

Data-Driven Model for Upper Limb Spasticity Detection

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Abstract: Upper limb spasticity (ULS) is a common pathophysiological changes manifest by a structural damage towards the central nervous system (CNS) that includes brain and spinal cord. The current clinical practice of spasticity assessment utilizes Modified Ashworth Scale (MAS) as a subjective tool to measure the severity of spasticity. Lack of objective value, poor sensitivity in detecting minimal changes, and dependency to the interpretation by the assessing clinicians are the several reasons of the inter and intra-rater variability of the measurement using MAS. These limit the use of MAS in diagnosing, treating, and monitoring spasticity especially in inexperienced clinicians, hence leading to inadequate spasticity management. To overcome this problem, a study is carried out to quantify and develop a data-driven model of ULS detection based on MAS. The characteristics that detect the existence of ULS according to MAS are identified and adopted to train the machine learning models for smart diagnosis purpose to assist the physicians to effectively manage spasticity.

Keywords: Upper limb spasticity, data-based model, smart diagnosis, Modified Ashworth Scale, machine learning

1. Introduction

Spasticity is a velocity dependent increase in muscle tone caused by the increased excitability of the muscle stretch reflex. Clinically, spasticity manifests as an increased resistance or an increment of muscle tone by muscles to passive stretching or lengthening [1]. Spasticity can occur in both upper and lower limbs of affected limb according to the location of lesions in the center nervous system (CNS). Spasticity is a common complication occur in any disease involving the central nervous system (brain and spinal cord) such as in stroke, cerebral palsy, traumatic brain injury, multiple sclerosis and arteriovenous malformation of the CNS , to name a few [2]. Spasticity is a manifestation of overactive muscles due to loss of inhibitory control from the CNS, cause altered balance between the innervations of intra and extrafusal fibers in a muscle [1].

Proper physical therapy and rehabilitation can at least prevent the worsening of spasticity [3]. An accurate assessment in diagnosing, treating, and monitoring of spasticity is required to ensure correct effective management is administered. Inadequate and less accurate assessment will lead to difficulty in managing patients with spasticity complication, hence, optimum functional level cannot be achieved. Recognising these problems, an alternative of assessment method to enhance the accuracy of the clinical examination is mandatory and crucial.

Diagnostic error during the clinical assessment should be avoided at all cost due to high medico-legal potential. Balogh et al, estimated that every human being will most probably encounter an impactful diagnostic error in a lifetime. [4]. Diagnosis error contributed to 17 percent of preventable adverse events, which includes error or delay in diagnosis, inability to employ indicated tests, usage of outdated tests' model or therapy, and the failure to act on results of testing and monitoring [5]. The diagnostic errors made by unassisted clinicians are due to multiple reasons such as memory bias, various presentation of disease, and ineffective communication [6]. There was an attempt to adapt the mathematical model of knee joint spasticity to recreate the characteristics of ULS in a part-task trainer as an effort to train the novice therapists elaborately without the risk of injuring patients [7].

Computer aided diagnosis serves as a potential method to reduce diagnostic error and assist in performing correct clinical assessment. Several reports have demonstrated the benefits in utilising computer aided technology in establishing skin cancer diagnosis using deep convolutional neural network (CNN) [8], with some studies evaluating the usage of computer aided diagnosis in improving the accuracy of diagnosing of breast cancer and detection of bone metastases that show variability in their performance [9].

In Malaysia's clinical setting, ULS severity assessment is very traditional and manual process. A clinical examination which involved multiple passive stretching of the examined limb at different set of velocity (slow stretch vs fast stretch). The objective measurement is obtained using a handheld goniometer and graded using Modified Ashworth Scale. This process is dependent on the skills and experience of the clinical assessors. Modified Ashworth Scale (MAS) is most widely used clinical scale for detection and classification of spasticity [10]. MAS shows good inter-rater reliability especially in upper limb spasticity assessment [11].

There is a previous study by the team to develop a data science platform for the development of ULS smart diagnosis system [12], and this is the more detailed study on the part of machine learning model training. The objective of this study is to develop a data-based model for ULS detection utilising data on spasticity collected among patients within Malaysian population with central nervous system lesions. By detecting the different patterns and trends in the data, the machine model is trained to recognise the occurrence of ULS based on certain features extracted from the expert knowledge of physicians. This paper is organised as follows: the next section will discuss the clinical data collection processes and the devices involved, followed by the description of the data pre-processing process, and the fourth section will be about the classification model training and its training result. The fifth and final section is the conclusion of this study.

2. Clinical Data Collection

The clinical data collection is conducted following the ethics approval granted by the Universiti Teknologi MARA (UiTM) Research Ethics Committee and the Ministry of Health Malaysia (MOH). The clinical data collection was carried out in UiTM Private Specialist Centre. Two Rehabilitation Physicians and a physiotherapist conducted spasticity assessment on the elbow flexor muscles. The sessions were assisted by 3 engineering students to provide technical assistance during the data collection process.

An integrated clinical data collection system is required for the collection of relevant parameters from the patients. There are 2 sensors, 1 wireless adaptor, and 1 wireless dongle in the data collection system. The details of the individual parts of the data collection system are elaborated in Table 1.

Table 1 - Individual parts of the clinical data collection system

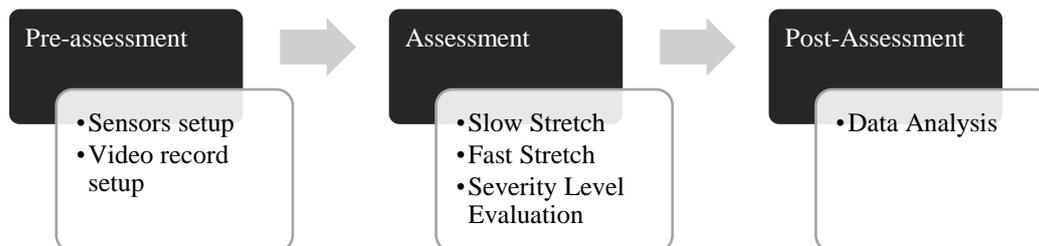
Equipment	Ref.	Specifications	
Wireless Twin-Axis Goniometers	[13]	Range	0-340° ($\pm 170^\circ$)
		Accuracy	$\pm 2^\circ$ measured over a range of $\pm 90^\circ$
		Resolution	+ 0.1° in a range of 180°
		Operating Temperature	+10 to +40 [°C]
Handheld Myometer	[14]	Rated Load	0 to 50 [kg] (for compression only)
		Accuracy	Better than 1% rated load
DataLITE Adaptor	-	Transmission Range	Up to 30 [m]
DataLITE PIONEER Wireless Dongle	[15]	Channels	16 sensors, up to 24 channels
		Transmission Range	Up to 30 [m]

The three sensors are to collect the two key data from the subjects respectively: wireless twin-axis goniometers for the elbow angle [deg] and handheld myometer for the elbow resisting force [N]. It should be noted that the magnitude of the elbow resisting force is a reaction force between the arm of the subject and the physician-in-charge. In order to reduce the stress of the target subjects and to ease the work of the physician, all the sensors selected are either built-in with wireless feature or have been converted into wireless sensor through a wireless adaptor. The goniometers has built-in wireless feature, while the DataLITE Adaptor in Table 1 is to transmit the data from the myometer wirelessly to the computer. The wireless dongle acts as the bridge of communication between the sensors and the computer.

At the same time, a video recording system was set up during the data collection session to record the data collection process. The footages are used for clarification and further review purpose in case of data irregularity. The video recording system consists of a phone camera and a tripod.

The clinical data collection session is divided into 3 phases, which is pre-assessment, assessment, and post-assessment phase. The pre-assessment phase involves the setting up all the sensors and the whole data collection system including the video recording equipment. Next, the physician will engage with the subject's spastic arm to conduct the passive stretching and give evaluation of the ULS severity level based on MAS. The involved physicians are well-acquainted with the diagnosis process of ULS and MAS. The post-assessment phase is the data analysis process to explore usefulness of the data obtained for the machine learning. The process flow is depicted in Fig. 1.

The assessment phase was divided into 3 exercises: Passive slow stretches applied on affected elbow flexors (repeated 3 times consecutively), Passive fast stretch applied on affected elbow flexors (repeated 3 times consecutively), and the spasticity classification based on MAS. The slow stretches allow the physician to determine the maximum passive range of motion (ROM) of the elbow joint, while the fast stretch is to provide velocity towards the examined elbow flexors muscles in order to activate the hyper excitability of the muscles. The hyper excitability manifests by 'catch', an angle where the biceps become hypertonic due to the activation of the stretch reflex. The angle where the catch occur were the primary data that were collected for further analysis. Severity of spasticity of the elbow flexors were evaluated based on MAS.

**Fig. 1 - Flow chart of clinical data collection and assessment**

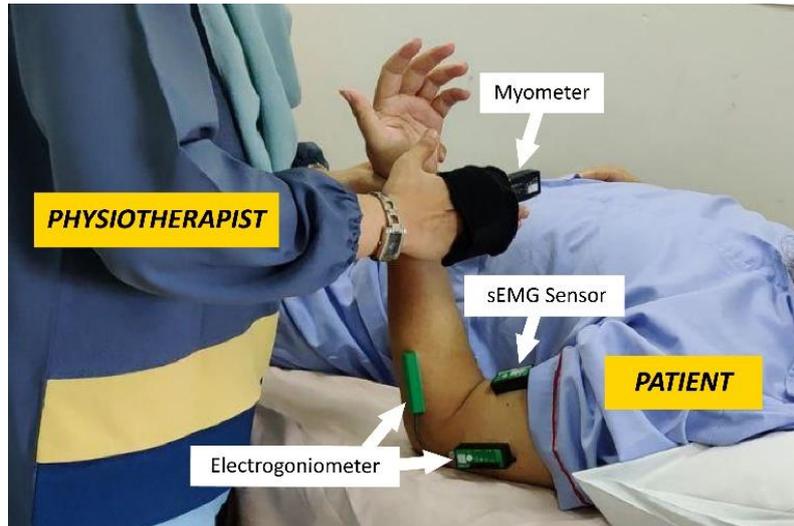


Fig. 2 - The sensor parameters are the elbow angle (θ_{elbow}) and elbow resisting force (F_{elbow}) of the subjects. For that purpose, a goniometer, and a myometer are needed. The wireless setup of the data collection eases the work of doctors/physicians as well as reducing the stress of our target patients during the data collection process

3. Data Pre-processing

To create a data-based model, the collected data must undergo the complete data science pipeline. The main parts of the pipeline are the data pre-processing, features extraction, machine learning model training and the model validation. It should be noted that only the fast stretches contain the valuable information for the classification according to the clinical practice. Thus, only the fast stretches of the clinical data are extracted and utilised. The signals acquired are in the raw form and no filter is applied beforehand. The raw data is shown in Fig. 3. Having the raw data, the next steps involve the cleaning and filtering of clinical data, feature extraction, and classification.

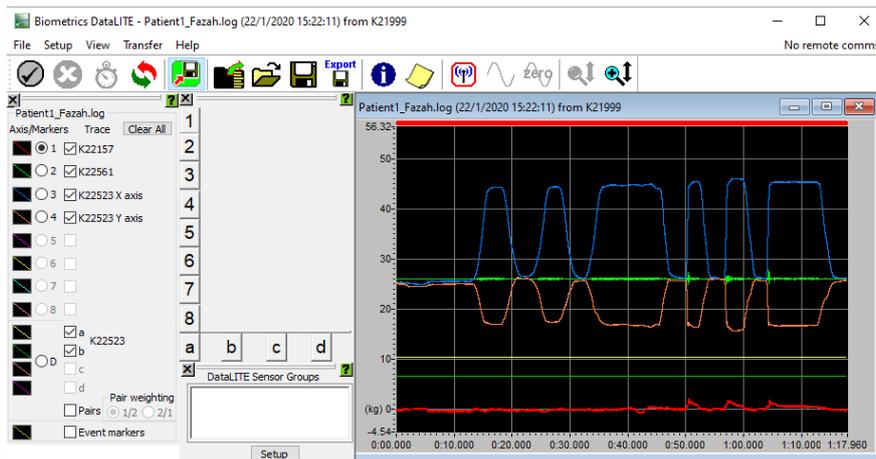


Fig. 3 - The acquired raw data of elbow angle [deg] and elbow resistance [N]

3.1 Cleaning and Filtering of Clinical Data

The raw data acquired must be pre-processed before any analysis could be done. Different methods have been studied and deployed as shown in Table 2. The elbow angle is pre-processed with a median filter to remove the outliers which is abnormal and do not fit into the data properly. Besides, a mean filter is applied onto the data to smoothen the data by taking the moving average. Besides the mean and median filter, the elbow resisting force is also pre-processed by setting the minimum value of the data window to be zero. The comparison of the elbow resistance before and after the pre-process is displayed in Fig. 4.

Table 2 - Summary of pre-processing methods

Sensors	Data Type	Pre-process Methods
Wireless Twin-Axis Goniometers	Elbow angle [deg]	<ul style="list-style-type: none"> ▪ Median filter : to remove outliers ▪ Mean filter : to smoothen the data
Handheld Myometer	Elbow resisting force [N]	<ul style="list-style-type: none"> ▪ Median filter : to remove outliers ▪ Mean filter : to smoothen the data ▪ The elbow resistance is adjusted to be zero-minimum

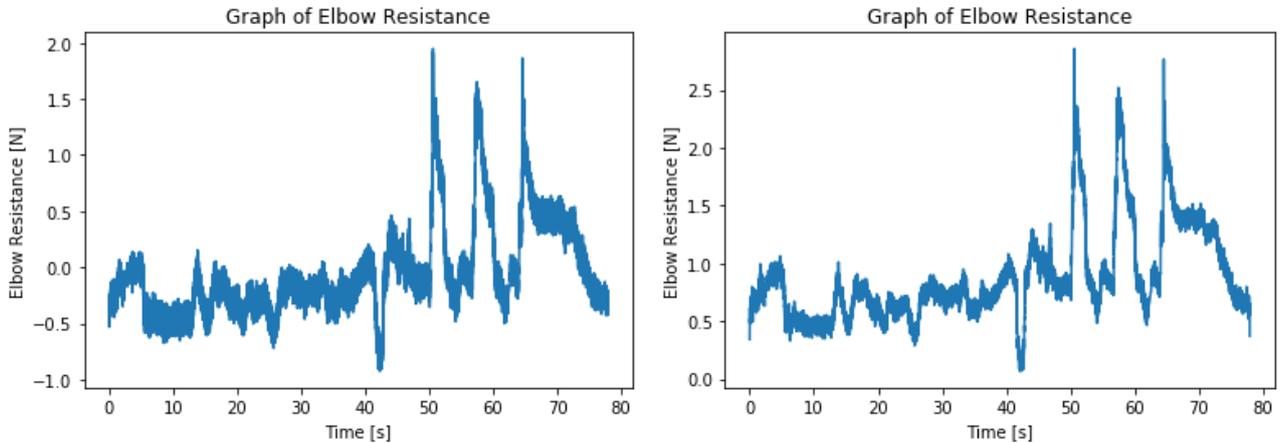


Fig. 4 - (a) Raw elbow resistance signal; (b) Elbow resistance after pre-processing

3.2 Feature Extraction

The features are extracted from the data based on the selected time window. In Fig. 5, it can be observed that there are six cycle of increases and decreases of elbow angle. Each cycle is identified by locating the local minima and local maxima. The boxes in Figure 3 show the six segments from one trial with the subject. The features for the machine learning model are extracted from each fast stretch. An interview has been conducted with the trained therapist to extract the expert knowledge in determining the important parameters for the classification.

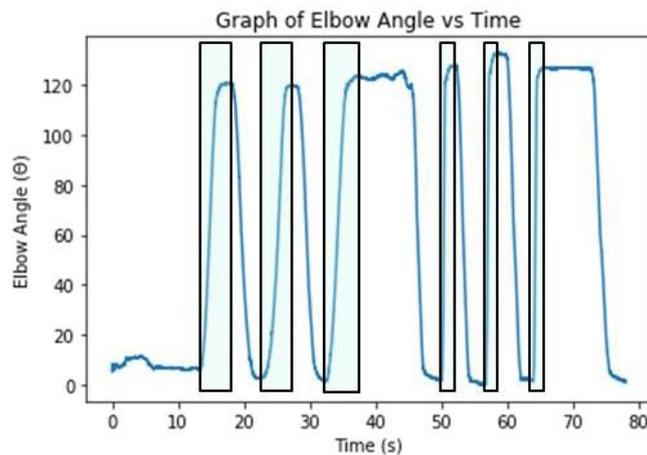


Fig. 5 - Identification of the passive ROM during slow and fast stretches

From each cycle, the features are identified and extracted for Machine Learning purpose as listed in Table 3.

Table 3 - Extracted features

Features	Explanation
Average Angular Velocity, ω	The average angular velocity of the stretch
$\Theta_{\text{Max } \omega}$	Elbow angle at the instance of the maximum instantaneous angular velocity
Range of Motion (ROM)	The passive range of motion of the stretch
$\theta_{\text{Max Force}}$	Elbow angle at the instance of the maximum force of the stretch
$\theta_{\text{Max Force/ROM}}$	Ratio of $\theta_{\text{Max Force}}$ to the ROM
Average Force after Catch	The average elbow resisting force after the catch
Average Slope of Force after Catch	The average rate of change of force after the catch
Max Force/End Force	The ratio of maximum force to the ending force of the stretch
End Force/Start Force	The ratio of the ending force to the start force of the stretch

4. Data-based Modelling

In this study, the machine learning model is trained to detect the occurrence of spasticity. Thus, this is a binary classification case, with 1 indicating the spasticity exists (equivalent to MAS Level 1, 1+, 2, 3 and 4) and 0 indicating no spasticity (MAS Level 0).

After the feature extraction process, the data is now ready for the machine learning model training. The 183 datasets are split into train set (to train the model) and test set (to validate the model). The ratio of train-test set splitting is 80:20. Therefore, 146 datasets are used to train the classifiers while the remaining 37 datasets are used for validating the trained model. The datasets are split and shuffled randomly into the training and testing set.

4.1 Value Normalisation

After splitting the train and test dataset, the extracted values are normalised by removing the mean value and scaled to unit variance, to avoid the small numeric attributes from being overshadowed by the larger numeric features [16]. The standardised value z is defined as follows:

$$Z = \frac{x-u}{s} \tag{1}$$

where x = training sample
 u = mean of training sample
 s = standard deviation of training sample

After the standardisation of all the values of the extracted features, the datasets are now ready for model training.

4.2 Model Training

A total of three different classifiers are trained and evaluated for this study, namely the Decision Tree, Random Forest, and Support Vector Machine (SVM). These three classifiers support binary classification as required for the detection of the spasticity. For the training for each classifier, the important hyperparameter is fine-tuned by doing broad grid search with large number gap followed by more detailed grid search with the smaller number gap. The hyperparameters are selected based on the “balanced accuracy” scoring method [17] from the 3-fold cross validation over the train set.

$$\text{Balanced Accuracy} = \frac{1}{2} \left(\frac{TP}{TP+FN} + \frac{TN}{TN+FP} \right) \tag{2}$$

where TP = True Positive
 TN = True Negative
 FP = False Positive
 FN = False Negative

For Random Forest classifier, the grid search is conducted upon the parameters of max features, the number of trees, and the splitting criterion. As for the decision tree classifier, the grid search is carried out upon the parameters of splitting criterion and the splitter. And for SVM, grid search is conducted upon the parameters of the kernel, gamma and C parameter.

4.3 Confusion Matrix

Confusion matrix is a matrix consists of n rows and n columns, where n is the number of classes for classification. In this case of binary classification, the confusion matrix is a 2×2 matrix with the label of 0 representing non-spastic while 1 representing positive spasticity. The rows are the true spasticity label of the respective data while the columns are the prediction of the classifiers. The confusion matrix of all the three classifiers are shown in Fig. 6

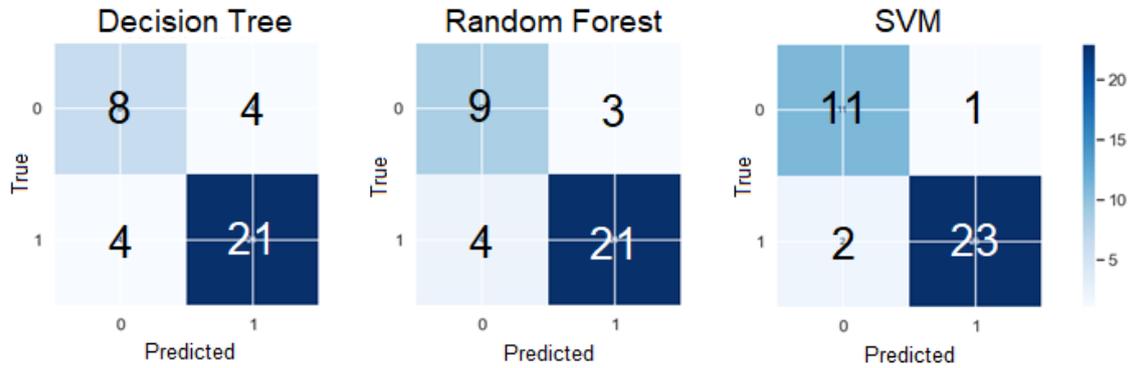


Fig. 6 - Confusion matrices of Decision Tree, Random Forest, and SVM (from left to right)

The top left corner of each matrix is where the true and predicted value are both 0, thus it is a True Negative (TN) box. The top right corner is where the true value is 0 yet the classifier predicts the value to be 1, and it is known as the False Positive (FP) box. The bottom left corner is where the true value is 1 but the predicted value is 0, and it is known as False Negative (FN) box. The bottom right corner is where both the true and predicted value are 1, and it is the True Positive (TP) box.

The matrices shown can only give an overview of the predicted values and their respective true values. The confusion matrix has to be further analysed to evaluate the performance of each trained model.

4.4 Performance Metrics

The performance of the classifiers is evaluated based on several metrics: accuracy, precision, and recall. Accuracy is the ability to predict the class based on the MAS level, which is the correct predictions out of the total attempts. The equation of the accuracy is as follows:

$$Accuracy = \frac{Correct\ Predictions}{All\ Predictions} \tag{3}$$

Precision is the ability of the classifier to accurately predict the positive instances. In other words, it is the ability of the classifier to not label a negative instance as positive [18]. In this study, the positive instances are the instances where there is spasticity, while negative instances are the instances without occurrence of spasticity (or MAS Level 0). The equation of the precision is as follows:

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

Whereas recall is the ability of the classifier to correctly predict all the positive instances. It is also known as the true positive rate (TPR) [19]. In this study, recall can be considered as the most important performance metrics, as it is necessary to predict all the occurrences of spasticity correctly. The equation of recall is as follows:

$$Recall = \frac{TP}{TP+FN} \tag{5}$$

As mentioned in the previous section, the evaluation of the train set is based on 3-fold cross validation, thus the performance metrics score will be presented in the form of mean score with the standard deviation. As for validation on the test set, there will be only one score for each performance metric. It should be noted that the value of test set is normalised separately before the validation process, to resemble the real-life validation process better. The results are compiled in Table 4, Table 5, and Table 6.

Table 4 - Accuracy of the machine learning models

Classifiers	Train Set	Test Set
Decision Tree	77% ± 11%	78%
Random Forest	87% ± 8%	81%
Support Vector Machine	80% ± 10%	92%

Table 4 shows the accuracy performance of the different classifiers. Random Forest is the best performing classifiers on the train set with the mean accuracy of 87%, while its performance on the test set validation is 81%. The SVM classifier has a mediocre mean accuracy of 80% for the train set but is the best performers on the test set with 92% accuracy. Decision Tree classifier is the worst performer in accuracy with 77% mean accuracy on train set, while able to obtain 78% correct classification of spasticity.

Table 5 - Precision of the machine learning models

Classifiers	Train Set	Test Set
Decision Tree	85% ± 11%	84%
Random Forest	88% ± 9%	88%
Support Vector Machine	88% ± 9%	96%

Table 5 shows the precision performance of the classifiers. Decision Tree classifier has an 85% of classification precision on the training set while has a 84% precision to detect spasticity in the test set. Random Forest and SVM classifiers have the same precision performance on the training set, while SVM performs better on the test set with a 96% high precision performance compares to the 88% precision of Random Forest classifier.

Table 6 - Recall of the machine learning models

Classifiers	Train Set	Test Set
Decision Tree	82% ± 5%	84%
Random Forest	94% ± 5%	84%
Support Vector Machine	83% ± 7%	92%

Table 6 shows that Random Forest is the most promising classifier for spasticity to detect all the positive spasticity occurrences correctly with a high precision of 94% on the test set, follows by the 83% of SVM and 82% of Decision Tree. However, the model validation on the test set shows that SVM performs better than the other two classifiers with a high precision of 92%, follows by 84% of both Decision Tree and Random Forest classifiers.

Based on the results shown, all the classifiers have decent performance of above 75% for all performance metrics. SVM is performing well on the test set and have the highest score on all the performance metrics, despite having lower score than Random Forest classifier in a few instances during the training process. The Random Forest classifier might have overfitting issue as it is performing well on the training set yet has a lower score on validating the test set.

5. Conclusion

The diagnosis of ULS in a clinical setting is a subjective process based on the experience of the physicians, and this will reduce the healthcare quality provided to patients with ULS. This study provides a system which could help to in the diagnosis of ULS by utilising the quantified data from the upper limb of the patients for ULS detection. This study produces an overview from the data collection process to the completion of the development of ULS detection models.

In this study, the clinical data collection process and the sensors involved are detailed. The collected data are then cleaned and filtered to enhance the data quality. The important features are then extracted from the fast stretches. From this study, it is shown that SVM has the highest scores on the test set for all the performance metrics in this study albeit having lower scores in some instances of training set. The machine learning model can be integrated with the wireless sensors and data acquisition system to aid the physicians in ULS detection. The wireless feature will ease the work of the physician without the cluttering of wires, and being small and portable enough to be used in a clinical setting.

Currently, the trained model could act as a supporting tool for the ULS detection based on MAS clinical assessment tool. In the future study, the research team will continue to collect more clinical data and carry out further analysis for the training of multi-classes classification of the ULS severity level based on MAS Level 0, 1, 1+, 2, 3, and 4.

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