Deep Neural Networks for Time Series Classification in Human Activity Recognition

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Abstract: Due to the application of Human Activity Recognition (HAR) in different fields such as health care, biometrics, and human-machine interaction, a plethora of research works proposing different neural networks have been conducted in the past. In this research, four deep learning models - Bidirectional Long Short Term Memory (LSTM), Convolutional Neural Network (CNN), ConvLSTM, and CNN-LSTM - were trained and tested on the WISDM Smartphone and Smartwatch Activity and Biometrics Dataset in a subject-independent pattern for predicting different classes of human activities. It was found that the CNN-LSTM model outperformed the rest of the neural network models in classifying the classes of hand-oriented and non-hand-oriented activities. It was also found that all the aforementioned models performed better in data from the accelerometer than the same from the gyroscope. Moreover, the difference in the efficiencies of the models in the two sensors was much more significant in watches than in the phones. Furthermore, in general, patterns in sensor data from watches were found to be more distinct from one another and thus were being captured more efficiently compared to the data from phones' sensors.

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Dataset Description: The dataset consists of raw sensor data of 51 different subjects performing 18 activities collected from accelerometer and gyroscope present within smart phone and smart watch. For each of the activities, the dataset consists of X, Y and Z values from different sensors. In the case of an accelerometer, these values measure the linear acceleration of the subject along three orthogonal axes. Similarly, in data obtained from a gyroscope, these values represent the angular velocity of the subject in three orthogonal axes.

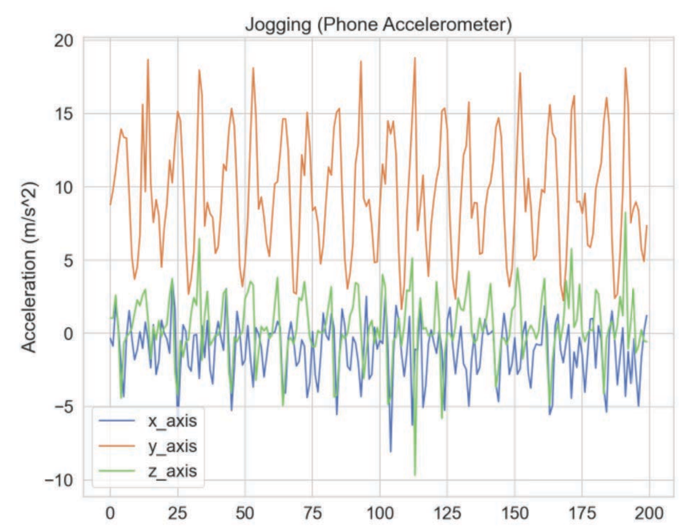

Fig.1.a. Accelerometer data

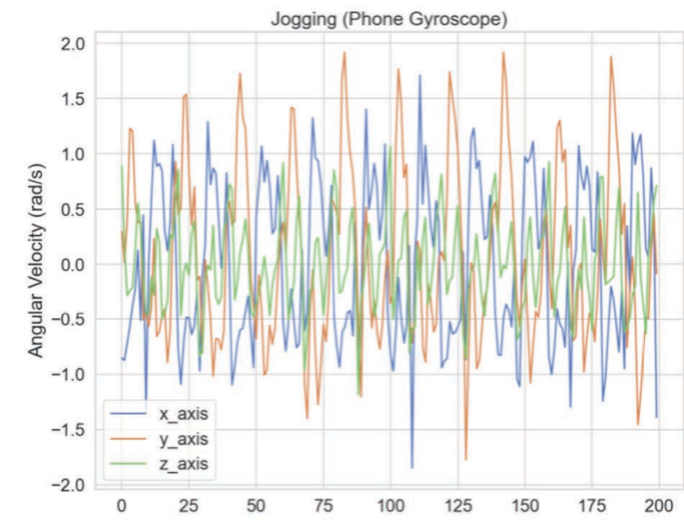

Fig.1.b. Gyroscope data

Analysis: In general, all the four models performed significantly better in classifying the activities using the data from the smartwatch than using the data from the phone. The highest accuracy for watch data was 86% while the same for phone data was 78%. When comparing the efficiency of the models among the sensors from the same type of device, sensor data from the accelerometer was found to be more useful in distinguishing different classes of human activities. The lower range-value for accelerometer data was 74% while the same for gyroscope was 66%. As for the models, CNN-LSTM outperformed all the other models by achieving an accuracy of 86% for the tasks of predicting different classes of non-hand-oriented and hand-oriented activities separately.

Conclusion: The accuracy that the model has achieved is certainly not the best but considering that it took a subject-independent approach (which is what will occur in a real life scenario) and it was trained and tested on raw data without applying any advanced preprocessing techniques, it is believed that this work will give a clear direction for the selection of models for future research for human activity recognition.
In our future work, emphasis on feature extraction and building a light-weight, and hence easily deployable, CNN-LSTM model for classifying a larger number of activities at once with higher accuracy will be considered.

Experimental Results:

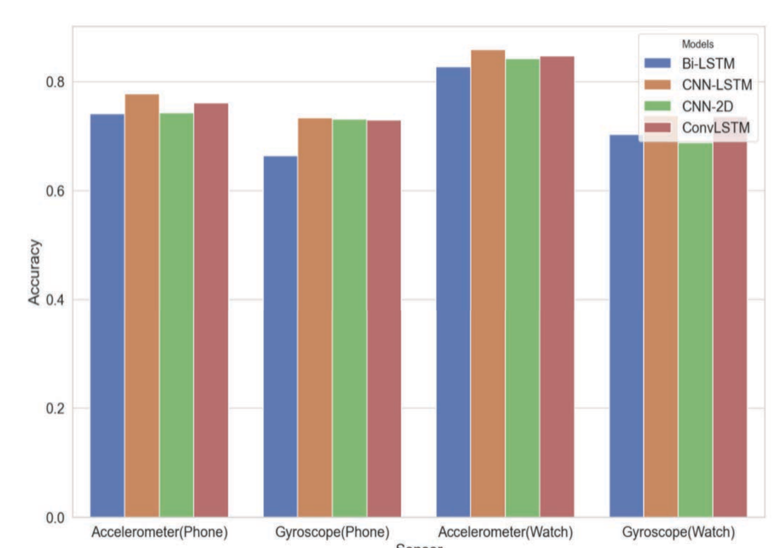

Fig. 2. Accuracy for non-hand-oriented activities

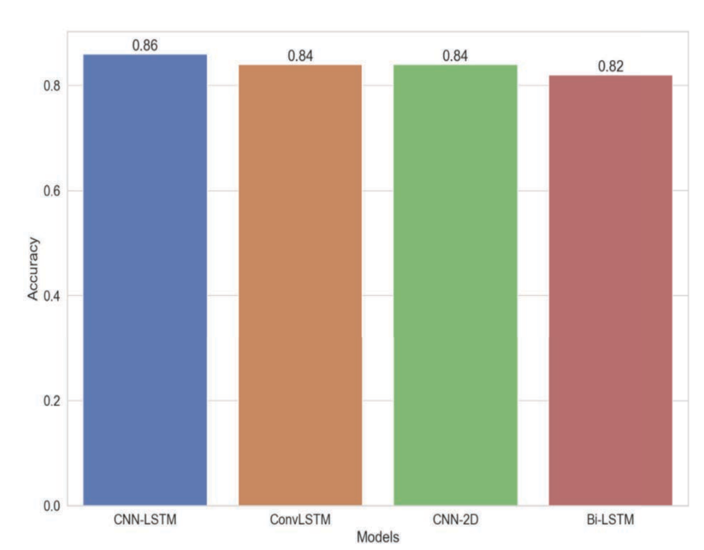

Fig. 3. Accuracy for hand-oriented activities

Fig. 4.a. Confusion matrix of CNN-LSTM

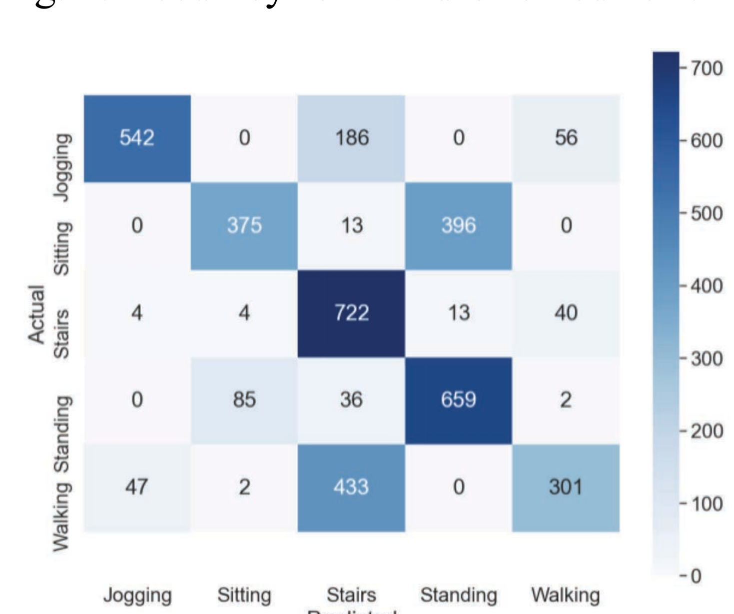

Fig. 4.b. Confusion matrix of Bi-LSTM

Activities	Bi-LSTM			CNN LSTM		
	Precision	Recall	F1 Score	Precision	Recall	F1 Score
Brushing	0.73	0.90	0.80	0.98	0.90	0.94
Clapping	0.92	0.80	0.85	0.98	0.98	0.98
Dribbling	0.90	0.89	0.89	0.93	0.71	0.81
Eating	0.70	0.75	0.73	0.74	0.80	0.77
Folding	0.77	0.81	0.79	0.79	0.87	0.83
Playing	0.86	0.80	0.83	0.77	0.88	0.82
Typing	0.86	0.84	0.85	0.96	0.82	0.88
Writing	0.88	0.78	0.83	0.84	0.96	0.89

Table 1. Performance metrics of Bi-LSTM and CNN-LSTM

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