Human Activity Recognition Using Deep Learning Algorithms

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***Abstract*—Rapid growth of the technological advancements has led to improve the quality of the life. Human activity recognition if one of them. Although the activity detection can be explored using videos, currently involvement of sensors indicates a positive impact of individual health monitoring and removing the barrier of healthcare. HAR system includes various operation modules such as data acquisition, pre-processing to remove noise and distortions, feature extraction, feature selection, and classification. State-of-the-art techniques have proposed traditional machine learning classifiers which are using poor feature extraction method that are incapable of recognizing complex activities. Advancements of high computational resources aid deep learning techniques to be used in modern HAR systems in various applications to retrieve features and classification more efficiently. This paper describes how to use accelerometer and gyroscope data to determine several human activities with proposed deep learning techniques such as CNN, LSTM and DNN. Thus the performances of the models are evaluated via recommended parameters and certain challenges and issues which may addressed in future research improvements.**

***Index Terms*—Activity recognition, Machine learning, wearable sensors, HAR, Deep learning, Accelerometers.**

I. Introduction

Human activity recognition (HAR) is a process that helps people identify their activities and improve their daily lives [1]. This technology can learn about their activities from the data collected by sensors [2]. Due to the development of computer interaction applications, such as human activity recognition, the technology has gained widespread acceptance. It can be used in various fields, such as video surveillance and home behavior analysis. Through this technology, people can easily classify their activities and obtain the necessary information from their daily routines. Technological advancements have led the sensor technology and computing performance onto another level so that HAR has become more popular and is widely used in regular life without affecting privacy much. Usually, in sensor-based methods, a set of dedicated body-worn motion sensors are used to gather information from different kinds of behaviors such as accelerometers, gyroscopes, and magnetometers. hence the angular velocity data would change according to human motion, they could be used to infer human activities. building mobile devices embedded with various sensing units with a small form factor allows individuals to wear them easily and convenient to carry them throughout the journey [3]. Moreover, these sensors have the characteristics of low cost, low power consumption, high capacity, miniaturization, and less dependence on surroundings [4].

Wearable devices are commonly used in healthcare applications to track a person's daily activity. However, their accuracy is still considered to be a major issue. There are still a lot of research efforts being conducted to improve the performance of these systems. Machine learning techniques have gained a lot of research interest due to their potential to improve the performance of various applications. However, now the development of deep learning models over the machine learning models for human activity recognition has got significant interest from researchers. Deep learning models such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) deep neural networks(DNN) commonly used in data-driven approaches when learning different features from raw sensor data to infer complex, sequential information hierarchically [5], [6]

The paper is organized as follows. Section II describes some related sensor-based activity recognition systems and their machine learning and deep learning algorithms. Section III provides a brief inside the public data set used for analysing and data preprocessing for the implemented work. Section IV provides details on the proposed three deep learning models which are Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Deep Neural Network (DNN) architectures. Section V illustrates the experimental results and compares them with each other with the help of performance parameters. Further, the improvements in the network structure are discussed. Finally, the last section provides a brief summary of this research.

II. Related Work

Various methods and prototypes have been presented in the literature for the detection of human activity. The data collected by the sensors used for this process include video data, as well as sensor data such as the angle, acceleration, and orientation of the device. Wearable devices such as smartphones can be used for this type of detection. Various algorithms and methods can be used for this. Decision tree, support vector machine (SVM), naive Bayes and other traditional machine learning methods were mainly used in early researches to classify the data collected by the sensors [7], [8].

III. Open Data Set

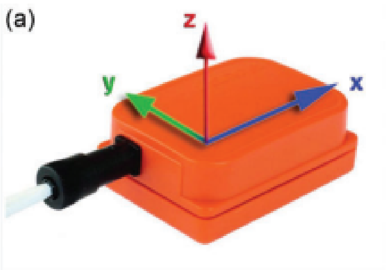

Fig. 1. Xesnse MTx Unit with x,y,z accelerometers, x,y,z gyroscopes and x,y,z manetometers

In this study use UCI (University of California) open data set to evaluate the performance of machine learning models. Experiment data is collected using a five Xsense MTx units used on torso, arms and legs. Using the motion sensors collect data of 19 daily activities and sports activities performed by 8 participants(4-male and 4 female between the age 20 and 30). Participants perform each activity in their own style for 5 minutes period of time. All the activities are performed at Bilkent University Sport Hal, in Electrical and Electronics Engineering Building and flat outdoor area in campus. Sensor units gathered data with a 25Hz sampling rate. Each unit contain 9 sensors (x,y,z accelerometers, x,y,z gyroscopes and x,y,z magnetometers) to collect data [9].

Fig. 2. Five Xense units position on human body

IV. Results and Discussion

In this section, final result from the conducted experiment in the methodology section are presented and discussed. To evaluate the results here used the confusion matrices, Precision, Recall, F1-Score and the Accuracy values.

A. CNN

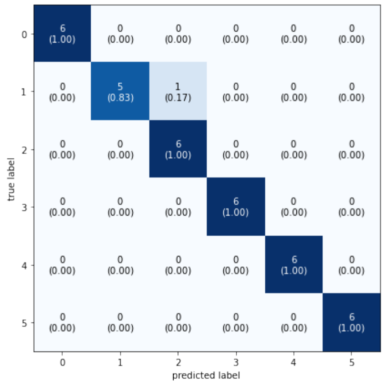

Fig. 3. Confusion matrix of the CNN model. (0 - jump, 1 - lying back, 2 - run, 3 - sit, 4 - stand, 5 - walk)

Fig. 3 shows that accurate classification is achieved on jumping, running, sitting, standing and walking activities. One data entry of the lying-back were classified as run. This Confusion matrix indicate that all activities identified correctly except the lying-back activity.

B. DNN

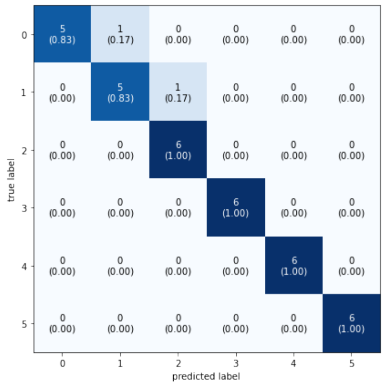

Fig. 4. Confusion matrix of the DNN model. (0 - jump, 1 - lying back, 2 - run, 3 - sit, 4 - stand, 5 - walk)

Fig. 4 shows that accurate classification is achieved on running, sitting, standing and walking activities. One data entry from the jump was classified as lying-back and one data entry from the lying-back were classified as run. This Confusion matrix indicate that all activities identified correctly except the jump and lying-back activities.

C. LSTM

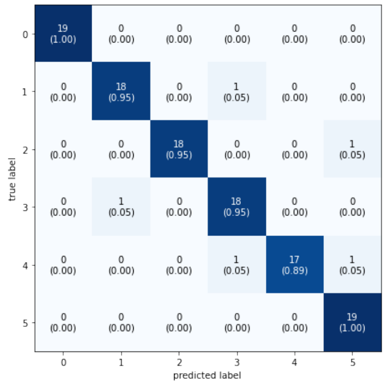

Fig. 5. Confusion matrix of the LSTM model. (0 - jump, 1 - lying back, 2 - run, 3 - sit, 4 - stand, 5 - walk)

Fig. 5 shows that accurate classification is achieved on jumping and walking activities. There are some miss classification, as examples lying-back classify as sitting, running classified as walking, sitting classified as lying-back and standing classified as sitting/walking.

$$Accuracy(\%) = \frac{TP + TN}{TP + FP + FN + TN} 100\% \tag{1}$$

$$Precision(\%) = \frac{TP}{TP + FP} 100\% \tag{2}$$

$$P_{macro}(\%) = \frac{1}{n} \sum_{i=1}^{n} Precision_i * 100\% \tag{3}$$

$$Recall(\%) = \frac{TP}{TP + FN} 100\% \tag{4}$$

$$R_{macro}(\%) = \frac{1}{n} \sum_{i=1}^{n} Recall_i * 100\% \tag{5}$$

$$F1 - Score(\%) = 2 * \frac{P_{maro} * R_{macro}}{P_{macro} + R_{macro}} 100\% \tag{6}$$

Where i represent one type of activity, and n represent total number of activities. Here TP - True Positive, TN - True Negative, FP - False Positive and FN - False Negative [10].

Precision is the ratio between correctly identified positive observation to all positive observations. As an example if get the ratio between correct classification of running activity to the correct classification plus wrong classification of the running activity, can define it as the precision of the running activity. Recall can be define as the ratio between correctly predict positive observation to all observation in actual class. High precision mean that high probability to find a correct result and high recall means high probability of finding more comprehensively. F1-Score is used to evaluate the balance between precision and recall values. F1-Score will get a high value when precision and recall value are similar. F1-Score get a low value when one of them perform better than the other one [10].

TABLE I
PRECISION, RECALL, F1-SCORE AND ACCURACY VALUES OF MACHINE LEARNING ALGORITHMS

Method	***Precision***	***Recall***	***F1-Score***	***Accuracy***
CNN	95%	94%	94%	94%
DNN	95%	94%	94%	94%
LSTM	97%	96%	97%	96%

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