Pattern matching techniques to automatically detect range of movement tests from wearable sensors.

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2021 32nd Irish Signals and Systems Conference (ISSC) | 978-1-6654-3429-4/20/$31.00 ©2021 IEEE | DOI: 10.1109/ISSC52156.2021.9467875

***Abstract* — Wearable sensor technology has steadily grown in availability within a wide variety of well-established consumer and medical devices. Wearable sensors have been used in many healthcare applications to monitor patients at home and throughout their rehabilitation. Data collected from wearable sensors allow monitoring of patient recovery during rehabilitation and assist clinicians in diagnosing. Activities of Daily Living (ADL) is considered as an assessment criterion for various disease conditions. Wearable devices enable the collection of information associated with different range of movement (ROM) tests that measure ADL. In an ambulatory monitoring setting, the volume of data collected by wearable sensors can become complex and challenging to process. Extraction of ROM tests can be laboursome, and often fraught with misclassification of movement. Hence it is difficult to analyse and make conclusions/predictions from movement datasets using manual assessment techniques. This paper examines whether ROM tests can be automatically detected and extracted from wearable sensor data using Artificial Intelligence (AI) techniques.**

This research examines and discusses clinical trial data collected from patients suffering from Axial SpondyloArthritis (AxSpA). AxSpA is a disease that affects spinal cord mobility. In this trial, Inertial Measurement Unit (IMU) sensors are attached to the lower back and neck of the patient, and data corresponding to clinical trial movements are recorded. An AI system is trained and tested using these datasets, and the prediction accuracy of the system is examined. The system will be capable of detecting ROM tests within long-term datasets once the AI system used in this analysis is sufficiently trained by an adequate amount of data for efficient pattern recognition.

Keywords— Wearable technology, Activities of Daily Living (ADL), Artificial Intelligence (AI), Axial Spondylo Arthritis (axSpA).

I. INTRODUCTION

Wearable sensors can generally measure and quantify the wearer's physiology. A wearer's physical changes, such as their body temperature or joint movement, can easily be identified by a wearable sensor [1]. Healthcare wearable devices are expected to grow in popularity due to their real-time monitoring and operational efficiency. Motor-related diseases such as posture, gait, and arthritis can be monitored by processing data from wearable sensors. Real-time patient health tracking through wearable and implantable sensors has many potential benefits in lowering healthcare costs, enhancing patient quality of life, and delivering efficient chronic disease management [2]. Wearable devices are gaining acceptance as personal health devices because they allow for constant real-time surveillance of human health outside healthcare settings [3]. Wearable sensors can capture data on a 24/7 basis as wearers go about their everyday life at home and work [4]. Since sensors can collect comprehensive 3-D sensor information, the amount of data collected by sensors for long-term assessment of ambulatory movement can be very high in volume. However, processing of this data is complicated and time-consuming when extracting specific movement data corresponding to ROM tests from a large dataset.

Inertial Motion Unit Sensors (IMUs) are electronic devices that contain a 3D accelerometer, gyroscope, and magnetometer. The accelerometer and gyroscope calculate the angular movement and velocity of the IMU sensor, and the magnetometer measures the orientation of the sensor. IMUs are commonly used to detect and monitor the physical activities of the human body. Data collected by an IMU sensor can be used to estimate human body position, orientation, and speed [5]. IMU sensors improve the efficiency of Health Wearable Technology (HWT) applications. HWT devices usually simultaneously collect data from multiple parts of the human body. In addition, HWT devices collect physiological data and process them in real-time to analyse various vital signs such as heart rate, blood pressure, body temperature, electrocardiogram (ECG), Electromyogram (EMG), and respiration rate [6]. Besides HWT applications, IMU sensors are also used in other healthcare applications such as fall detection, immobility detection, measuring step count, distance estimation, and detecting standard functional tests for quantification and progression of various disease conditions [7].

Activities such as caring for oneself and the body, including personal care, mobility, and feeding, are referred to as Activities of Daily Living (ADL). Cognitive skills such as thinking and planning, motor skills including coordination and dexterity, and sensory-perceptual skills are required to confidently perform ADLs [8]. ROM tests and standardised functional tests can be used to fully or partially assess the capacity of an individual to perform ADL. Various ROM tests and standardised functional tests are used to investigate different disease conditions and are influenced by the specific part of the body affected by the disease [9].

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Psoriatic Arthritis (PsA), Reactive Arthritis (ReA), Axial Spondyloarthritis (axSpA), and Ankylosing Spondylitis (AS) are diseases within the broad category of Spondyloarthritis (SpA) [10]. AxSpA is a rheumatic condition that affects the axial skeleton and causes inflammation and structural changes [11]. ROM tests used for axSpA assessment consist of flexion, extension, lateral flexion, and rotation. Flexion is a forward bending motion; extension is a backward bending motion, whilst lateral flexion can be described as side stretching, and rotation is upper body rotation [12]. All these activities require movement of the lower back and neck. Functional tests for axSpA are shown in Figure 1.

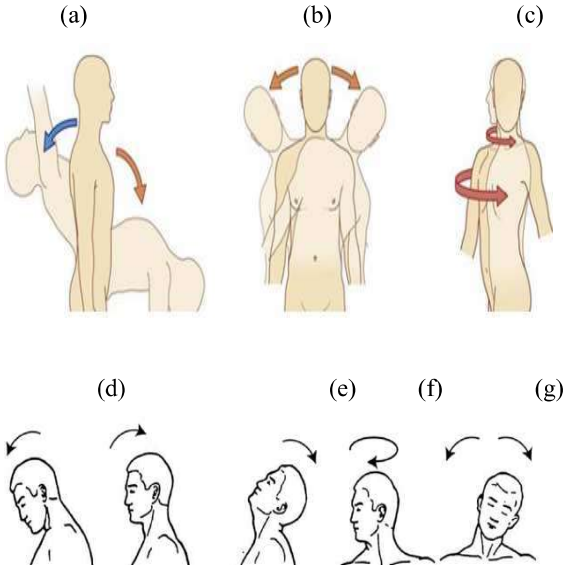

Fig. 1. (a) Lower back flexion and extension (b) Lower back lateral flexion (c) Lower back rotation (d) Neck assessment flexion (e)Extension for neck (f) Neck Rotation (g) Neck lateral flexion [13].

In clinical assessment, IMU sensors are attached at specific points on the patient's trunk and neck. Patients perform controlled movements throughout assessment under the guidance of a clinician [14]. With lower back assessment, the value from the upper sensor is usually called trunk, pelvic is the lower sensor output and the difference between trunk and pelvic provides a lumbar value. For neck assessment, the upper sensor output is occiput, T3 is the lower sensor value and the difference between these two is called cervical spine [15].

II. Materials and Methods

A. ViMove Sensors

The device used in this research to track participant movement is the ViMove system. ViMove is a low-powered, wireless, IMU-based movement monitoring device developed by DorsaVi. ViMove is validated and used for various clinical trials related to lower back pain [16]. Figure 2. shows the various components of the ViMove system. Two IMU sensors are attached to the participant according to the manufacturer's guidelines [17]. Accurate positioning of each sensor ensures proper data collection. The lower (sacral) sensor is positioned between the posterior superior iliac spines. A fitting template helps to affix the sensor accurately. The upper lumbar (trunk) sensor is positioned using the fitting template to position the upper sensor over the T12 vertebra. Two EMG sensors are integrated into the middle section.

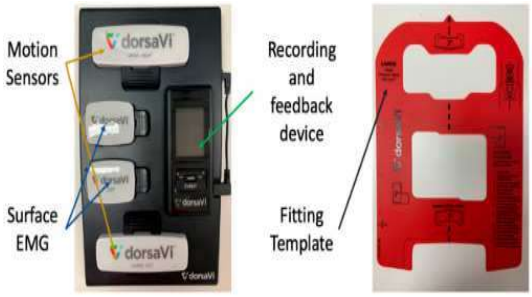

Fig. 2. ViMove system components [18].

The system contains a sensor Recording and Feedback Device (RFD), which stores sensor data. This device has a facility to manually indicate the start and end of specific movement routines, and transfers all data to the controlling computer for processing. RFD has the size and weight of a mobile phone, and hence the participant can easily hold it while doing prescribed exercises. Furthermore, it can generate alerts for unwanted movements and remind the participant to complete their exercises [18]. In addition, it contains a test profile for each ROM test and standardised functional test that includes description of the trial, number of repetitions, and test controls.

B. Study Design

This research analyses data collected from a FOREUM research trial [19]. This dataset contains movement data of patients suffering from axSpA. A primary objective of this study is to assess the reliability and accuracy of ViMove sensors to measure the spinal mobility of trial participants. The complete dataset contains clinical trial movement data recorded from 45 participants. Throughout the FOREUM study, each participant completed various ROM tests and standardised functional tests. During each session, the patient performed each functional test consecutively three times. The first set of tests were directed under clinician supervision when participants completed each functional test according to the clinician's advice. The second set of tests were performed without clinician supervision, during which each participant completed each functional test according to documentation and helpful videos. The third set of data corresponds to ambulatory movement. Each participant wore the ViMove sensors at home for 24 hours or more and performed the ROM tests and standard functional tests as part of their regular daily routine. Supervisory and unsupervisory clinical assessments were conducted over two consecutive days. The main challenges associated with ViMove whilst assessing axSpA are the range and speed of participant's movements, and the stability and balance of patients while performing exercises, and pelvic tilt that happened during movements [20].

Each ViMove sensor generated a comma-separated variable file containing accelerometer, gyroscope and magnetometer readings. The reliability and accuracy of the ViMove sensors were proven by extracting functional tests manually and automatically and examining correlations for both methods in terms of the maximum, minimum, range, and mean values with the ViMove generated values. Data was analysed manually by exporting the event markers to Microsoft Excel. Automatic data pre-processing was then subsequently implemented using Python algorithms. This independent

validation was assessed for five randomly selected participant's data. The comparisons between manual, automatic and ViMove generated data are shown in TABLE I.

TABLE I. COMPARISON OF ANGULAR VALUES BETWEEN MANUAL METHODS, VIMOVE DEVICE, AND PYTHON ALGORITHM.

Lumbar Flexion calculated manually				
	Rep 1	***Rep 2***	***Rep 3***	***Mean***
Max flexion	40.004	39.557	39.557	39.70
Min flexion	4.364	3.525	4.308	4.066
Range	35.640	36.032	35.249	35.640
Lumbar flexion generated by ViMove				
	Rep 1	***Rep 2***	***Rep 3***	***Mean***
Max flexion	40.004	39.557	39.557	39.71
Min flexion	4.364	3.525	4.31	4.07
Range	35.640	36.032	35.249	35.64
Lumbar flexion generated by Python algorithms				
	Rep 1	***Rep 2***	***Rep 3***	***Mean***
Max flexion	40.004	39.557	39.557	39.71
Min flexion	4.364	3.525	4.308	4.066
Range	35.640	36.032	35.249	35.640

Validation results showed that the ViMove device was reliable and accurate when compared to the independent assessment techniques. This dataset was then used as a source of data for this research.

C. Data Preprocessing

This study will require a detailed investigation of the measurement outputs of several body-worn sensor nodes placed on the upper body to capture kinematic data. A quantitative research methodology will be applied to the study since data output will be examined for correlative relationships, multiple measurements will be captured throughout each phase of the study, and statistical tests will be applied to data. Therefore, data pre-processing steps are significant for this research (see Figure 3).

A rotation angle matrix was generated from raw sensor data using quaternions with accelerometer and gyroscope readings. A Quaternion is a convenient mathematical notation for representing spatial orientations and rotations of elements in three-dimensional spaces. The magnetometer data of each IMU were excluded from angular calculations since the participant's direction of movement while standing or sitting has no significance for the identification of each standardised functional test. Data analysis revealed that some pelvic movements occurred once trunk movement had been initiated, leading to discrepancies between both sets of movements. The observed movement in these cases starts at the beginning of trunk movement and eliminates the rest of pelvic movements. It matches the normalised time duration for trunk and pelvic movements and helps to generate patterns for trunk movements more accurately.

While performing the ROM test for axSpA, the inclination of the upper sensor is higher than that of the lower sensor. Hence trunk movements usually have greater angular values than associated pelvic movements. Except for regular functional tests from IMUs, data corresponding to other random body movements is treated as noise.

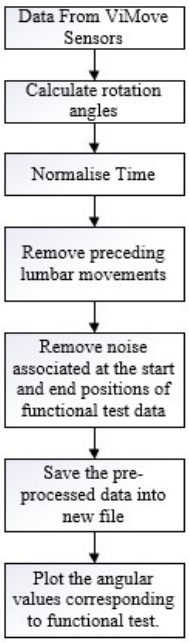

Fig. 3. Data pre-processing stages.

Data pre-processing for noise removal is critical for the design of a better AI system. In this analysis, the reduction of noise was carried out by an algorithm. In the first step, the algorithm traces the duration of each movement to be completed and an average time duration for each of the functional test is calculated. If the measured time is less than that of the expected one; the current cycle is considered as noise. The second step compares the maximum and minimum angular values for each movement. The threshold is set for the least maximum and minimum values expected for each movement. Comparing the measured maximum and minimum with the expected one helps to identify further noise within the start and end of each functional test. Figure 3. shows the data pre-processing steps, which include normalizing time and saving and exporting processed data to a CSV format. This dataset is used for training and testing the AI system. For clinical trial data, extracting movements manually is a time-consuming procedure for multiple participants with different functional tests. For long-term data capture, it is difficult to extract data for each functional test from the entire dataset manually.

D. Pattern Recognition and Pattern Matching

Deep learning is a field of research that aims to simulate intelligent behavior in computer systems. It is a subbranch of AI and ML (Machine Learning) that enables the computer system to learn without programming for specific tasks [21]. Deep learning uses unsupervised data for making predictions. Unsupervised datasets are not fully labelled and are usually large in size. Hence predicting outputs from this dataset needs complex programming methodologies. AI algorithms and other ML techniques are efficient in implementing deep learning concepts for large datasets [22].

Pattern recognition and pattern matching techniques are used together to extract ROM tests from clinical data [23]. The AI system is trained to generate matching patterns for each ROM test using clinical trial data. After the AI system has been built, it is tested on a real time patient movement dataset. A feed backward ANN is used to model the system. To use machine learning (ML) techniques in an ANN environment, two separate datasets are needed. The first is used to train the ANN system; the second is used to measure and test the ANN system's performance. The training dataset is used by the semi-supervised ANN to learn the structure of patterns before evaluating its accuracy. The trained ANN system then predicts the output values with respect to testing data. Accuracy is a metric for measuring the effectiveness of ANN models and it represent the percentage of correct predictions made by the model [24].

III. RESULTS

A Python quaternion library was used to calculate the quaternion vectors for angular rotations [25]. And previous positional coordinate data were combined with this vector to generate the final positional coordinate of each object (sensor). Quaternions for angular values (u, v, w) were calculated as:

$$q0 = \cos(w/2)\cos(v/2)\cos(u/2) + \sin(w/2)\sin(v/2)\sin(u/2)$$
$$q1 = \sin(w/2)\cos(v/2)\cos(u/2) - \cos(w/2)\sin(v/2)\sin(u/2)$$
$$q2 = \cos(w/2)\sin(v/2)\cos(u/2) + \sin(w/2)\cos(v/2)\sin(u/2)$$
$$q3 = \cos(w/2)\cos(v/2)\sin(u/2) - \sin(w/2)\sin(v/2)\cos(u/2)$$

Equation. 1. Quaternions calculated for angular values

The quaternion library returned the quaternion coordinates corresponding to accelerometer and gyroscope angular values. The rotational angle for quaternion coordinates (q0, q1, q2, q3) was calculated using the formula below.

$$\begin{bmatrix} \phi \\ \theta \\ \psi \end{bmatrix} = \begin{bmatrix} \arctan\frac{2(q_0q_1+q_2q_3)}{1-2(q_1^2+q_2^2)} \\ \arcsin(2(q_0q_2 - q_3q_1)) \\ \arctan\frac{2(q_0q_3+q_1q_2)}{1-2(q_2^2+q_3^2)} \end{bmatrix}$$

Equation. 2. Rotation angle calculated for quaternion coordinates.

These angular rotation values with normalised time fields were extracted. Sensor data was pre-processed to eliminate unwanted sensor outputs, and improved the data analysis efficiency. An example of a data file for supervised monitoring is shown in Figure 4.

The unsupervised monitoring dataset was more complex than supervised monitoring data. This dataset contained movement data corresponding to all movements performed by the patient whilst wearing the ViMove sensors. The duration and sensor noise content are longer than that of supervisory monitoring. An example of data collected throughout unsupervised monitoring is shown in Figure 5.
Noise associated with functional tests during supervised and unsupervised clinical trial data was removed using a High Pass Filter (HPF) and a Low Pass Filter (LPF) simultaneously [26]. The HPF passes signals with a frequency higher than the cut-off frequency, and LPF passes signal values less than a defined cut-off frequency.

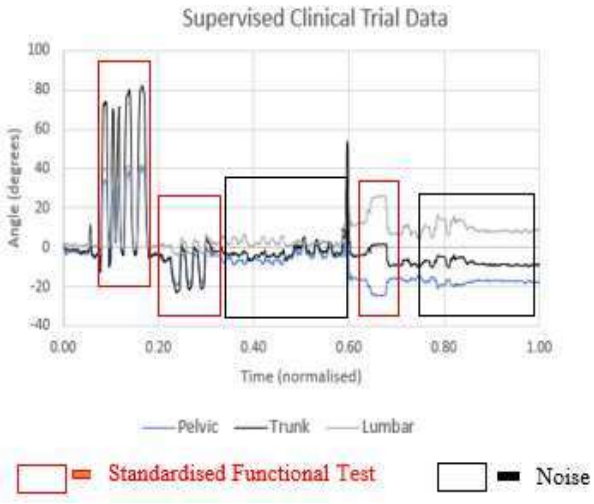

Fig. 4. Supervised monitoring movement record.

Movements corresponding to flexion and right lateral flexion contained high positive values and were filtered using the HPF, removing low-frequency noise associated with the data.

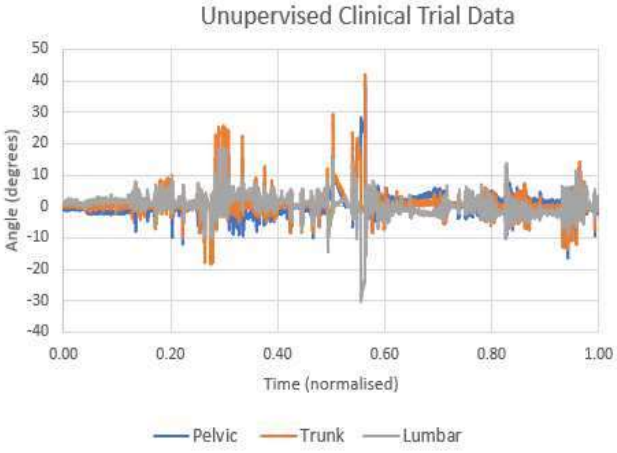

Fig. 5. Unsupervised monitoring movement record.

But it reduces data corresponding to extension and left lateral flexion, which are negative values. The LPF was applied to raw data for extension and left lateral flexion movement. During data analysis found that most of the noise values occur with frequency in between -5 to +5. The cut-off frequency for HPF was set to -5.0, and for LPF, it is set to 5.0. Figure 6 shows left lateral flexion movement extracted from unsupervised movement data using LPF.

The combined output from LPF and HPF again contained some noise values at the start and end and between each specific movement. A technical person analyses the recorded data to extract the exact start and stop time of a particular movement by examining values between two event markers if they are present within the exported dataset. The algorithm described earlier investigated the start and end point of each functional test within the sensor data. Initially the algorithm segmented each movement and checked for maximum and minimum values for each one, as well as the time duration required for each movement.

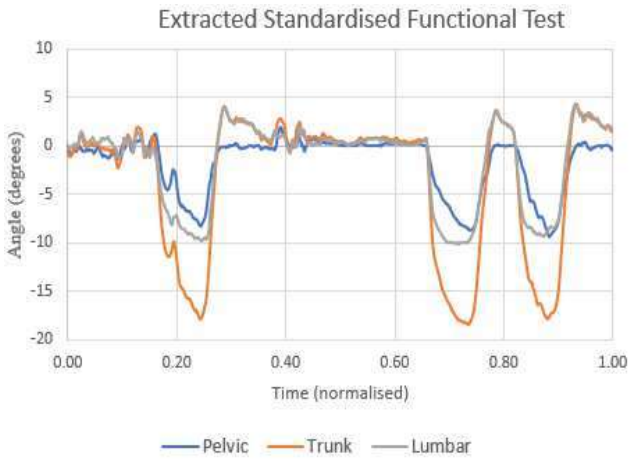

Fig. 6. LPF output for left lateral flexion movement

Whilst checking each movement cycle, if the time duration was less than a functional test movement threshold time, it was considered as noise.

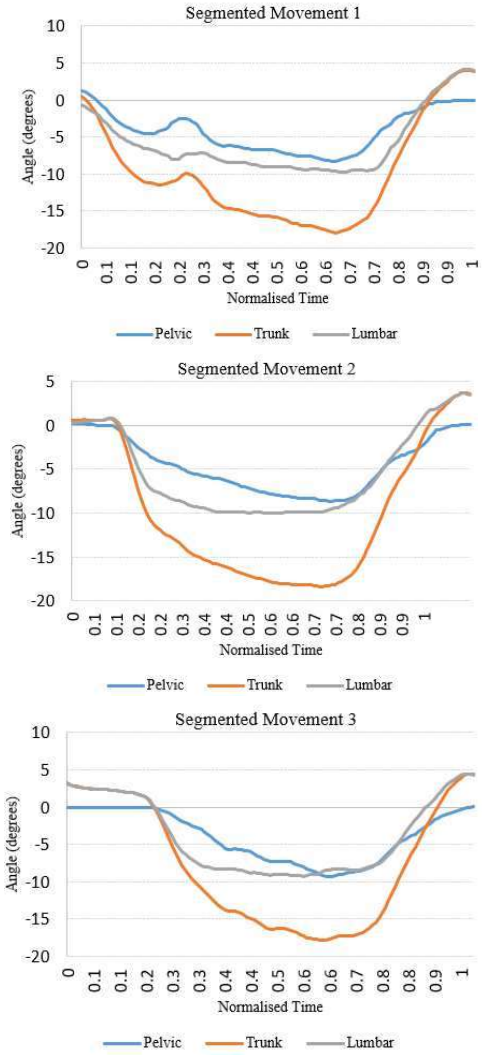

Fig. 7. Extracted movements for left lateral flexion.

The same process was continued until three consecutive movement repetitions were identified for each functional test, or the end of the file was reached. The algorithm segmented each movement individually and stored each one in individual files with normalised time values. Figure 7 shows segmented movement after removing all noise within the start and end of a specific 'left lateral flexion' movement.

Data records for ambulatory monitoring are complex and high in data volume. It is difficult to identify ROM tests from data records manually. An AI system was trained with movements from supervised and unsupervised clinical data [27]. This system was developed to automatically patterns from ambulatory data corresponding to ROM tests. Figure 8 shows a movement record for ambulatory movement.

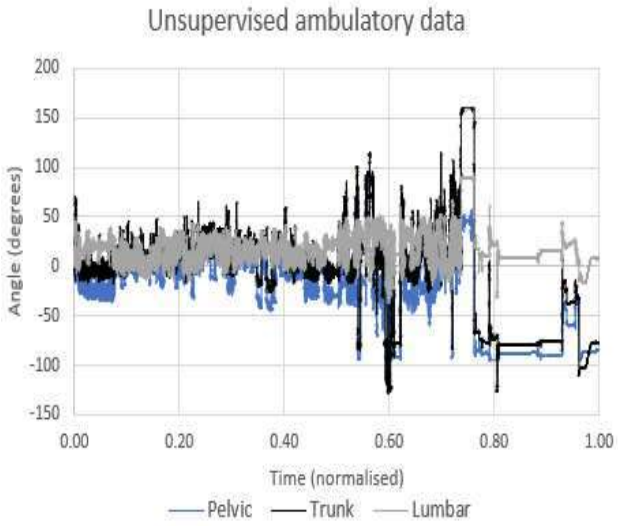

Fig. 8. Ambulatory monitoring movement record.

The ROM test patterns worked with ANN are flexion, extension, left and right lateral flexion. An ANN model was trained with Keras and TensorFlow together [28]. Initially, a system was modeled with TensorFlow alone [29]. It had 12 inputs with one pattern to each input, and the number of outputs was fixed to 4. The number of intermediate layers was fixed to 2^{12}. The ANN was designed with an activation function of 'tf.tanh', and the highest accuracy among five trials for flexion was 88.78% and extension was 80.71%. For left lateral flexion it was 73.7%, and for right lateral flexion was 71.77%. Loss value for flexion was .6381, for extension .6238, for left lateral flexion .7382 and right lateral flexion was .7842.

A deep learning system based on TensorFlow and Keras was combined and tested in four different scenarios.

- Test case1: activation function of Rectified Linear Unit (ReLU), optimiser function of 'sigmoid adam' and loss value function 'binary_crossentropy'.
- Test case 2: Loss value function - Mean Squared Error (MSE).
- Test case 3: Loss function - Categorical cross-entropy
- Test case 4: Activation functions 'softmax' and 'relu' are combined and the loss value function applied is MSE.

The loss value for each of these systems with number of participants (number N=5 and N=20) is shown in Table 1:

From each of the studies shown in Table I, it was confirmed that the ML model based on TensorFlow' and 'Keras'

combined the activation functions of 'relu' and 'sigmoid', and with the loss value function of MSE showed less loss values in predicting ROM tests from the long term data [30].

TABLE II. LOSS VALUE FOR DIFFERENT ANN SYSTEMS

	N=5				N=20			
Fun Test	*Flex*	*Ext.*	*LLF*	*LRF*	*Flex*	*Ext.*	*LLF*	*LRF*
1.	.128	.269	.328	.385	.462	.495	.687	.673
2.	.016	.028	.085	.084	.057	.040	.153	.195
3.	.041	.067	.093	.099	.329	.412	.349	.363
4.	.003	.009	.013	.023	.021	.033	.051	.098

A trained system can generate similar patterns other than the exacted one used for training. That will increase the system accuracy for pattern matching. This demonstrates that pattern matching algorithms can work efficiently to automatically extract ROM test patterns from long-term ambulatory monitoring datasets with high accuracy.

IV. CONCLUSION

ADL is considered a critical outcome factor for different medical conditions. Clinical trials are an efficient way to collect ADL information from patients. Wearable devices improve the collection of movement data from the patient over a long duration. Movement datasets contain information about all ADL functionalities of an individual. An ANN system that has been trained with different clinical trial datasets for pattern recognition and pattern matching is capable of automatically detecting different ROM data patterns from long-term datasets. If the techniques used in this analysis will detect ROM tests of human movement from long-term datasets, then sensors will be able to measure patient activity and recovery at home over a long time period.

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