HUMAN ACTIVITY RECOGNITION USING MACHINE LEARNING

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ABSTRACT

Smartphones are now nearly ubiquitous; their numerous built-in sensors enable continuous measurement of activities of daily living, making them especially well-suited for health research. Researchers have proposed various human activity recognition (HAR) systems aimed at translating measurements from smartphones into various types of physical activity. In this review, we summarized the existing approaches to smartphone-based HAR. For this purpose, we systematically searched Scopus, PubMed, and Web of Science for peer-reviewed articles published up to December 2020 on the use of smartphones for HAR. We extracted information on smartphone body location, sensors, and physical activity types studied and the data transformation techniques and classification schemes used for activity recognition. Consequently, we identified 108 articles and described the various approaches used for data acquisition, data preprocessing, feature extraction, and activity classification, identifying the most common practices, and their alternatives. We conclude that smartphones are well-suited for HAR research in the health sciences. For population-level impact, future studies should focus on improving the quality of collected data, address missing data, incorporate more diverse participants and activities, relax requirements about phone placement, provide more complete documentation on study participants, and share the source code of the implemented methods and algorithms.

Keywords - HAR, smartphone sensors

1.INTRODUCTION

The demands for understanding human activities have grown in health-care domain, especially in elder care support, rehabilitation assistance, diabetes, and cognitive disorders. [1,2,3]. A huge amount of resources can be saved if sensors can help caretakers record and monitor the patients all the time and report automatically when any abnormal behavior is detected. Other applications such as human survey system and location indicator are all benefited from the study. Many studies have successfully identified activities using wearable sensors with very low error rate, but the majority of the previous works are done in the laboratories with very constrained settings. Readings from multiple body-attached sensors achieve low error-rate, but the complicated setting is not feasible in practice. This project uses low-cost and commercially available smartphones as sensors to identify human activities. The growing popularity and computational power of smartphone make it an ideal candidate for non-intrusive body-attached sensors. According to the statistic of US mobile subscribers, around 44% of mobile subscribers in 2011 own smartphones and 96% of these smartphones have built-in inertial sensors such as accelerometer or gyroscope [4,5]. Research has shown that gyroscope can help activity recognition even though its contribution alone is not as good as accelerometer [6,7].

Because gyroscope is not so easily accessed in cellphones as accelerometer, our system only uses readings from a 3-dimensional accelerometer. Unlike many other works before, we relaxed the constraints of attaching sensors to fixed body position with fixed device orientation. In our design, the phone can be placed at any position around waist such as jacket pocket and pants pocket, with arbitrary orientation. These are the most common positions where people carry mobile phones. Training process is always required when a new activity is added to the system. Parameters of the same algorithm may need to be trained and adjusted when the algorithm runs on different devices due to the variance of sensors. However, labeling a time-series data is a time consuming process and it is not always possible to request users to label all the training data. As a result, we propose using active learning technique to accelerate the training process. Given a classifier, active learning intelligently queries the unlabeled samples and learns the parameters from the correct labels answered by the oracle, usually human. In this fashion, users label only the samples that the algorithm asks for and the total amount of required training samples is reduced. To the best of our knowledge, there is no previous study on applying active learning to human activity recognition
problem. The goal of this project is to design a light weight and accurate system on smartphone that can recognize human activities. Moreover, to reduce the labeling time and burden, active learning models are developed. Through testing and comparing different learning algorithms, we find one that best fit our system in terms of efficiency and accuracy on a smartphone.

2.METHODOLOGY

- Collect datasets from the online resources.
- Datasets is divided for test and train.
- The pair of data in train dataset is converted to single data by taking average and the data is trained.

- Using SVM algorithm which has the best accuracy as a result of the output.
- The test data is shuffled and the precision of the model is obtained.

3.1. EXISTING SYSTEM

In this Existing model of classfication or reviously proposed models the accuracy is 90 and less than it.. The datasets are used in earlier models are old that may result in reduction of accuracy of the outcome of the model and also small so that the data used for training is insufficient to produce greater accuracy.

3.2 PROPOSED SYSTEM

In this part we have combined the two different newly created datasets into one dataset by taking average and verified the model by precision of accuracy of test data and shuffles test data .Our system composed of several step to classify the activity of human, the block diagram of our system is shown below.

3.3. BLOCK DIAGRAM

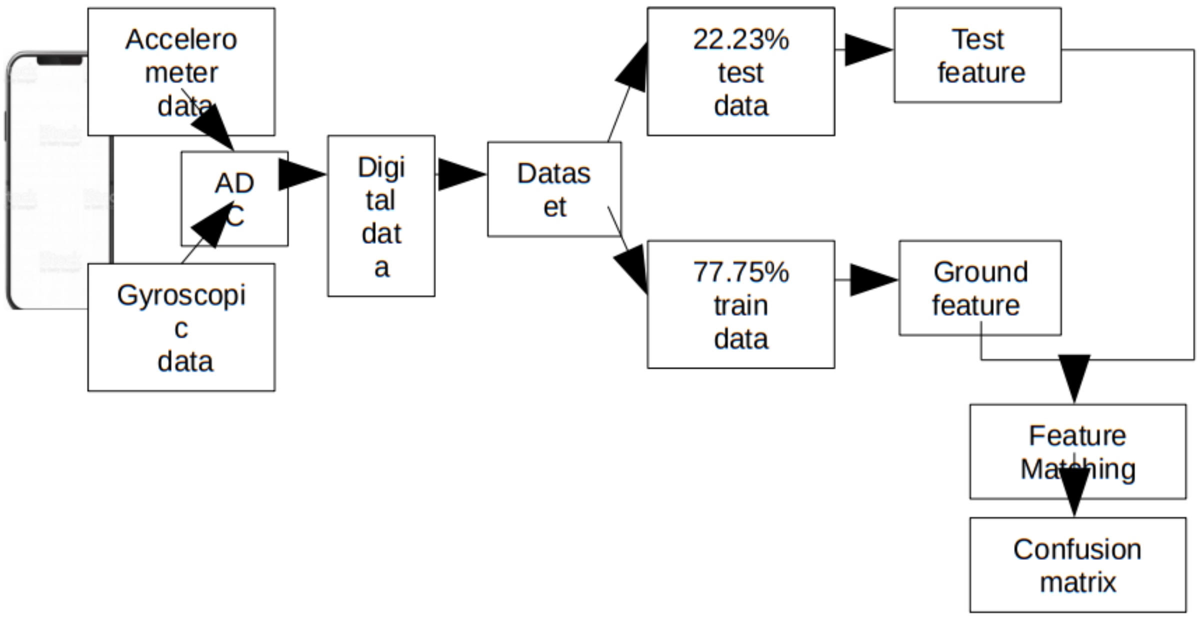

Fig 1:Block Diagram

4.DATASETS

We use the term data acquisition to refer to a process of collecting and storing raw sub-second-level smartphone measurements for the purpose of HAR. The data are typically collected from individuals by an application that runs on the device and samples data from built-in smartphone sensors according to a predefined schedule.

The most commonly used sensors for HAR are the accelerometer, gyroscope, and magnetometer, which capture data about acceleration, angular velocity, and phone orientation, respectively. All these data are preprocessed and the noises are removed and are obtained as datasets.

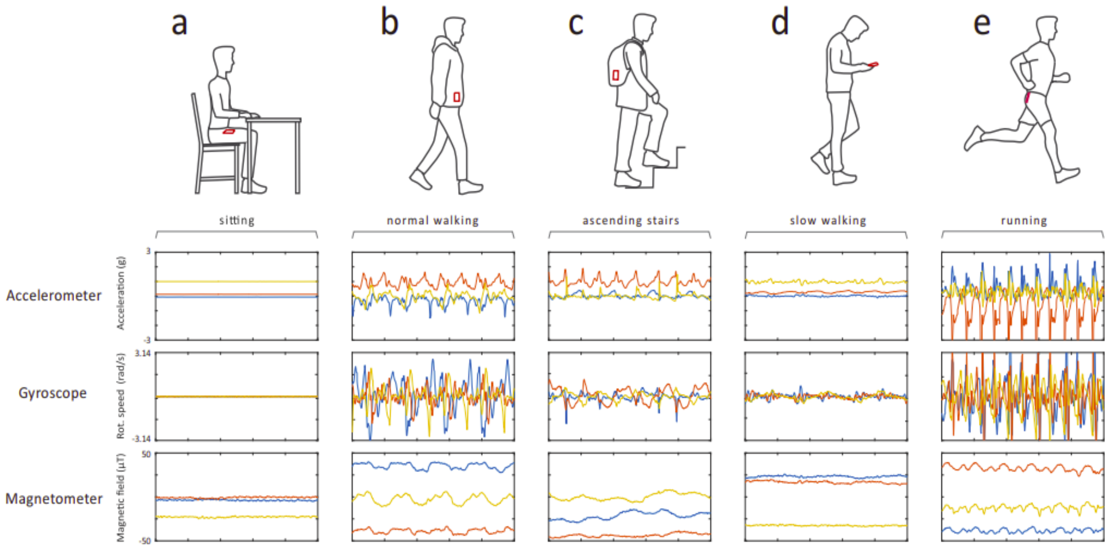

Fig 2: Dataset

4.1. EVALUATION METRICS

The confusion matrix can be shown in the figure below:

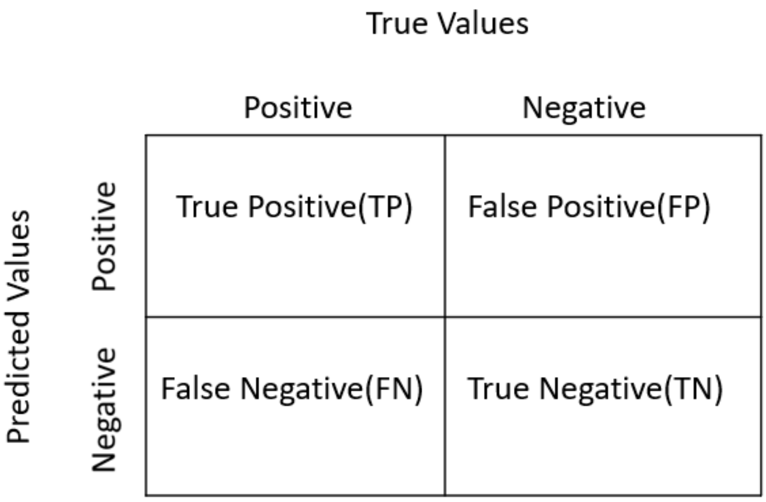

Fig 3: Evaluation Metrices

A confusion matrix is a classified architecture in which observed and expected values are referred to as true positives or true negatives.

1. True positive (TP) is the first kind, in which parameters are designated as true and are also true. The first part is entirely positive (TP).
2. The second type is false positives (FP), which occur when the identified quantities are incorrect yet true.
3. A false negative is the third (FN). The value was correct, but it was negative.
4. True negative (TN), with negative and projected negative numbers, is the fourth option.

4.2. PERFORMANCE METRICS

ACCURACY:

The number of parameters predicted correctly from all types of predictions from the model is termed the accuracy of the classifier.

Formula to calculate the accuracy of the algorithm is given below:

$$Accuracy = [(TP + TN) / TP + FP + TN + FN)] * 100$$

PRECISION:

Precision is a parameter that briefs the number of patients who predicted heart disease and had actual heart disease.

Formula to calculate the precision of the algorithm is given below:

$$Precision = [(TP) / (TP +FP)] *100$$

4.3. ACCURACY GRAPH

From the plot of accuracy we can see that the model could probably be trained a little more as the trend for accuracy on both datasets is still rising for the last few epochs. We can also see that the model has not yet over-learned the training dataset, showing comparable skill on both datasets.

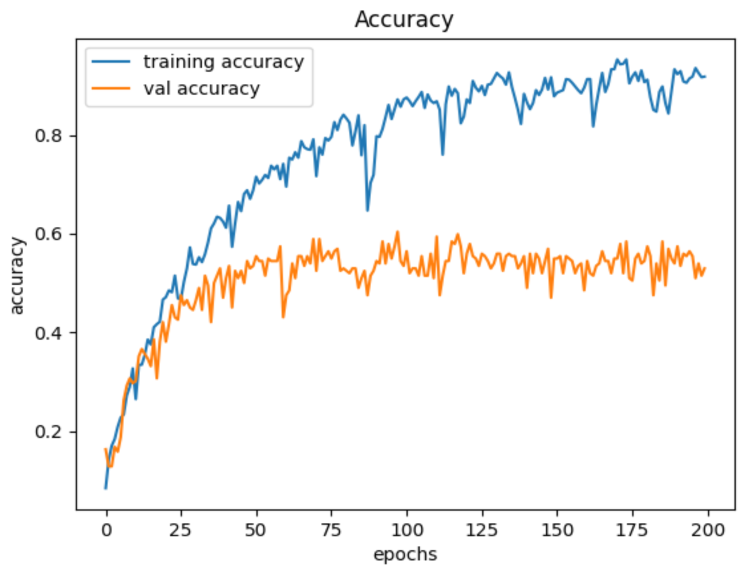

Fig 4:Accuracy

4.4. LOSS GRAPH

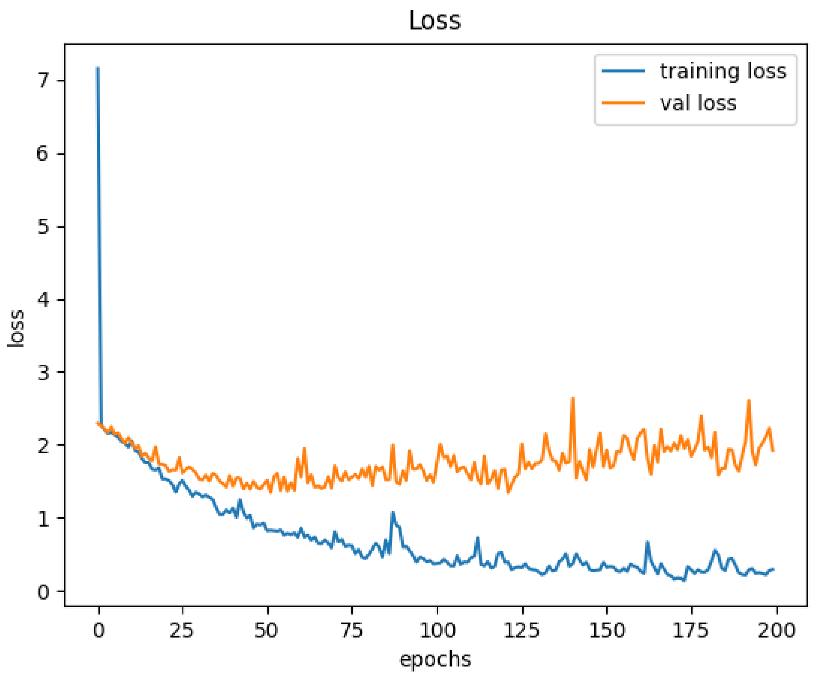

Fig 5:Loss

From the plot of loss, we can see that the model has comparable performance on both train and validation datasets (labeled test). If these parallel plots start to depart consistently, it might be a sign to stop training at an earlier epoch.

Previous model

```
#Output
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       377
           SITTING       0.92      0.87      0.90       364
          STANDING       0.89      0.93      0.91       390
           WALKING       0.96      0.99      0.97       335
WALKING_DOWNSTAIRS       0.99      0.95      0.97       278
  WALKING_UPSTAIRS       0.98      0.98      0.98       316

          accuracy                           0.95      2060
         macro avg       0.96      0.95      0.95      2060
      weighted avg       0.95      0.95      0.95      2060

```

Fig 6:Previous Result

Proposed model

```
print(classification_report(y_test, y_predict))
```

```
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       377
           SITTING       0.98      0.95      0.97       364
          STANDING       0.96      0.98      0.97       390
           WALKING       0.99      1.00      1.00       335
WALKING_DOWNSTAIRS       1.00      0.98      0.99       278
  WALKING_UPSTAIRS       0.99      1.00      1.00       316

          accuracy                           0.99      2060
         macro avg       0.99      0.99      0.99      2060
      weighted avg       0.99      0.99      0.99      2060
```

Fig 7: Proposed Result

4.5. RESULT PREDICTED

After completion of training process .The model is ready for classify images of different activities of human. In this the Trained model is loaded and and the input is loaded into int the form of a csv format and the the data gets stored in a varible . The input data which have is more similar to trained data class is the output of activity performed. The activity is classified according the trained model more the epoch and more the activities data to the trained model and the System will be more efficient.

4.6. CONFUSION MATRIX

Out[20]: <AxesSubplot:>

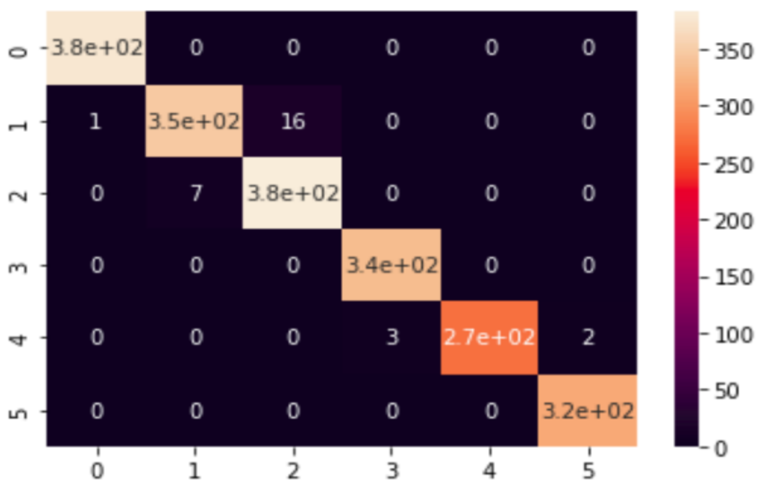

Fig 8: Confusion Matri

5. CONCLUSION

Human activity recognition has broad applications in medical research and human survey system. In this project, we designed a smartphone-based recognition system that recognizes five human activities: walking, limping, jogging, going upstairs and going downstairs. The system collected time series signals using a built-in accelerometer, generated 31 features in both time and frequency domain, and then reduced the feature dimensionality to improve the performance. The activity data were trained and tested using 4 passive learning methods: quadratic classifier, k-nearest neighbor algorithm, support vector machine, and artificial neural networks.

The best classification rate in our experiment was 84.4%, which is achieved by SVM with features selected by SFS. Classification performance is robust to the orientation and the position of smartphones. Besides, active learning algorithms were studied to reduce the expense of labeling data. Experiment results demonstrated the effectiveness of active learning in saving labeling labor while achieving comparable performance with passive learning. Among the four classifiers, KNN and SVM improve most after applying active learning. The results demonstrate that entropy and distance to the boundary are robust uncertainty measures when performing queries on KNN and SVM respectively. Conclusively, SVM is the optimal choice for our problem.

5.2. FUTURE SCOPE

We can input the databases with large data into the model which will be in part of Big Data concepts. With the use of deep neural networks, future work in this field seems a lot more promising. Also, we can implement two classifiers as a hybrid model and check how the model will perform which can increase the efficiency and performance metrics of the model.Future work may consider more activities and implement a real-time system on smartphone. Other query strategies such as variance reduction and density-weighted methods may be investigated to enhance the performance of active learning.

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