Human Activity Classification using MHEALTH Dataset

DHAVALKUMAR BHARATKUMAR LIMBACHIYA and ESHWAR SHASHIKUMAR SASTRY, RPTU Kaiserslautern-Landau, Germany

Human-centred computing is an emerging branch of technology that seeks to design and develop technologies that prioritize the experience of the users. It seeks to achieve a goal of improving the human lives by enhancing the abilities of humans and their capabilities and thereby improving the quality of life. It helps understand human behaviour using computer systems. One of the most recent and effective applications of this is to use this to sense human motions using wearable sensors and gather information about human actions. In the context of this dataset, we discuss the recordings of 10 subjects performing everyday actions while carrying body-mounted wearable sensors. The wearable sensors are used to capture the required readings that are used further to classify the human actions.

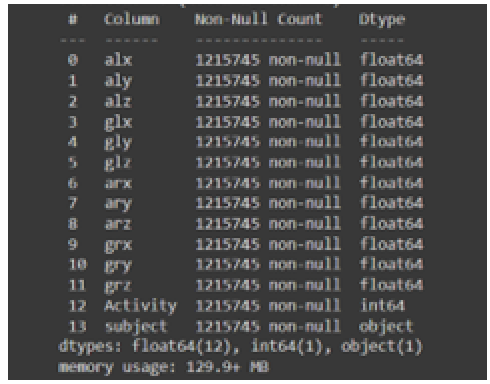
1 INTRODUCTION

Wearable technology is becoming more and more common. Various devices such as fitness bands, mobile phones come with built in sensors in them. These can be used to track various kinds of human activities. This information can be critical in building and technical equipment in the field of predicting healthcare, elder care, military applications and much more. In this paper, we understand the process to classify the sensor data into such multiple classes defining various human activities. This paper compares the multiple ways we can use this sensor data to build effective classification mechanisms using different Machine Learning classifiers and determining the most effective approach that helps predict and classify human actions on one of the major human activity datasets – MHEALTH Dataset

2 METHODOLOGY

2.1 DATASET

The MHEALTH (Mobile HEALTH) dataset is a valuable resource for researchers and healthcare professionals. It consists of comprehensive recordings of body motion and vital signs for 10 individuals of diverse backgrounds, who were monitored while performing a variety of 12 physical activities. The data was collected using advanced wearable sensors, specifically Shimmer2, which were attached to the chest, wrist, and ankle. These sensors were designed to measure the acceleration, rate of turn, and magnetic field orientation of different body parts. Additionally, the chest sensor was equipped with 2-lead ECG measurements, which can be used to monitor heart activity and detect arrhythmias or examine the effects of exercise. The main advantage of having and working on this data was because this dataset consisted of clean data and contained no null values. It can be observed from fig. 1.



```
 #   Column    Non-Null Count    Dtype
---  ------    --------------    -----
 0   alx       1215745 non-null  float64
 1   aly       1215745 non-null  float64
 2   alz       1215745 non-null  float64
 3   glx       1215745 non-null  float64
 4   gly       1215745 non-null  float64
 5   glz       1215745 non-null  float64
 6   arx       1215745 non-null  float64
 7   ary       1215745 non-null  float64
 8   arz       1215745 non-null  float64
 9   grx       1215745 non-null  float64
 10  gry       1215745 non-null  float64
 11  grz       1215745 non-null  float64
 12  Activity  1215745 non-null  int64
 13  subject   1215745 non-null  object
dtypes: float64(12), int64(1), object(1)
memory usage: 129.9+ MB
```

Fig. 1. Figure depicting non null values of data

Also, subject wise re-sampling was not necessary in our case as all the data collected from each subject contributed equally towards our analysis (see fig. 2).

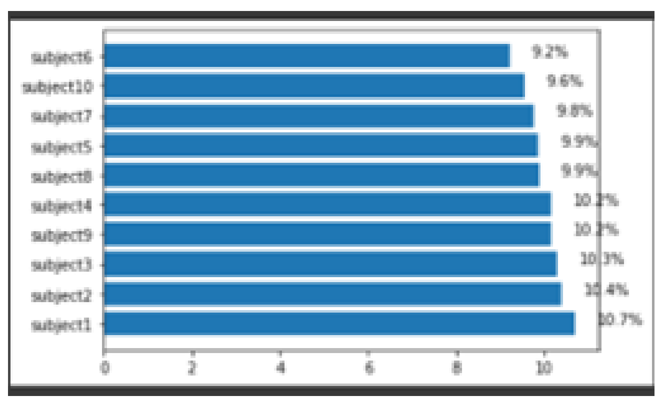


Fig. 2. Figure depicting contribution of each subject

As stated above the dataset consisted of the subjects performing 12 activities. So the data collected had 12 labels/ categories of activities represented by the respective label classes as follows (see fig. 3):

Authors' address: Dhavalkumar Bharatkumar Limbachiya, sut23dil@rhrk.uni-kl.com; Eshwar Shashikumar Sastry, tyv13sit@rhrk.uni-kl.com, RPTU Kaiserslautern-Landau, Germany.

```
0: 'Nothing',
1: 'Standing still (1 min)',
2: 'Sitting and relaxing (1 min)',
3: 'Lying down (1 min)',
4: 'Walking (1 min)',
5: 'Climbing stairs (1 min)',
6: 'Waist bends forward (20x)',
7: 'Frontal elevation of arms (20x)',
8: 'Knees bending (crouching) (20x)',
9: 'Cycling (1 min)',
10: 'Jogging (1 min)',
11: 'Running (1 min)',
12: 'Jump front & back (20x)'
```

Fig. 3. Figure depicting the activity label in MHEALTH dataset

As a part of the analysis and model building process, We are mainly using acceleration and gyroscope sensor data for the classification of the given activity. The fig. 4 depicts the plot of acceleration values noted by the left ankle and right arm sensors for a particular participant when they were doing nothing.

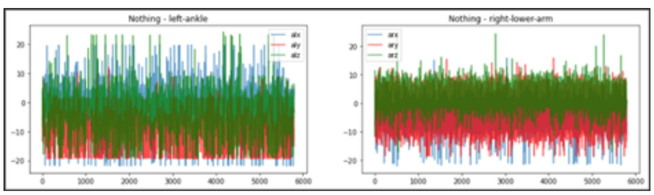


Fig. 4. Figure depicting the acceleration values for activity-"Nothing"

The fig. 5 depicts the plot of the acceleration parameter as noted by the left ankle and the right arm sensors when the participant was walking.

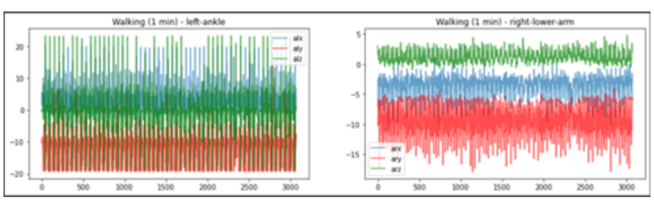


Fig. 5. Figure depicting the acceleration values for activity-"Walking"

Similarly, the fig. 6 depicts the values collected by the sensors when the participant was asked to climb stairs.

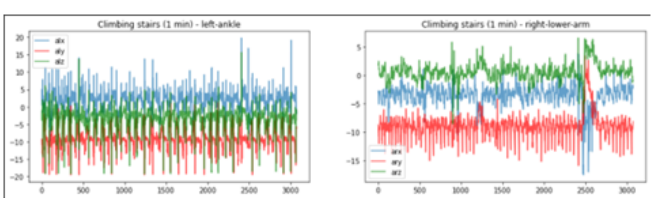


Fig. 6. Figure depicting the acceleration values for activity-"Climbing Stairs"

These plots help us better understand the patterns in the observed readings for various corresponding user activities. It can be observed that the values of acceleration recorded by the sensors were much higher when the person was doing a dynamic activity as compared to doing nothing or for a stationary/ static activity.

2.2 PRE-PROCESSING THE DATA

An exploratory data analysis was performed to check data distribution and balance between data points. We observed that the data was highly unbalanced based on activity performed by subjects. The class 0 (Activity= "Nothing") had a lot of data points in the dataset as compared to the other classes of activities. Moreover, class 12 (Activity = 'Jump front & back(20x)' has least data points.(see fig. 7)

```
0     872550
1      30720
2      30720
3      30720
4      30720
9      30720
10     30720
11     30720
5      30720
7      29441
8      29337
6      28315
12     10342
Name: Activity, dtype: int64
```

Fig. 7. Figure depicting data points of each activity

The below bar plot depicts the class imbalance-

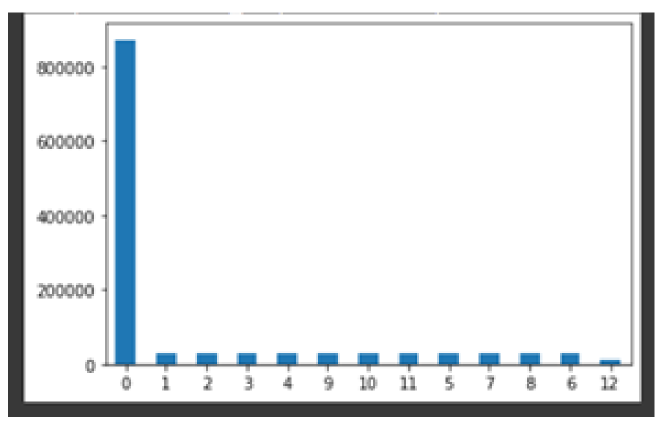


Fig. 8. Figure depicting class imbalance amongst activities

So, we re-sample the dataset based on activity value counts. We down sampled the dataset to remove the class imbalance such that the activity label 0 had around 40k values (like that of the other classes). The below plot of the re-sampled data helps demonstrate the down sampled dataset (see fig. 9).

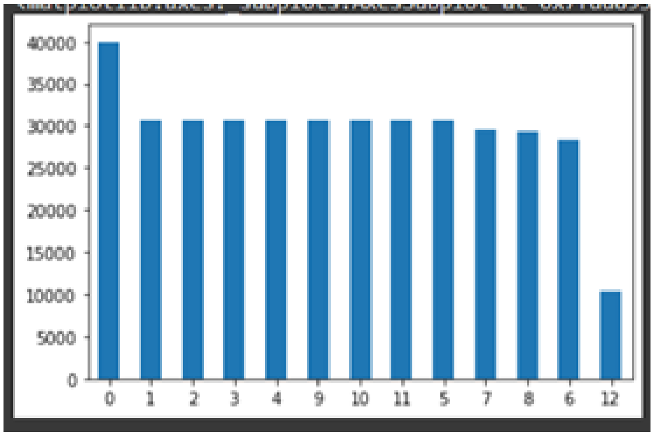


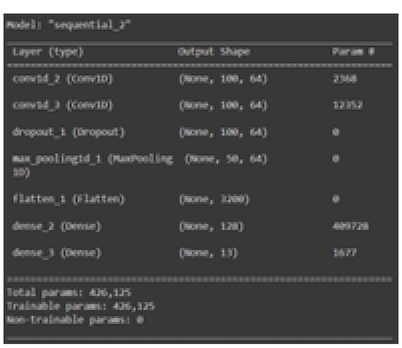
Fig. 9. Figure depicting resampled data plot

In order to handle the outliers in data, the features lying outside the 98 percent confidence interval were dropped. A StandardScalar component is used to normalize the data to bring them to the same approximations before passing them to the various classifiers for classifying the data

2.3 MODELING

For human activity classification, we performed experiments using machine learning based algorithms like Logistic Regression, Random Forest, k-Nearest Neighbour, Decision Tree & CNN based approach using 1D CNN network. The pre-processed data needs to be split into train and test sets. For this we are using a leave a participant out approach. In our train set, we have data points from subject 1 till subject 8 and the test set has data points for subject 9 and 10. These train and test sets are only used for training and analysing ML based models. For the 1D CNN based model, we create a time series based train and test sets- using the above mentioned "leave a participant out" approach, with time steps of 100 and sliding window size of 50. To summarize, we have two sets of train and test set i.e. One train-test set for ML based model and one time series-based train-test set for CNN based approach. In order to evaluate the model performance, we consider F1 Scores as it is a good blend of precision and recall and overall, a good metric for evaluating unbalanced data.

The architecture of the CNN used in our study is shown below.


Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv1d_2 (Conv1D)	(None, 100, 64)	2368
conv1d_3 (Conv1D)	(None, 100, 64)	12352
dropout_1 (Dropout)	(None, 100, 64)	0
max_pooling1d_1 (MaxPooling1D)	(None, 50, 64)	0
flatten_1 (Flatten)	(None, 3200)	0
dense_2 (Dense)	(None, 128)	409728
dense_3 (Dense)	(None, 13)	1677

Total params: 426,125
Trainable params: 426,125
Non-trainable params: 0

Fig. 10. 1-D CNN Model Summary

Table 1. Comparison of performance of models

Model	F1 Score
Logistic Regression	52.0487
Random forest	43.821
kNN	50.137
Decision Tree	48.438
1-D CNN	88.397

2.4 RESULTS

The F1 scores obtained (see table 1) from the various classification approaches can be seen in the above table. The fig. 11 represents the confusion matrix obtained from the CNN based approach of classifying the data. As it can be observed, the CNN based model provided the best classification for our problem as compared to the other approaches although the activity "Lying down" is confused for the activity "Climbing Stairs" by the model. It has to be further noted that models can be optimized further if statistical features are considered for model training and inference. Performing an additional step of feature engineering could perhaps yield better results and help overcome the limitation explained above.

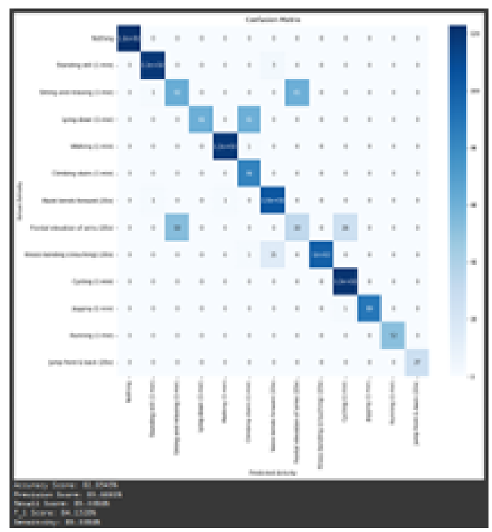


Fig. 11. Figure depicting Confusion matrix of 1-D CNN mode

3 CONCLUSION

This study aims at implementing different Machine Learning classification models on the publicly available dataset, MHEALTH, for the purpose of human activity detection. The dataset was pre-processed, scaled and normalised. Multiple Machine Learning models were trained for activity detection and their performances were compared on this dataset. It was observed that the CNN model performed better as compared to the other classification techniques used in our study. As future work, we plan to implement feature engineering practices and implement Deep Learning models like Recurrent Neural Network for activity and human behaviour prediction.

4 REFERENCES

Banos, O., Garcia, R., Holgado, J. A., Damas, M., Pomares, H., Rojas, I., Saez, A., Villalonga, C. mHealthDroid: a novel framework for agile development of mobile health applications. Proceedings of the 6th International Work-conference on Ambient Assisted Living an Active Ageing (IWAAL 2014), Belfast, Northern Ireland, December 2-5, (2014).

Banos, O., Villalonga, C., Garcia, R., Saez, A., Damas, M., Holgado, J. A., Lee, S., Pomares, H., Rojas, I. Design, implementation and validation of a novel open framework for agile development of mobile health applications. BioMedical Engineering OnLine, vol. 14, no. S2:S6, pp. 1-20 (2015).