoT.				
An IoT based wearable smart glove for remote monitoring of rheumatoid arthritis patients (2019) [30]	Made use of a smart glove to aid physiotherapists in accessing patient's flexion of fingers performed at home. Sent data from an embedded glove to physiotherapists utilizing a smart phone and an Arduino app	Focused only on upper limbs Focused on rheumatoid arthritis patients	Yes	No	Moderate
Smart Object for Physical Rehabilitation Assessment (2018) [31]	Utilized smart crutch embedded with sensors, enabled for wireless communications . Utilizing the smart crutch, it was possible to track the development of balance over time and create correlation between these changes and the exercises performed	Focused only on lower limbs	Yes	No	Moderate
On wearable devices for motivating patients with upper limb disability via gaming and home rehabilitation (2018) [32]	Discussed recent additions that aim to aid the rehabilitation process of patients who have been afflicted with upper-limb impairments following a stroke by involving a combination of game-based learning methods.	Focused only on upper limbs	Yes	No	Moderate

III. SYSTEM DESCRIPTION

The Smart Wear system combines a series of wearable gadgets for use in natural interactions with a range of hardware and software tools that assist data collection and analysis. The system consists of a pair of smart gloves and socks that can be utilized for upper and lower limb rehabilitation in natural environments. The smart gloves are responsible for collecting patients' flexion, force and position data while the smart socks extract values of force and position. The collected data can be viewed via a mobile application with the goal of assisting patients in evaluating their performance over time through the visualization of metrics associated with completed physical rehabilitation sessions. The Figure 3.1 illustrates the system architecture that is divided into phases.

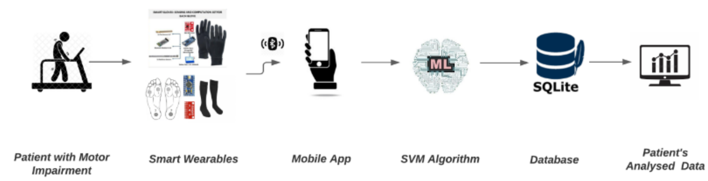

Fig. 3.1 The Smart Wear System Flow

The system architecture is broken down into phases. The first phase is dedicated to patients with motor impairments, enabling access to rehabilitation through natural interaction via exercises facilitated by the wearable devices. The next phase is composed of the wearable devices developed with Arduino Platform to enable patients interact with the rehabilitation exercises. The third phase is comprised of the mobile application to be used by patients for calibrating the smart wearables in order to achieve personalized rehabilitation experiences. The fourth phase consists of the machine learning algorithm implemented for the classification of motor impairments based on calibration values and data extracted from the smart wearables. The subsequent phase is typically represented by the data server that stores the rehabilitation results, exercises and session settings. The software technologies used on the server side is SQLite. At the last phase, the analysed data is presented on the mobile application for patient data management and for displaying progress reports from the various rehabilitation sessions. Figure 3.2 shows a block diagram of the system architecture that has been implemented.

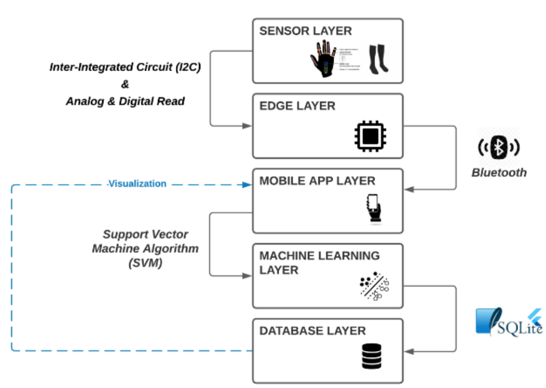

Fig. 3.2 Block Diagram of the Wireless Sensor Network Architecture

The layers are respectively broken down in figure 3.2. The IMUs (MPU-6050) and analogue sensors (Adafruit Short Flex

Sensor (ADA1070) and Force Sensitive Resistor (FSR-402)) on the gloves and socks make up the Sensor Layer. After calibration, the Edge Layer, which is made up of Arduino Nano and Arduino Pro-Mini microcontrollers, acquires IMU data via I2C (Inter-Integrated Circuit) and analogue sensor readings via the AnalogRead technique. This information is provided to the Mobile App Layer through Bluetooth protocol. Data generated from the Mobile App Layer through calibration as expressed by degree of movement, or feedback force from the limbs are processed and sent to the Machine Learning Layer for classification. The Machine Learning Layer accesses the calibration data and makes use of the Support Vector Machine Algorithm (SVM) to analyse and classify all personalized data from calibration sessions. The Database Layer further stores all analysed data from the Machine Learning Layer in the Mobile Application, as well as user profile accounts and all exercise monitoring data from the rehabilitation sessions. Users can later access and view this stored data in the form of charts and graphs to track their rehabilitation progress.

A. Hardware (Embedded Systems)

The embedded system covers the Sensor Layer and the Edge Layer of the WSN architecture as shown in Figure 3.2. The Sensor Layer is made up of the Force and Flex Sensors, the Analogue to Digital Converter (ADC), Inertial Measurement Unit (IMU) and the Bluetooth Module. The Edge Layer consists of the Arduino Nano and Pro-Mini Microcontrollers. The smart gloves sensing and computation set is illustrated in figure 3.3, showing all sensors utilized for each glove.

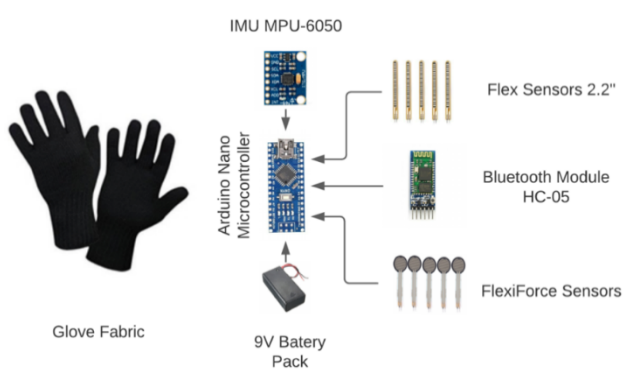

Fig. 3.3 System Architecture of the Smart Gloves

The circuit was designed and patched on a Veroboard to make the circuit as small as possible. The implemented smart glove prototype is depicted in Figure 3.4, showing the flex and force sensing devices mounted on the fingers and on the top of the gloves.

Fig. 3.4 Hardware components attached on the gloves (Left to right: face down, face up)

Fig. 3.5 System on breadboard

The smart socks sensing and computation set showing the set of all sensors used for each sock is illustrated in Figure 3.6.

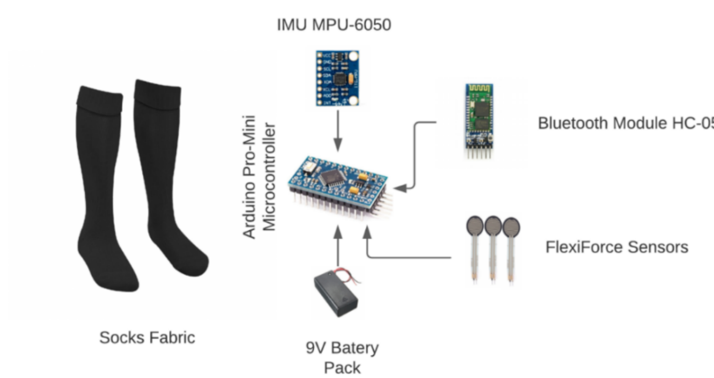

Fig. 3.6 System Architecture of the Smart Socks

The circuit was designed and patched on a Veroboard to make the circuit as small as possible. Figure 3.7

shows the final mounted prototype of the smart socks for both lower limbs.

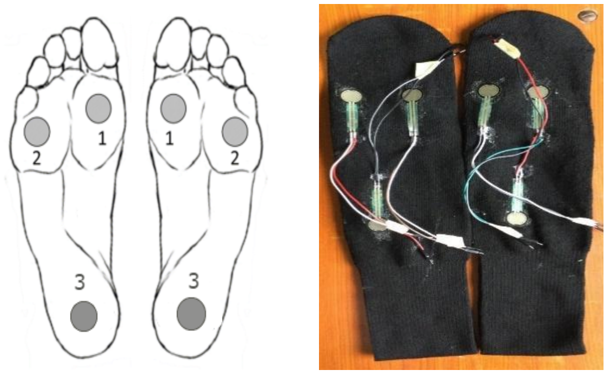

Fig. 3.7 Hardware components attached on the socks

Electrical casings were used to enclose and protect their respective circuits. A three-by-six (3 X 6) inches plastic casing was used for enclosing the electrical circuits of the Smart Gloves while a three-by-three (3 X 3) inches casing was used for that of the Smart Socks. Figure 4.5 shows the enclosing casings of the circuits. The electrical casings house the Arduinos, IMUs and Bluetooth modules, as well as other components that make up the electrical circuits. These electrical circuits are to be strapped firmly to the wrists and calves after wearing the gloves and socks respectively.

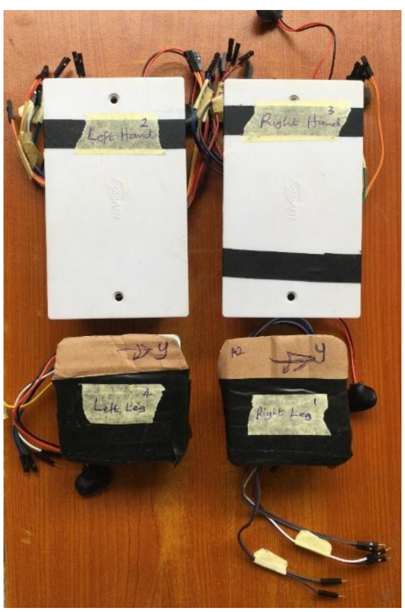

Fig. 3.8 Electrical casing for the Smart Gloves (up) and Socks (down) Circuits

B. Software

The interactive user interface application was developed using the Python programming language. It uses simple buttons spaced apart with a very natural black color that aids readability and improves transparency. It uses big white fonts for people with cognitive disabilities. The ML model is a classification model that makes classifications based on a certain number of features. The classification algorithm implemented in the application is the Support Vector Machine, the reason for this choice shall be explained in the later section. In an SVM algorithm, the features represent the number of dimensions. It is an eager learning approach because as data points are fed into the algorithm, it starts introducing hyperplanes to distinguish each class from each other and then waits for a test tuple to properly classify it. The software section of the system design is further broken down into the machine learning algorithm and the software deployment.

i. Machine Learning Processes: This section discusses the step-by-step procedures of building the Machine Learning model and deploying for commercial use. The steps involve processes which include data collection, data cleaning, data encoding, training the model and performance evaluation. Data collection is most difficult stage of any Machine Learning related task. Sampling bias must be avoided. Sampling must be random. Intensive research on several hospitals were carried out to this regard over a couple of weeks, where over 150 patients afflicted with major motor impairments were examined, interrogated about their ability to perform, and subjected to certain tasks. The major impairments identified amongst these patients were Arthritis, Cerebral Palsy, Parkinson Disease, Left Sided Stroke and Right Sided Stroke. Uniformity was ensured to prevent the dataset from being biased towards any particular motor impairment. Data cleaning was another important step to improve the accuracy of the model, and prevent overfitting caused by irrelevant features in the sample space. Thus, 150 rows of data was acquired and outliers were removed (values that lie far from other data points). In this case, the outliers were patients that performed extremely well in the activities for a particular motor impairment. Data encoding techniques were implemented to provide a simpler format to pass data into our ML model. Models only understand numerical data, so all features and labels must be encoded appropriately, so that the model can understand. Binary encoding was utilized for 10 unique features, while ordinal encoding was applied for the labels. A binary value of 1 represented the ability to perform the activity, while a binary value of 0 represented the inability to perform that same exercise or activity. The labels denoted the different motor impairments considered, namely Arthritis, Parkinson Disease, Cerebral Palsy and Stroke. The features were dependent on the following parameters: rotational acceleration (ability of move hand and/or leg), force (ability to apply pressure on hand and/or leg) and flexion (ability of bend the fingers). Each of these features where assigned to both the left and right sides of both limbs. The encoding threshold for force, flex and rotational acceleration were 10N, 25 degrees and 1rad/s respectively. Averages are taken over the five fingers of each hand and three pressure points below each foot. Hence, values of force, flex and rotational acceleration above or below the threshold determined the binary value assigned. The model architecture was built using the Sci-kit Learn framework and trained using a Linear kernel. The linear kernel was chosen to prevent overfitting (modelling the noise in the training data, such that the model sees patterns that do not exist, and hence performs badly on unseen data). Overfitting usually occurs on datasets with high number of features and small number of observations. The data set was split in a ratio 0.8:0.2 for the training data and test data respectively. The Scikit SVC implements the One vs One approach. This produces better results as it considers all classes before making predictions, although it is the much slower approach. Plotting a confusion matrix is relatively easy with Sk-learn. An ideal model would show a high rate of true positives on the graph. Precision, recall, accuracy, and f1 score were evaluation metrics used for the model.

Precision is the ratio of the correctly predicted true positives to the total number of true positives. Simply put, a high precision score prevents false accusations, or misclassifications. The mathematical formula is given by:

$$Precision = TP/TP + FP \qquad (1)$$

Recall is described as the ratio of the correctly predicted true positives to all the observations. Simply put, a high recall score prevents missing out relevant points. It is given by:

$$Recall = TP/TP + FN \qquad (2)$$

Usually, Precision and Recall is a tradeoff. The more you predict as True, the higher your chance of misclassifications and the lower your chances of missing relevant points. Alternatively, the more you predict as false, the lower your chances of misclassifications, but the higher your chances of missing relevant points. In most cases, depending on the task you want to solve, A high recall could be better, or a high precision could be better.

Accuracy is the ratio of the total correctly predicted outcomes to the total outcome/observations. This metric is not completely reliable as it is only best when the dataset is symmetric (the values of false negatives and false positives are almost the same). It is denoted as:

$$Accuracy = TP + TN/TP + FP + FN + TN \qquad (3)$$

Accuracy is avoided in classification tasks because in imbalanced datasets, the developed models would still perform very good. For example: let us say there is a data set of 1000 people, 950 are terrorists and 50 are non-terrorists. We could simply tune the model to call every single person a terrorist, and the accuracy would be 95%. Thus, it shows it is not really a good measure of the model's performance. For instance, in a terrorist-catching model, it is preferred to have misclassifications than miss the actual terrorists, so in this case, a high recall and low precision is preferred. However, in our developed model, a high precision and high recall is preferred, because missing out on classifying motor impairments is just as bad as assigning a wrong motor impairment.

F1 score is the weighted average of recall and precision. This metric considers both the false positives and the false negatives. It is similar to accuracy but is more useful in the sense that it takes into account the cost. In the case of uneven class distribution, this is an important advantage over accuracy. The mathematical formula is;

$$F1\text{-}score = 2 * (Recall * Precision) / (Recall + Precision) \qquad (4)$$

These four metrics were used to assess the ML model's performance and verify that it was not overfitting to the training data.

ii. Deployment: The model was deployed on a desktop application. Python Kivy was used to create the desktop application. Kivy is a python opensource framework used for building mobile applications. The front-end presents the user with the option to log into the app. The user puts on the smart-wearables and data extracted from these sensors are processed and encoded, then passed into the trained model which outputs the predicted motor impairment. The type of impairment is updated in the database under the user's username. Based on the type of motor impairment predicted, exercises are suggested to the user to perform during sessions. After each exercise session, the database is updated with the user's rehabilitation data. The results are extracted to the front end from the database and displayed in graphs and charts by the push of a button. The mobile application is built with Python A dynamic programming language preferred by a lot of data scientists and machine learning engineers as well as server-side developers. Python is said to be a good replacement for Java because it combines both functional programming and object-oriented programming. The desktop application running on the laptop can connect to multiple slaves without buffering data.

IV. RESULTS

The experimental results presented below illustrates, verifies and validates the entire system functions. The tables show the results derived from the various machine learning algorithms implemented hence, helped as a tool for deciding which model to adopt finally. The *recall* metric demonstrates how good the model is at capturing relevant samples for a particular class. The *precision* metric shows how good the model is at not making wrong classifications for a particular class. The *accuracy* metric illustrates how good the model is at overall classification for both classes (i.e. has Arthritis or does not have Arthritis). The weighted average of both recall and precision is determined by the *F1-score.* The Support Vector Machine model was finally adopted because its F1-score was the highest among the other classification algorithms.

Decision Tree

Table 4.1 Performance metrics for Decision Tree

Metric	Impairment	Precision	Recall	F1-score	Support
	Arthritis	1.00	0.78	0.88	9
	Cerebral Palsy	1.00	1.00	1.00	4
	Left-Side stroke	0.67	0.67	0.67	3
	None	1.00	1.00	1.00	2
	Parkinson Disease	0.67	1.00	0.80	2
	Right-Side stroke	0.80	1.00	0.89	4
Accuracy				0.88	24
Macro avg		0.86	0.91	0.87	24
Weighted avg		0.90	0.88	0.88	24

K Nearest Neighbors

Table 4.2 Performance metrics for K-NN

Metric	Impairment	Precision	Recall	F1-score	Support
	Arthritis	1.00	0.67	0.80	9
	Cerebral Palsy	0.80	1.00	0.89	4
	Left-Side stroke	0.75	1.00	0.86	3
	None	1.00	1.00	1.00	2
	Parkinson Disease	0.67	1.00	0.80	2
	Right-Side stroke	1.00	1.00	1.00	4
Accuracy				0.88	24
Macro avg		0.87	0.94	0.89	24
Weighted avg		0.91	0.88	0.87	24

Support Vector Machine

Table 4.3 Performance metrics for SVM

Metric	Impairment	Precision	Recall	F1-score	Support
	Arthritis	1.00	0.78	0.88	9
	Cerebral Palsy	1.00	1.00	1.00	4
	Left-Side stroke	0.75	1.00	0.86	3
	None	1.00	1.00	1.00	2
	Parkinson Disease	1.00	1.00	1.00	2
	Right-Side stroke	0.80	1.00	0.89	4
Accuracy				0.92	24
Macro avg		0.92	0.96	0.94	24
Weighted avg		0.94	0.92	0.92	24

Naïve Bayes

Table 4.3 Performance metrics for Naïve Bayes

Metric	Impairment	Precision	Recall	F1-score	Support
	Arthritis	1.00	0.78	0.88	9
	Cerebral Palsy	1.00	0.75	0.86	4
	Left-Side stroke	0.75	1.00	0.86	3
	None	1.00	1.00	1.00	2
	Parkinson Disease	0.50	1.00	0.67	2
	Right-Side stroke	0.75	0.75	0.75	4
Accuracy				0.83	24
Macro avg		0.83	0.88	0.83	24
Weighted avg		0.89	0.83	0.84	24

From the results of the different developed models, it is easy to determine why the SVM was finally chosen. It displayed the highest recall and precision values, along with the highest accuracy available.

Confusion matrix

Below shows the confusion matrix for the SVM model

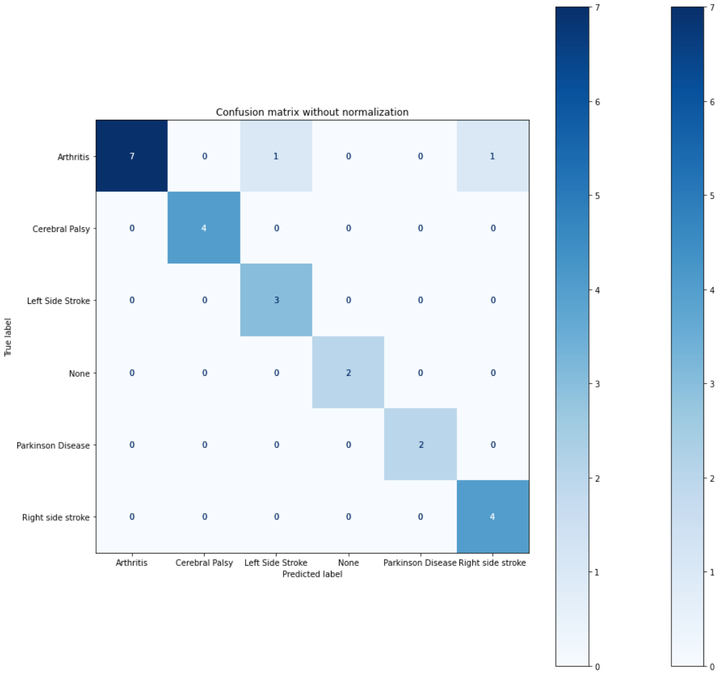

Fig. 4.1 SVM confusion matrix

Exercise Results

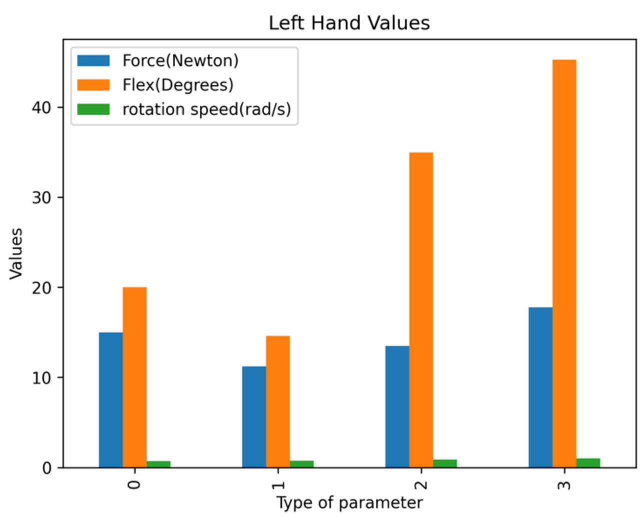

Fig. 4.2 Rehabilitation Results for Left Hand

V. CONCLUSION

This project work satisfied the major aim of building smart wearables for the physical rehabilitation of motor impaired patients. It consists of a system that was developed to be used in physiotherapy, specifically in physical and motor rehabilitation of hands, fingers and feet. The designed technology aims to help healthcare professionals improve their work by effectively monitoring patients and objectively evaluating the results of physiotherapy sessions. The system provides appropriate rehabilitation solutions to patients with motor impairment using machine learning approaches. Thus, the system allows for people with loss of motor function substantially regain or improve their motor function, thereby reducing recovery timeframes. Due to the system's mobility, the patient is able to remain at home and complete the rehabilitation exercises prescribed. This solution is suitable for use at home due to the ease with which it can be installed and calibrated by non-specialists for use in a non-clinical environment. Psychologically, patients feel better in their own environment, which accelerates rehabilitation. Even with the project achieving its main aim, there is always room for improvement in terms of features and scalability. For further works, providing physiotherapists remote access to monitor patients’ rehabilitation sessions and analysed data for aide in critical cases by building an e-health management dashboard, is recommended. Also, implementing Virtual Reality with serious games would result in providing more interactive and personalised user rehabilitation experience. Every system is subject to limitations as no system is 100% efficient. Due to the rapid evolution of technology, this field has not been fully explored. As a result, there are very limited reference works thus, finding and acquiring datasets was a major limitation. Also, the Kivy framework used was limited to some user gestures and icons.

Despite all improvements that can be made to the project, the solution already implemented represents a valid and ready solution to be used in physiotherapy clinics or in patients' homes to assist people in the motor rehabilitation of their upper and lower limbs. It also serves as a tool for physiotherapists to analyse results of rehabilitation sessions in an objective way, and provides a cheaper rehabilitation solution for patients with motor impairments to improve their motor function, thereby reducing recovery timeframes.

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