International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 11 | Nov 2026 www.irjet.net p-ISSN: 2395-0072

HUMAN ACTIVITY RECOGNITION USING SMARTPHONE SENSORS

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Abstract - *Human Activity Recognition (HAR) is the identification of physical activity performed by individuals. With modern smartphones having access to inertial sensors such as accelerometers and gyroscopes, there are many opportunities for these to be used for activity recognition. This paper outlines a proposed framework for recognising common human activities using the smartphone sensor data. This will include: selecting public datasets, understanding the data, pre-processing, feature engineering, classification using machine learning techniques and evaluating results. Using a public dataset, such as the UCI Human Activity Recognition Using Smartphones dataset, will provide the data needed. This dataset contains recordings for 30 volunteers performing 6 different activities. The data also includes features extracted from the sensors making it ideal for classification [1]. As the algorithm is still to be finalised and no new experiments have been carried out it cannot be claimed that the algorithm will achieve accurate results. The aim of this paper is to outline a reproducible methodology and evaluation of results using accuracy, precision, recall, F1-score and confusion matrix. The proposed work can be used to help fitness applications, context aware mobile applications and activity monitoring. Challenges will be encountered due to sensor positioning, variance between users, privacy issues and real world conditions.*

Keywords - Human Activity Recognition, Smartphone Sensors, Accelerometer, Gyroscope, Machine Learning, Classification, UCI HAR Dataset.

1. INTRODUCTION

Smartphones have become a ubiquitous commodity containing motion and orientation sensors. These can be used in order to determine if the user is currently walking, sitting, standing or doing some other activity. Human Activity Recognition (HAR) is the process that takes raw sensor data and provides meaningful information about what activity the user is currently doing. This is an important area of research within the fields of mobile computing, ubiquitous computing, health monitoring, fitness tracking and context aware applications [2],[3].

Traditional methods of activity monitoring often require specialist hardware or manually written data. Using HAR on a smartphone reduces this need as inertial sensors already exist within the device. Raw sensor data is often given in the form of numerical time series data. A system must be created which analyses this data and learns how to classify different activities.

This paper details the proposed research project of a student using public data. The structure of this paper is similar to the example provided in the IRJET reference however the content is specific to the topic. The main aim of this paper is to provide a clear and replicable methodology as well as being honest about the current state of the project.

2. BACKGROUND AND PROBLEM STATEMENT

The smartphone accelerometer gives three axis (x, y and z) acceleration data. The gyroscope provides angular velocity data for three axes. Together these sensors provide complementary information about body movements. Sensor data will be affected by phone orientation, placement on the body, user movement and sampling rate.

The main task is to classify a sequence or set of extracted feature data from the sensors into one of several activity classes. Some activities such as walking and climbing stairs will be dynamic. This means they will have more varied movement patterns. Static activities such as sitting, standing and lying down will be less dynamic. These can be more challenging to identify. Similar activities, transitions, noise and different phone positions can cause misclassification.

2.1 Problem Statement

Define a machine learning pipeline to classify certain daily activities using inertial data from the smartphone sensors. Define a valid method to evaluate this pipeline using a public dataset.

2.2 Motivation

Smartphone-based recognition is attractive because it may enable activity-aware applications without requiring users to purchase another sensor device. A well-evaluated system could support daily activity summaries, exercise assistance, context-aware interfaces, and research in mobile health. Nevertheless, such a system should not be treated as a medical diagnostic tool without additional validation.

2.3 Scope of the Work

We will focus on six fundamental human activities within the UCI HAR dataset. These include walking, walking upstairs, walking downstairs, sitting, standing and laying. This study proposes a software based classification project. In real time, using a phone, fall detection, medical applications and complex activity recognition are not within scope.

Figure 1. Conceptual relationship between smartphone sensors, signal processing, and activity classes.

3. OBJECTIVES

- Investigate how smartphone acceleration and gyro information can be used for Activity Recognition.
- Identify a suitable public dataset and understand its composition.
- Build an analysis pipeline to handle data exploration, pre-processing, feature management and classification.
- Leave the choice of the final algorithm until after we have considered the data and implementation constraints.
- Evaluate the performance of the trained classifier using a range of class sensitive measures.
- Discuss any issues regarding privacy, generalisation, sensor positioning and real world constraints.

4. RESEARCH QUESTIONS

RQ1: [Q1] How well can the inertial sensing data from smartphones be used to classify typical stationary and dynamic activities? [Q2] What metrics are useful for getting a good understanding of the performance per class? [Q3] What issues need to be considered when translating results from a public benchmark dataset into real-world smartphone usage?

5. LITERATURE REVIEW

The field of activity recognition has evolved from rule-based and statistical approaches to supervised and deep learning methods. Activity recognition typically involves acquiring sensor data and performing various steps such as pre-processing, segmentation, feature extraction/representation learning, classification and assessment [3]. This will depend upon decisions made at each step.

5.1 Smartphone Accelerometer Activity Recognition

Kwapisz et al. investigated activity recognition using cell phone accelerometers. They demonstrated how activity recognition could be performed practically using labelled examples of everyday activities [4]. This demonstrated that mobile devices can be used to generate useful activity data for classification.

Additionally, it demonstrates that data needs to be simplified or modelled to capture typical behaviour of the activities.

5.2 Public Dataset

A public activity recognition dataset using smartphones was introduced by Anguita et al. [1]. This provides a dataset which can be used for reproduction of experiments. In the UCI repository, it describes that data was collected from 30 participants between the ages of 19-48. Each participant wore a Samsung Galaxy S II smart phone around their waist, whilst performing activities. Accelerometer and gyroscope data was recorded at a sampling rate of 50Hz. There are 10,299 instances and with 561 features extracted from both the time and frequency domains. A train/test split is provided to allow the users to separate participants into train and test sets [1].

5.3 Recognition Pipelines and Evaluation

Bulling, Blanke and Schiele present a tutorial on using inertial sensors attached to the body to recognise human activities. This shows a recognition pipeline as well as design considerations [3]. An important aspect from their work was the integration of data preprocessing, feature representation and the choice of model. In addition, Lara and Labrador have also presented a review of recognition methods using wearable sensors for activity recognition [5].

5.4 Recent Reviews

A systematic review has been conducted on smartphone-based HAR within health studies. This summary included 108 studies and found common trends in sensor placement, data transformation and classification [6]. However, there was a need to improve the quality and diversity of data to reduce sensitivity to phone placement. This was reviewed in a 2024 survey by Dentamaro et al, which includes information on integrated smartphone sensors, preprocessing, feature extraction and popular classifiers [7].

5.5 Research Gap and Position of Project

Based on the literature it appears that simply achieving good benchmark results will not always produce reliable results. Factors such as phone placement, inter-user variation, overlapping windows and data specific pre-processing can alter results. The student project proposed focuses on clear data processing and evaluation by class. This project does not include any novel algorithms, but aims to provide clear documentation on a workflow that can be used and tested.

6. PROPOSED SYSTEM AND ARCHITECTURE

The proposed system converts sensor-derived input into a predicted activity label. The main modules are shown below.

Stage	Description	Output
1. Public dataset	Use a documented, licensed dataset such as UCI HAR.	Sensor features and activity labels
2. Data inspection	Check file structure, labels, data types, missing values, and subject identifiers.	Validated dataset summary
3. Preprocessing	Apply only transformations justified by the dataset format; avoid duplicate scaling or leakage.	Model-ready data
4. Feature handling	Use the supplied 561 features initially; consider selection only within training data.	Feature matrix
5. Model training	Compare candidate classifiers after algorithm selection.	Trained classifier
6. Evaluation	Evaluate on the designated held-out test set.	Metrics and confusion matrix
7. Interpretation	Inspect class-wise errors and practical limitations.	Evaluation report

6.1 System Architecture

Sensor Data (Accelerometer and Gyroscope) → Load Dataset → Data Pre-processing and Feature Extraction → Classifier Training → Held-out Testing → Predicted Activity Label. Output performance report

Figure 2. Proposed system architecture (conceptual representation; not an implementation result).

6.2 Input and Output

The input is the numeric feature vector of a sensor window and the known activity in supervised learning. The output is a prediction of whether the user was walking, walking upstairs, walking downstairs, sitting, standing or laying. The output can then be shown to the user in a real scenario, and can be stored as a time stamped summary if wished by the user.

6.3 Functional Requirements

Load public dataset and store mapping between features and labels.

Split dataset into training and testing.

Train only on training data and ensure the test data remains unseen when choosing the best model.

Make predictions, calculate metrics and confusion matrix.

Store information about what version of the dataset was used, any pre-processing that was done, the algorithm used and software settings

6.4 Non Functional Requirements

Process should be repeatable, reasonably fast, easy to understand for a student developer and respect data privacy. If the process is deployed on a phone in the future, memory usage, battery usage, speed of response and ability to work offline should be considered

7. DATASET DESCRIPTION

The UCI Human Activity Recognition Using Smartphones dataset is selected as a proposed public data source because its description and benchmark split are publicly documented [1]. It should be downloaded from the official UCI Machine Learning Repository and cited in the final submitted paper.

Dataset property	Published description
Participants	30 volunteers, aged 19–48
Device and placement	Samsung Galaxy S II carried at the waist
Sensors	Three-axis accelerometer and three-axis gyroscope
Sampling frequency	50 Hz
Activity classes	Walking, walking upstairs, walking downstairs, sitting, standing, laying
Processed examples	10,299 instances
Feature count	561 time- and frequency-domain features
Original split	70% of volunteers for training; 30% for testing
Repository DOI	10.24432/C54S4K

7.1 Activity Classes

Class	General movement characteristics
Walking	Repeated cyclic body movement during level walking.
Walking upstairs	Walking movement with upward stair progression.
Walking downstairs	Walking movement with downward stair progression.
Sitting	Relatively stationary seated posture.
Standing	Upright posture with comparatively limited movement.

Laying	Recumbent posture with comparatively limited movement.

The descriptions above are general interpretations of the labels, not additional measurements from the dataset. The dataset was collected under a defined protocol and should not be assumed to represent every age group, phone model, carrying position, or daily-life situation.

7.2 Data Quality and Preparation

Verify the data has been correctly formatted. This includes checking each feature row contains the correct labels and that there are only 6 classes in the class column. Check the training data and test data conform to the structure described in the repository. Training data should not be randomly mixed with test data if it will cause the subjects to overlap. The official split should be used so we can have an equivalent benchmark.

7.3 Ethics

The UCI dataset is released under the Creative Commons Attribution 4.0 International licence [1]. We should acknowledge the source of the data and make sure we comply with any terms set by the licence. As we will not be using any direct personal identifiers in our classification we do not need to. If collecting any new sensor data in the future we should ensure we collect the data with informed consent, keeping it to a minimum and explaining how we will store and remove records.

8. PROPOSED METHODOLOGY

8.1 Step 1: Data Acquisition

Download the official UCI HAR dataset. Make sure you save any documentation that comes with the dataset. Note the date and version of the dataset. Don't merge the train and test files.

8.2 Step 2: Inspecting the Data

Inspection the data to see how many rows there are, how many features, classes, subjects and what kind of data. Check for any missing or infinite values and duplicate rows. Be honest and list the findings from the dataset.

8.3 Step 3: Pre-processing

The UCI HAR have pre-processed data so the features should be used as they are. However, if you do want to use the raw data in a later extension of the project, you must explain how you have filtered the data, segmented it, separated gravity and body acceleration and created the windows. In the original benchmark, they used a window size of 2.56 seconds (128 values) with 50% overlap and signal pre-processing [1].

8.4 Step 4: Feature Engineering

Start with the 561 features provided. Any normalisation, feature selection or dimensionality reduction should be done using only the training data. This means we won't be biasing our model by looking at the testing data. Feature selection can help reduce any redundant features but make sure you give reasoning behind why you have selected these features.

8.5 Step 5: Choosing an Algorithm

We haven't decided on our final algorithm yet. Some good examples of algorithms which can be used to compare would be Decision Tree, Random Forest, Support Vector Machine (SVM) and Logistic Regression. Decide on an algorithm based on how well it predicts, how easy it is to understand, how computationally expensive it is and how easy it is to replicate.

8.6 Step 6: Training & Validation

Train each of the models using the training data. If you are going to tune any hyperparameters, make sure you use cross-validation or validation data from only the training participants. Don't touch the official test data until your model is complete and your parameters are set. Set random seeds where appropriate and make note of the versions of software used.

8.7 Step 7: Predictions

Use the trained model to predict the activity label using the feature vectors in the test data. Compare the predicted labels to the true labels. Only save the predictions if needed for evaluation. Don't include any identifying information.

8.8 Step 8: Replicability

Keep a brief log of your experiment. Include information such as the citation for the dataset, features chosen, pre-processing steps, classifier setup, train/test split and date. Only update the final paper once you have run the code successfully and can verify your results.

9. PERFORMANCE EVALUATION PLAN

None results yet. The following are the criteria that you should use to evaluate the suggested implementation. Fill in the values once you have run the experiment.

9.1 Evaluation Metrics

Metric	Meaning	Reason for use
Accuracy	Correct predictions divided by all predictions.	Overall correctness, but can hide class-specific errors.
Precision	True positives divided by predicted positives for a class.	Shows how often a class prediction is correct.
Recall	True positives divided by all actual examples of a class.	Shows how many examples of that class are detected.
F1-score	Harmonic mean of precision and recall.	Balances precision and recallws.
Confusion matrix	Counts actual versus predicted class combinations.	Reveals which Activities are confused.
Inference time	Time needed to produce a prediction.	Useful if real-time phone deployment is later attempted.

9.2 Proposed Results Table (To Be Completed)

Table 3. Planned comparison template. The entries "Not measured" are intentional and must not be replaced by estimated or copied scores.

Classifier	Accuracy	Macro F1	Inferenc e time	Status
Decision Tree	Not measured	Not measured	Not measured	Candidate only
Random Forest	Not measured	Not measured	Not measured	Candidate only
SVM	Not measured	Not measured	Not measured	Candidate only
Logistic Regressio n	Not measured	Not measured	Not measured	Candidate only

9.3 Confusion Matrix Analysis

You should generate a confusion matrix. This will inform you which classes are being correctly classified (on the diagonals) and which are being mis-classified (off-diagonals). If some errors occur between sitting/standing or walking upstairs/downstairs then this should be noted.

9.4 Validity and fair comparisons

All models should use the same training/test split and target labels. Any pre-processing should not give the model any information from the testing set. Using macro average F1 scores will help when comparing performance across all classes. Accuracy gives you a simple overview of the performance on all classes. You should include specific details of your configuration and should not compare performance across different splits as if this was the same experiment.

9.5 Expected Outputs

We expect you to produce a repeatable comparison table, confusion matrix, precision/recall/F1 scores per class and a short explanation of the errors you have noticed.

10. DISCUSSION

Using a smartphone for HAR will give a practical solution for classifying activity by using the sensors already available. This pipeline separates data preprocessing, training, and testing to allow for replicability. As well as this, having access to the benchmark in the public domain will make it easier for other students to run the initial experiment.

10.1 Potential Applications

There are many potential applications for this type of system, such as getting a summary of everyday activity, improving fitness, developing context aware mobile systems, aiding rehabilitation research and developing assistive technology. It is important that any recognition systems are tested on the target users and environment. Just having a good benchmark result is not enough to confirm the system is safe to use.

10.2 Technical Issues

The sensor orientation and how the device is held may affect the distribution of the data. The user could be walking at different speeds and doing activities in varied ways. The phone may be held in the users hand, in their pocket, bag or attached to their waist. Models trained with the device in one specific way may not perform as well if it is used in another way. There could also be sensor noise, missing data and calibration issues depending on the device [6][7].

10.3 Privacy Considerations

The motion data can show information about how someone is living their life. If the system were to be implemented, it is important to communicate what data is being collected, why it is needed, if it is being processed locally and how long it will be stored for. Only the minimum amount of data should be collected, the user should have the option to opt-out and the activity predictions should not be used to make high impact decisions without proper validation.

10.4 Limitations

This paper describes a proposed workflow, with background based on the literature. The algorithm has not yet been decided on, therefore there is no source code or logs of the experiment. No accuracy scores have been recorded. The

activities in the public benchmark are limited and the sensor orientation is controlled. Therefore there is no claim to be made that the proposed system would achieve a certain level of performance or can be used in real world situations.

10.5 Future Work

Implement and evaluate the performance of chosen classifiers. Document the parameters used during experimentation. Examine the confusion matrix. Investigate how the classifier generalises across individuals. Future work can also investigate raw signal processing. Other activities can be investigated. The phone can be placed in different positions. Energy consumption can be investigated. Inference on device can be investigated. Explainable predictions can be investigated. If new data is collected, information about the demographics of participants should be recorded. Informed consent should also be obtained.

11. CONCLUSION

Human Activity Recognition using sensors found on a smartphone is a useful application of sensor processing and machine learning. Using data from accelerometers and gyroscopes, we can process and classify this data into activities. This paper outlines a methodology using a publicly available dataset. Within the methodology, there are several steps taken such as exploring the data, pre-processing, feature processing, choosing a model and evaluating the results. It also defines what metrics should be used. It is important to make sure there is no leakage by keeping the benchmark split of the data. Only the results that have been recorded should be reported. The algorithm and experiments will need to be finalised. Therefore we cannot claim any performance. However once it has been implemented and validated, this project can give a good example of Human Activity Recognition using smartphones at a student level and how this can be limited in practice.

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