Anomaly Detection Based Human Activity Recognition and Classification Using Sensor Data

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Abstract- *Recognition of human activity focuses on identifying various human motions and behaviors using data acquired from multiple types of sensors, a branch of computer science. A branch of research focusing on environment-supported systems has taken an interest in the problem of activity and decline. This system uses a variety of technological information to monitor body movements and try to determine what activities are being done for healthcare purposes, among other applications. In this case, besides the knowledge of the artifact, the research of the fall plays a very important role. Falls are a common cause of injury and death, so it is important that the fall is diagnosed as soon as possible. This study not only provides the discovery of fall and working knowledge used in many activities in daily life, but also allows the discovery of falls when both use and practice are taken into account.*

Investigations using smartphone sensor data were carried out using a publicly available standardized HAR dataset called the UCI-HAR dataset, which contains activities associated with everyday life. After proper development of the data, the features are extracted with the help of feature selection techniques, followed by the support of gradient boosting classifier (xgb), which is the final step to classify the group output. The results of the study show that gradient-supported boosting outperforms previous similar methods.

Keywords- Human Activity Recognition, Sensors, Accelerometer and Gyroscope, Machine Learning, HAR dataset, XGBoost.

I. INTRODUCTION

Activity recognition is defined as identifying or detecting activity based on sensors' information processing [1, 2]. These sensors can be motion sensors, cameras, wearable sensors, or environmental sensors, such as pressure sensors and Radio-Frequency Identification (RFID) [1]. Sensor technology has gained revolutionary design, size, accuracy, computational power, communication range, and manufacturing cost [3]. Currently, sensors are embedded in almost every electronic appliance, ranging from baby toys, smart phones, or space crafts and submarines. The incorporation of sensors aims to make objects intelligent, more innovative, and more useful [4]. Human activity recognition (HAR) has become an essential research topic over the last two decades due to its emergent applications in various fields, such as health monitoring systems, surveillance and security, gaming, and virtual reality [1]. In all these applications, activity recognition is a vital part [5]. HAR systems are broadly classified into three types, i.e., wearable HAR systems, non-wearable HAR systems, and hybrid HAR systems [3, 6]. The wearable HAR systems consist of motion sensors like accelerometer, gyroscope, and magnetometer, mounted at some embedded device and worn on a particular body location such as wrist, waist, neck, and others, to recognize the human daily living activities [7]. The non-wearable HAR systems consist of environment sensors like cameras, pressure sensors, acoustic sensors, RFID, and others deployed in the environment to monitor human activities [6, 8]. On the other hand, the hybrid HAR systems consist of wearable and non-wearable sensors that capture human activities with a better detection rate [9].

Regarding the wearable HAR systems, the raw data coming from the motion/inertial sensors are used to extract multiple features to train the Machine Learning (ML) classifiers or Deep Learning (DL) models on these features for identifying the underlying activities [10]. Thus, these systems are cost-effective [11]. However, users must wear them to get their movements monitored by wearable HAR systems [12, 13]. Unlike the non-wearable HAR systems, they have no coverage issues, and they can recognize the user's activity unless they wear them at the specified location [14]. In vision-based HAR systems, the images captured from cameras are used to extract the different features. Then the extracted features are used to train different ML classifiers to recognize the activity performed in the captured image [15].

1.1 Sensors in HAR

In today's world, almost everyone has a Smartphone that is equipped with a rich set of sensors that can be used as an alternative platform for HAR. The sensors found in Smartphone's such as the accelerometer, digital compass, gyroscope, GPS, microphone and camera can be used to derive the necessary data required for HAR. Human activity recognition has numerous applications in a wide range of domains such as healthcare, social networks, safety, environmental monitoring, and transportation and surveillance systems. Different sensors are used for classification of the human activities. The two sensors used in the data collected for this research are accelerometers and Gyroscopes. The accelerometer is a type of electronic sensor that measures the acceleration forces acting on an object in order to determine its position in space and monitor its movement. This calculates the triaxial acceleration (total acceleration) and the estimated body acceleration to give its position in space. A gyroscope sensor is a device that can measure and maintain an object's orientation and angular velocity. The gyroscope gives us the Triaxial Angular velocity. These two sensors are readily available in Smartphone's and served the purpose of data collection for this research.

HAR plays an imperative role in healthcare, especially in medical diagnosis and fitness monitoring [16]. Children and the elderly are the most vulnerable members of our society, and hence they need constant monitoring. So, if they require any immediate medical attention, Human Activity Recognition can predict their action and with post-processing, we can alert the respective authorities. Wu et al. [17] researched the possibility of using a portable pre-impact fall detector to detect imminent falls before the body hits the ground. Using triaxial accelerometers connected to the waist, wrist, and head, Kangas et al. [18] tested various low-complexity fall detection algorithms. HAR also has applications in the sports domain. For the Chum Kiu motion series in martial arts, Ernst A. Heinz et al. [19] performed an initial experiment with inexpensive body-worn gyroscopes and acceleration sensors. Miikka Ermes et al. [20] proposed a system to evaluate the athletic performance of the test subject in supervised and unsupervised settings. HAR can also recognize anomalies in security footage thus, being pivotal in surveillance systems. Chang et al. [21] proposed a system that was able to identify and predict suspicious and violent activity in a group of inmates. Given the large number of observations made per second, the temporal nature of the observations, and the lack of a simple way to link accelerometer data to known movements, this is a difficult problem to solve. The major challenges faced in the implementation of HAR are test subject sensitivity, location sensitivity, activity complexity, limited energy and computational resources [22].

1.2 HAR Activity Classification

HAR systems are broadly classified into three types, i.e., wearable HAR systems, non-wearable HAR systems, and hybrid HAR systems. The wearable HAR systems consist of motion sensors like accelerometer, gyroscope, and magnetometer, mounted at some embedded device and worn on a particular body location such as wrist, waist, neck, and others, to recognize the human daily living activities. The non-wearable HAR systems consist of environment sensors like cameras, pressure sensors, acoustic sensors, RFID, and others deployed in the environment to monitor human activities. On the other hand, the hybrid HAR systems consist of wearable and non-wearable sensors that capture human activities with a better detection rate. Regarding the wearable HAR systems, the raw data coming from the motion/inertial sensors are used to extract multiple features to train the Machine Learning (ML) classifiers or Deep Learning (DL) models on these features for identifying the underlying activities. Thus, these systems are cost-effective. However, users must wear them to get their movements monitored by wearable HAR systems. Unlike the non-wearable HAR systems, they have no coverage issues, and they can recognize the user's activity unless they wear them at the specified location. In vision-based HAR systems, the images captured from cameras are used to extract the different features. Then the extracted features are used to train different ML classifiers to recognize the activity performed in the captured image. However, with the evolution of DL models, the DL models extract the features, and there is no need to get the hand-crafted features. Therefore, the non-wearable HAR systems are easy to use and give better results, but their accuracy highly relies on the environmental lighting condition. Moreover, their coverage for activity recognition is limited to the range of underlying cameras. Furthermore, they highly affect the privacy of human beings. Although RGB depth cameras' intervention, the privacy concern has been mainly resolved, yet the non-wearable HAR systems are very costly. In the ambient HAR systems, the sensors deployed in the environment collect the data of human activities and send it to a centralized system where some other features are extracted from the received data and then used all the extracted features to classify the human activities. Like the vision-based HAR systems, the ambient HAR systems are also easy to use. However, the primary issue is the limitation of the coverage area for activity recognition within a specific range. Moreover, their performance is highly affected by environmental interference and noise. Among all three HAR systems, wearable HAR systems are the most suitable and widely used HAR systems due to their portability, cost-effectiveness, and better performance. Therefore, this research focuses on wearable HAR systems. So far, much research work has been done to efficiently recognize human daily living activities. Different studies have used various learning algorithms for HAR. However, the machine learning performance varies concerning the underlying device, the number of sensors in a device, and the position of the sensing device where it is kept. Furthermore, the performance of a machine learning algorithm also depends on the properties of the underlying dataset [22]. Most of the existing HAR datasets are embraced with missing samples/values due to the memory, power, and processing constraints of an underlying device used for data acquisition. Moreover, the missing samples in a dataset have caused poor behavior in machine learning algorithms for HAR. During the data acquisition, some difficulties were encountered with sensors' failures and the incorrect positioning of the device. Also, the different frequencies of the various sensors may cause problems in the fusion of the multiple sources. In this work, we performed a comparative analysis of eight widely used machine learning techniques to identify human activities with a single sensor and multi-sensor combination available in a mobile device. The comparative analysis uses a publicly available dataset after extrapolating the missing samples by applying the k-Nearest Neighbor (KNN) data imputation technique. The main objective of this research is to analyze the performance of eight commonly used machine learning algorithms to figure out which algorithm performs best at which sensors' data combination. On the other hand, the main contribution is to recommend using data imputation and AdaBoost algorithm for HAR.

The Human Activity Classification using Sensors or wearable's devices are shown below in figure.

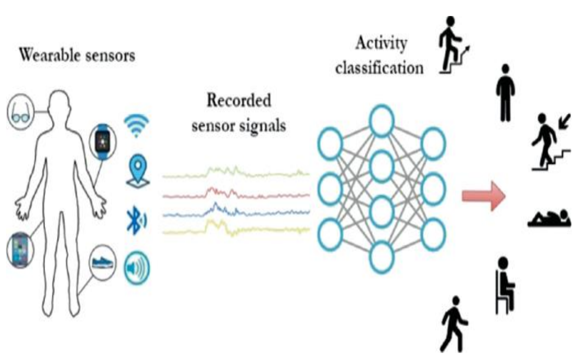


Fig. 1: HAR Activities Classification.

II. LITERATURE REVIEW

The performance of a machine learning algorithm varies based on the sensing device type, the number of sensors in that device, and the position of the underlying sensing device. Moreover, the incomplete activities (*i.e.*, data captures) in a dataset also play a crucial role in the performance of machine learning algorithms. Therefore, Author's in [23] perform a comparative analysis of eight commonly used machine learning algorithms in different sensor combinations in this work. We used a publicly available mobile sensors dataset and applied the k-Nearest Neighbors (KNN) data imputation technique for extrapolating the missing samples. Afterward, we performed a couple of experiments to figure out which algorithm performs best at which sensors' data combination. The experimental analysis reveals that the AdaBoost algorithm outperformed all machine learning algorithms for recognizing five different human daily living activities with both single and multi-sensor combinations. Furthermore, the experimental results show that AdaBoost is capable to correctly identify all the activities presented in the dataset with 100% classification accuracy.

In recent years, mainly due to the application of smartphones in this area, research in human activity recognition (HAR) has shown a continuous and steady growth. Thanks to its wide range of sensors, its size, its ease of use, its low price and its applicability in many other fields, it is a highly attractive option for researchers. However, the vast majority of studies carried out so far focus on laboratory settings, outside of a real-life environment. In this work [24], unlike in other papers, progress was sought on the latter point. To do so, a dataset already published for this purpose was used. This dataset was collected using the sensors of the smartphones of different individuals in their daily life, with almost total freedom. To exploit these data, numerous experiments were carried out with various machine learning techniques and each of them with different hyper parameters. These experiments proved that, in this case, tree-based models, such as Random Forest, outperform the rest. The final result shows an enormous improvement in the accuracy of the best model found to date for this purpose, from 74.39% to 92.97%.

Variety and volume of data make human activity recognition especially interesting field for machine learning. It has thus seen incredible growth in past several years taking part in big data questions as well. In a broad sense question of HAR - human activity recognition is a very complex one, often times dealing with large amounts of data not belonging to a predefined class. However, this paper [25] deals with supervised learning classifications task, focusing on several activity classes known as Activities of Daily Living - ADL. Generalized models for common activities and issues are looked into, and issues that appear due to the huge volume of data that is recognized as "other" when the models are applied to the real life data sets. Support vector machine method (SVM), Naive Bayes classifiers, KNN, Random Tree and Bagged Trees (Ensemble) algorithms are applied, and venturing into ANN.

Human Activity Recognition (HAR), based on sensor devices and the Internet of Things (IoT), attracted many researchers since it has diversified applications in health sectors, smart environments, and entertainment. HAR has emerged as one of the important health monitoring applications and it necessitates the constant usage of smartphones, smart watches, and wearable devices to capture patients' daily activities. To predict multiple human activities, deep learning (DL)-based methods have been successfully applied to time-series data that are generated by smartphones and wearable sensors. Although DL-based approaches were deployed in activity recognition, they still have encountered a few issues when working with time-series data. Those issues could be managed with the proposed methodology. This work [26] proposed a couple of Hybrid Learning Algorithms (HLA) to build comprehensive classification methods for HAR using wearable sensor data. The aim of this work is to make use of the Convolution Memory Fusion Algorithm (CMFA) and Convolution Gated Fusion Algorithm (CGFA) that model learns both local features and long-term and gated-term dependencies in sequential data. Feature extraction has been enhanced with the deployment of various filter sizes. They are used to capture different local temporal dependencies, and thus the enhancement is implemented. This Amalgam Learning Model has been deployed on the WISDM dataset, and the proposed models have achieved 97.76%, 94.98% for smart watch and smartphones of CMFA, 96.91%, 84.35% for smart watch and smartphones of CGFA. Experimental results show that these models demonstrated greater accuracy than other existing deep neural network frameworks.

The advancement and availability of technology can be employed to improve our daily lives. One example is Human Activity Recognition (HAR). HAR research has been mainly explored using imagery but is currently evolving to the use of sensors and has the ability to have a positive impact, including individual health monitoring and removing the barrier of healthcare. To reach a marketable HAR device, state-of-the-art classifications and power consumption methods such as convolutional neural network (CNN), data compression and other emerging techniques are reviewed here. The review of the current literature creates a foundation in HAR and addresses the lack of available HAR datasets, recommendation of classification and power reduction techniques, current drawbacks and their respective solutions, as well as future trends in HAR. The lack of publicly available datasets makes it difficult for new users to explore the field of HAR. This paper [27] dedicates a section to publicly available datasets for users to access. Finally, a framework is suggested for HAR applications, which envelopes the current literature and emerging trends in HAR.

Sousa Lima et al. [28] (2019) provide a complete, state-of-the-art outline of the current HAR solutions in the context of inertial sensors in smartphones, and, Elbasiony and Gomaa [29] (2019) introduce a detailed survey on multiple HAR systems on portable inertial sensors (Accelerometer, Gyroscopes, and Magnetometer), whose temporal signals are used for modeling and recognition of different activities. Nweke et al. [30] (2019) provide a detailed analysis of data/sensors fusion and multiple classification systems techniques for HAR with emphasis on mobile and wearable devices. Faust et al. [31] (2018), studied 53 papers focused on physiological sensors used in healthcare applications such as Electromyography (EMG), Electrocardiogram (ECG), Electrooculogram (EOG), and Electroencephalogram (EEG). Ramasamy Ramamurthy and Roy [32] (2018) presented an overview of ML and data mining techniques used for Activity Recognition (AR), empathizing with the fundamental problems and challenges. Finally, Morales and Akopian [33] (2017) provide an overview of the state-of-the-art concerning: relevant signals, data capturing and preprocessing, calibrating on-body locations and orientation, selecting the right set of features, activity models and classifiers, and ways to evaluate the usability of a HAR system. Moreover, it covers the detection of repetitive activities, postures, falls, and inactivity.

III. PROPOSED MODEL

This paper is to build a model that will predicts the human activities such as Walking, Walking to Upstairs, Walking to Downstairs, Sitting, Standing or Laying using sensor recorded data. In this thesis data is being collected by using two important sensors like Gyroscope and accelerometer. The dataset consist of sensor data recorded from thirty different people with attached sensors to their body.

By using the sensors like Gyroscope and accelerometer which are basically also attached in our smart phones, have captured '3-axial linear acceleration'(named tAcc-XYZ in the dataset) from accelerometer and '3-axial angular velocity' (named tGyro-XYZ in the dataset) from Gyroscope with several variations.

After collecting the data, they are cleaned using various filters. The sensor signals are pre-processed using noise filters and then sampled to fixed width window with 50% of overlap. From each window, a feature vector is calculated by calculating variables from time and frequency domain. It the thesis, each datapoint by the sensors is called as window which will have different readings.

The acceleration signal obtained from the sensors is separated into body signal and gravity signal using some low pass filters. After that angular velocity is derived in time to obtain the Jerk signals. Jerk signals are calculated for Body Acceleration readings. The magnitude of these signals was calculated using Euclidian norm. The magnitudes are represented as features.

3.1 Proposed Model Steps

Step 1: Read the Dataset.

Following data cleaning steps are applied:

1. Check for duplicate and Null Values.
2. Check for data imbalance.

Following feature engineering steps are applied:

1. Select static activities like sit, stand and lie down.
2. Select moving activities like Walking, Walking-Upstairs, Walking-Downstairs.
3. Apply EDA on Static and Dynamic Activities.
4. Apply Acceleration magnitude to differentiate between static and moving activities. For separation following observations are applied.

- If Acceleration Mean is < -0.8 then the Activities are either Standing or Sitting or Laying.
- If Acceleration Mean is > -0.6 then the Activities are either Walking or Walking Downstairs or Walking Upstairs.
- If Acceleration Mean > 0.0 then the Activity is Walking Downstairs.
- We can classify 75% the Activity labels with some errors.

1) Position of Gravity Acceleration also matters for activity. Following observations are applied.
   - If angle of X-axis, and gravity Mean > 0 then Activity is Laying.

5. Again save the data to train.csv and test.csv.
6. Read train data and test data from the csv files.
7. Create the proposed model using train data.
8. Evaluate the model by printing confusion matrix and various results
9. Apply DBSCAN clustering model.
10. Remove the Outliers using LOF, Isolation Forest and ABOD.
11. Apply PCA and Gaussian Random Projection.
12 Again apply t-SNE.
13. Apply Random search and Grid Search.
14. Train the model using the classifiers.
15. Evaluate the model by printing confusion matrix and various results.

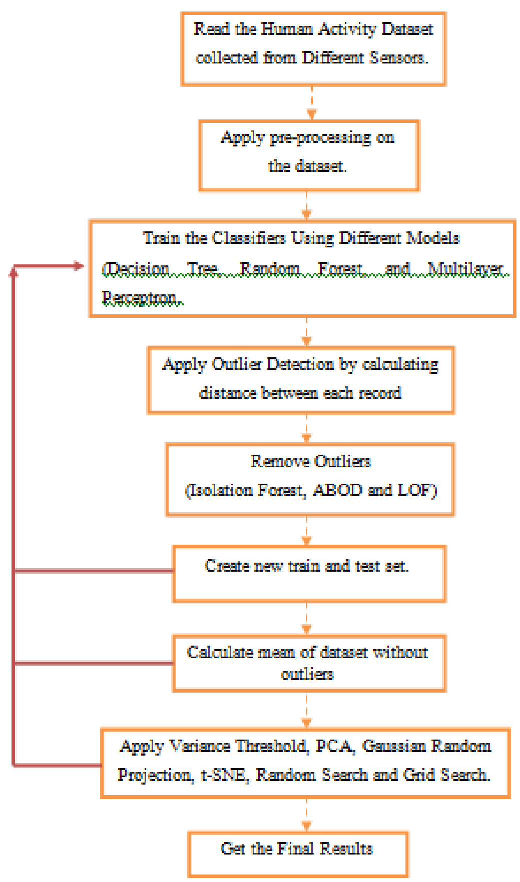
In the proposed model, Human Activities are recognized using various Classifiers on UCI-HAR dataset. The proposed model uses classification algorithms as well as Outlier Detection models to remove the outliers to make the dataset more concise.

In the first step, we just remove the Null Values and train the models. After Training the testing is performed by using Decision Tree, Random Forest and Multi-Layer Perceptron algorithms. After testing the outliers are detected and removed. After removing the outliers, again the models are tested. The models performed better after removing the outliers.

In second Step, again outliers are removed and PCA is applied. After PCA, the models are trained and tested against the accuracy.

In the third step, Grid search and Random search algorithms are applied on the filtered dataset. After that the models are tested with different K-folds. Finally the results are tested against Baseline models (DT and KNN) and some advance models like Random forest, Gradient Boosting, XGBoost, MLP and Extra Tree Classifiers.

4.3 Flowchart of proposed model



IV. CONCLUSION

This paper consists of the standard dataset for human activity recognition that is openly accessible from the WISDM group. It constitutes raw data accumulated via the accelerometer of the smartphone. Initially, we imposed a windowing method (overlapping), supplemented by a 250 ms window size along with 25% of overlapping. Five time-domain features were acquired by utilizing this approach, in order to improve machine learning models outcome.

Further, k-fold cross validation with 5 folds was implemented on each classifier and each classifier is then used to analyze the data. The effect of a machine learning classifier is examined based on overall accuracy values. Hence, Gradient Boosting Classifiers exhibit the characteristics of the best performer with overall accuracy of 90.89% on old dataset and 91.58% on new dataset.

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