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Abstract: in this paper, a seamless connection between sensor technology and machine learning (ML) has been presented which has wide applicability in rehabilitation and physical medicine. The intent is to identify an ML algorithm which has a better performance, easy to deploy, and has less training time and consumes less computational resources. In short, we propose an algorithm which maximizes the synergy between a sensor and ML by maximizing classification performance and easy to do implementation, which is robust in computational power and lower in resource consumption. The premise of the work is to show the important considerations for evaluating ML algorithms for Upper-limb activity recognition for Physical medicine and rehabilitation field.

Keywords: upper limb (UL); machine learning; movement

1. Introduction

An accurate human movement analysis [1,2,3,4,5,6,7, 34] has several applications, including upper-limb (UL) rehabilitation, assessment of neurological diseases, tracking the trajectory of improvement or deterioration of arm movements, and assessing athlete performance. UL movement can be measured using wearable sensing or non-obtrusive optical marker tracking techniques. Wearable sensing techniques are simple, non-obtrusive and self-contained [4]. Moreover, these techniques can be used to record long-term UL movements while the participants can perform activities of daily living (ADL) at home [8,9,10]. Wearable inertial sensing is a compact wearable device containing a tri-axial accelerometer and or tri-axial gyroscope [23, 24, 25, 26].

The main problem with inertial sensors is to ingrate their signal recordings over a long phase of time [27, 28, 29, 31, 32]. As a result, their noise accumulates, leading to invalid posture or UL movement classification. This error can accumulate in as few as the 60s. In [5] authors showed that inertial sensing data resulted in drift after every minute. Kalman filtering techniques have been used in [5] to reduce the drift and fuse gyroscope data with inertial sensing data. However, the Kalman filter was able to reduce the drift only for a smaller period, mainly in the non-movement paradigms. Vicon technology (i.e. marker-based UL tracking) is relatively accurate but suffers from noise and light deflection errors [11,12,13].

Machine learning algorithms have the potential for rapid classification and avoiding inherent issues of inertial sensing such as drift and accumulated noise. This new data-driven paradigm, i.e. combination of ML and sensing approach can be used efficiently for UL classification purposes. Recently, human activity has been recognised using ML [6, 14, 15, 16, 17]. ML has successfully been applied to recognise gestures, neurological disorders such as Parkinson's disease [19, 18, 30, 27], multiple sclerosis [8] and assessment of motor functions as well as arm movements usage in stroke patients [9, 10].

Many of the previous studies demonstrate the application of inertial sensors and the use of ML in clinical populations. However, to the best of our knowledge, no specific guidance presently exists to advise clinicians on the classification and benchmark of this ML approach, which is important being at the intersection of data science, human upper-limb movements and neurological disorders.

Hence, ML has broad applicability and potential for the inertial sensing classification; however, understanding whether to develop a deep learning model or a simple Naïve Bayes [24, 25, 26, 27] modelling approach for a specific set of data is of foremost importance.

A timely application of the combined ML and sensing classification approach to monitoring rehabilitation trajectory in stroke patients or people living with disabilities could assist clinicians. Quantification of the movement trajectory of UL in rehabilitation medicine entails classifying motor units of measurement, which are matched with the clinical outcomes. For example, an ML algorithm (hidden Markov model with logistic regression) has been applied to the inertial sensing data for UL recognition of primitives, which has achieved an overall classification performance of 79% [8]. At the same time, this research failed to address research challenges such as computational complexity and costs. Thus the main objective of this research is to compare the hand movement classification accuracy across several well known machine learning algorithms.

The remainder of this paper is organised as below. Section 2 describes the overall methodology with the description of data set. A brief description of ML algorithms are also presented in this section. Section 3 presents the results and this paper is concluded in the conclusion section followed by the future works.

2. Methodolgy

2.1. Data Sets

In order to demonstrate the steps in identifying the optimal machine learning algorithm for inertial movement data, we utilised data collected in a previous study from the University of California, Irvine's (UCI) machine learning database (Vicon Physical Action Data Set [19, 33]). The data was collected from seven male and three female participants (aged 25 to 30). In 20 experiments, each participant performed ten normal and ten aggressive postures. Ethical regulations have been followed during the data collection according to the code of ethics of the British psychological society. Each physical activity's data (an action) was collected separately from each trial. Each action was made for approximately 10 seconds per participant, resulting in a time series of 3000 data points with a sampling rate of 200 data points in a second (200 Hz). In this data set, two markers have been placed on the right and left arms of the participant. These markers are considered a good indicator of human upper limb movement. The Vicon data has been used extensively in rehabilitation, physical medicine and hospitals [19, 33].

2.2. Description of the Data

The data is 3D in nature and has x, y and z coordinates representing the position in the space of every marker. In this paper, since we are interested in the UL movements, the first five markers' (m1, m2, m3, m4 and m5) position data were used as a feature set. Two markers were attached as a segment of the human body, and hence four segments of data were obtained, starting from the head to the right arm (R-Arm) and the left arm (L-arm), as shown in Figure 1. An illustration of the data is explained in the Table 1 below:
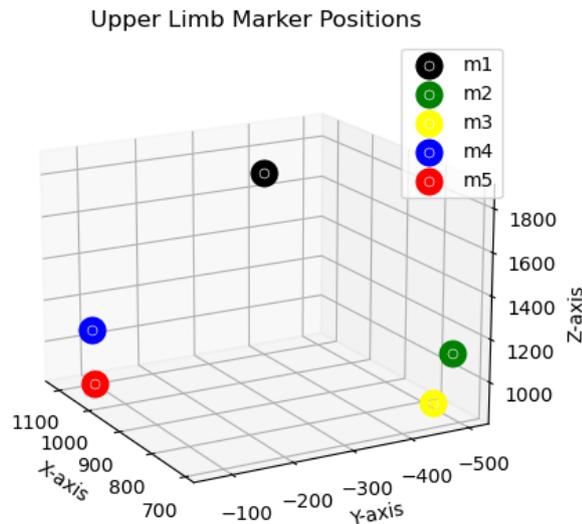
Figure 1. Upper limb (UL), marker positions (m1, m2, m3, m4, m5) attached to head (black), left arm (green and yellow) and right arm (blue and green), respectively.

Table 1. The 3D spatial data of Vicon markers attached to the human limbs or segments.

Segment	Head	L-Arm	R-Arm
Markers	m1	m2 – m3	m4 – m5
Coordinates	(x,y,z)	(x,y,z)	(x,y,z)

Five different movement data were considered for this study, i.e. Waving, Handshaking, Clapping, Punching and Hammering. All the data are a good candidate for representing of the UL movements, providing an appropriate feature space for the machine learning algorithms explained in the section.

2.3. Machine Learning (ML) Methods

This research sought to identify the ML algorithm that performs well on positional data such as Vicon data and or inertial sensing data. The purpose is to identify functional data primitives and/or features with a very high classification rate and practical use, i.e., with low learning rates and computational time. Although, ML methodologies have also been applied to computer vision-based data, as shown by the authors in the previous studies [20, 21, 25].

During the training phase of ML algorithms, a relationship between data characteristics (primarily the statistical features) and its labels (classes) is established. Eventually, building a model which utilises the pattern of data characteristics to identify a new data sample as one of the primitive blocks. Finally, this classification is verified against the ground-truth or human-annotated labels, resulting in classification performance.

We considered both generative and discriminative algorithms. Generative algorithmic models tend to find the underlying probabilistic distribution of data for each class or label to identify data characteristics that enable pattern matching of new samples to a given class. In contrast, discriminative algorithms model the boundaries between classes and not the data themselves. They seek to identify the line or plane separating the classes so that, based on location relative to the plane, a new data sample is assigned to the appropriate class.

This study has selected three algorithms based on their high classification performance in human UL activity. Namely, Support Vector Machines (SVM) with a radial basis kernel function (RBF), Naïve Bayes classifier and 1-D Convolutional Neural network (CNN) [34]. All algorithms were designed in
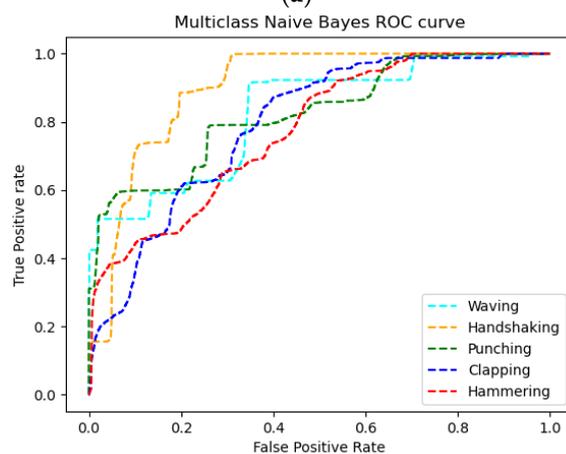
Python 3.8 using the scikit-learn library. The results and the accuracy of the algorithmic performance to classify the UL data is shown in the result section of this paper.
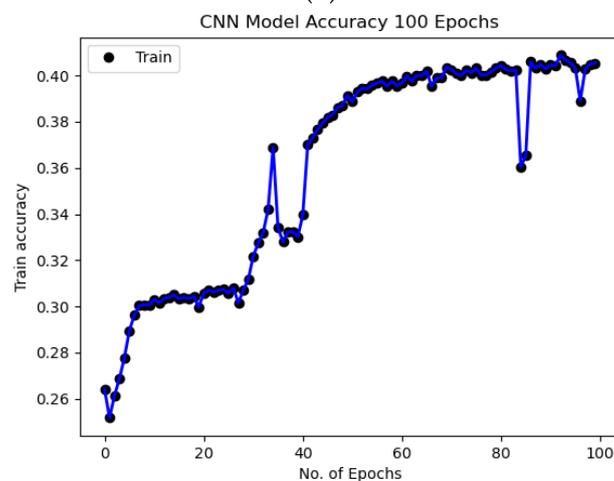
3. Results

Preliminary results have been presented in this under preparation report. The results are based on Naïve Bayes, SVM and CNN.
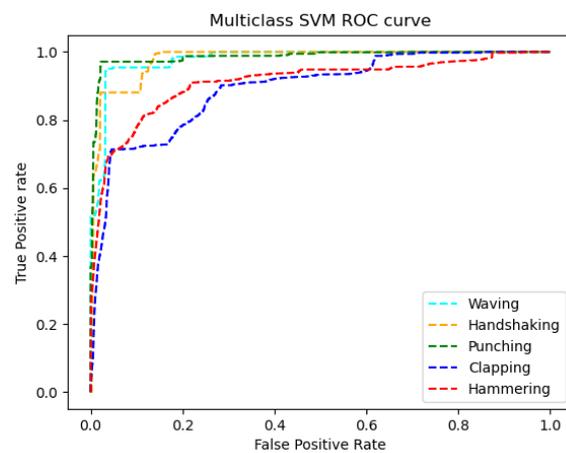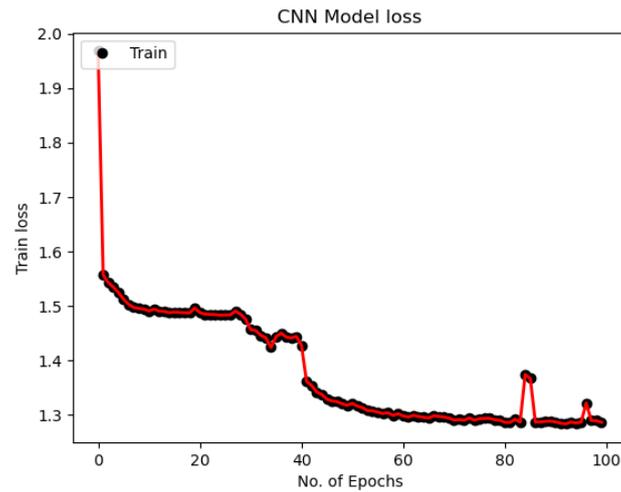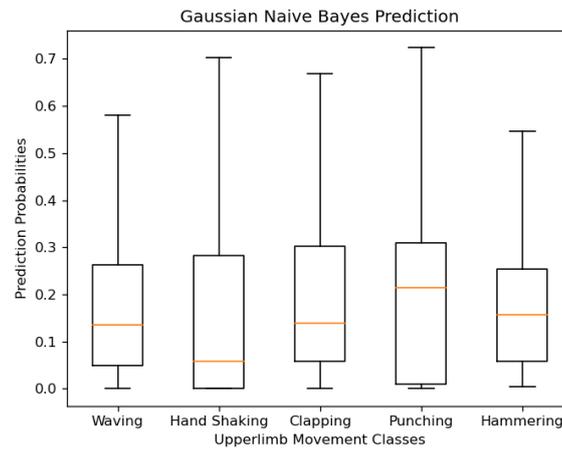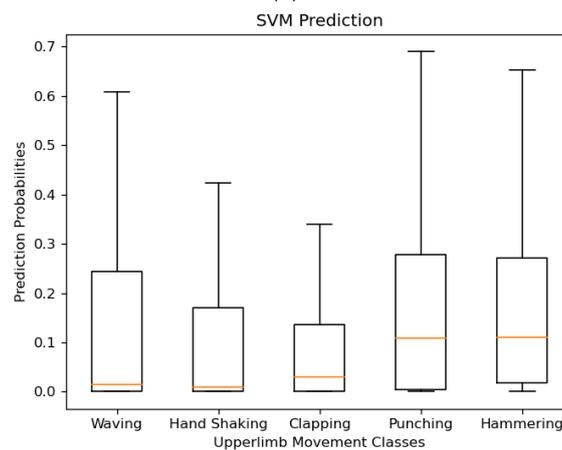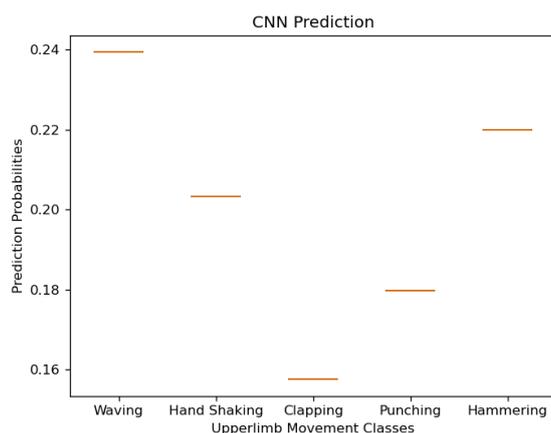
(a)

(b)

(c)

(**d**)

Figure 2. Preliminary results of Machine Learning based classification of sensor data. **(a)** Support Vector Machine (SVM) classification performance, **(b)** Naïve Bayes classifier's performance, **(c)** 1-D Convolutional Neural Networks (CNN) classifier training accuracy, **(d)** and CNN Model's loss.

(**a**)

(**b**)

(c)

Figure 3. Prediction probabilities boxplots of Machine Learning algorithms on test dataset. **(a)** Support Vector Machine (SVM) classification performance, **(b)** Naïve Bayes classifier's performance, **(c)** 1-D Convolutional Neural Networks (CNN) classifier.

4. Conclusion

In conclusion, we present classification performance comparison of three representative machine learning algorithms. This comparison will be useful especially for clinicians inorder to optimise patients' motion capturing needs. In this paper, we have shown practical and computational considerations towards the implementation of motion capture sensing approach in a quantitative way. In particular, our findings can be useful to define a strategy which provides a solution for the classification of functional primitives of body movements. So far SVM had the best classification accuracy, followed by the Bayes classification and CNN.

Future Work

This study has some limitations and we are planning to cover it in future. This study demonstrates the use of ML algorithms and their head to head comparison while classifying different UL functional primitives and tasks. We aim to build a universal system which switches between the most appropriate ML algorithm and retains the highest accuracy specific ML algorithm for a particular task. Due to limited data set, we did not explore the clinically valid UL postural movements, for example of stroke or people living with disabilities or other impairments, identification as a functional primitive.

Also, variability in data was not identified properly, which could be a reason for CNN to not to perform. A collaboration with ML experts and clinicians is suggested. A more refined data with more degrees of freedom or kinematics can be beneficial to define a better feature matrix for ML algorithms.

The most important aspect is that our approach allowed us to demonstrate the practical implications required in the motion classification using sensor data.

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