Human Activities Recognition Based On Iterative Clustering With Feature Mapping Using MLP

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Abstract- *Wearable sensors provide a user-friendly and non-intrusive mechanism to extract user-related data that paves the way to the development of personalized applications. Within those applications, human activity recognition (HAR) plays an important role in the characterization of the user context. Outlier detection methods focus on finding anomalous data samples that are likely to have been generated by a different mechanism.*

This thesis combines outlier detection and HAR by introducing an algorithm that is able both to detect information from Sensor Data and activities inside the dataset and to extract data segments of a particular activity from a different activity dataset. Several machine learning algorithms have been previously used in the area of HAR based on the analysis of the time sequences generated by wearable sensors. Deep neural networks (DRNNs) have proven to be optimally adapted to the sequential characteristics of wearable sensor data in previous studies. A neural network based algorithm is proposed in this thesis for Human Activity Recognition and Clustering Based outlier detection in HAR. The results are validated both for intra- and inter-subject cases and both for outlier detection and sub-activity recognition using different datasets. The Proposed Model outperforms the existing models.

Keywords- HAR, Sensors, Accelerometer, Machine Learning, Multi-layer Perceptron, Outliers Detection.

I. INTRODUCTION

Wearable devices allow capturing diverse range of physiological and functional data for applications in sports, well being and health care. Activity Recognition has many applications in the world today. Activity Recognition can be defined as identifying and recognizing a person's actions such as standing, sitting, walking, laying down, walk upstairs, walk downstairs etc. Various researchers have been suggested various techniques for human activity recognition some of which are discussed below. Wearable devices allow capturing diverse range of physiological and functional data for applications in sports, well being and health care. Deep Learning is a technique belonging to Machine Learning which involves working with algorithms based on the structure and functions of the brain which is used to infer and extract information from large data sets. In [1] combination of two types of features, shallow and learnt, is done to show that the modern day devices are capable of human activity recognition. This can be done by getting the computation time from various low-power devices such as wearable devices and IoT. Transferring the already learned knowledge from an already existing environment to the new target environment has proven to be a more practical, efficient and cost-effective approach while building contextual models for new smart environments. This approach reduces the data collection effort. Models trained via feature based knowledge transfer framework can even outperform non-transfer learning models by up to 8% in accuracy as suggested in [2]. Recent advances in wireless sensor networks have created a possibility of tending to human needs by recognizing and analyzing their current activities. In [3] a framework that efficiently recognizes human activities in smart homes based in spatio-temporal mining technique is proposed. Human body motion analysis is an initial procedure for understanding and perceiving human activities. A multilevel approach is proposed for human activity and social role identification by combining different levels of human activity into a multilevel framework, where the interactions between these levels are modeled is proposed in [4]. Participants are grouped in pairs and each person gives feedback and modifies his/her behavior according to the feedback received from the other participant. This exchange of feedback between the pair of participants takes place simultaneously until the interaction goals are met. In [5] a method is proposed to show how a participant in a dyadic interaction adapts his/her body language to the behavior of the other participant, given the target for the interaction and context. Recently, attributes have been analyzed and treated as high-level semantic information which will help us is achieving efficient and accurate classification. Multitask learning is one of the methodologies used to achieve this goal, which shares low-level features between attributes and actions as suggested in [6]. Acceleration based human activity recognition has generated a lot of interested and has been a key area of focus. In [7], an approach which uses a spectral- geometry based algorithm is implemented for acceleration- based human activity recognition. This study introduces a new approach to implementing assistive smart homes. An intelligent agent architecture and intention recognition (IR) mechanism that may be used to form an ambient assisted living (AAL) system to assist with ADLs within smart homes (SH) is proposed in [8].

1.1 Various Approaches to HAR

To achieve the goal of recognizing human activity, a HAR system is required. The two most commonly used techniques for this purpose are sensor-based and vision-based activity recognition. We can classify them, as shown in Figure 1.1.

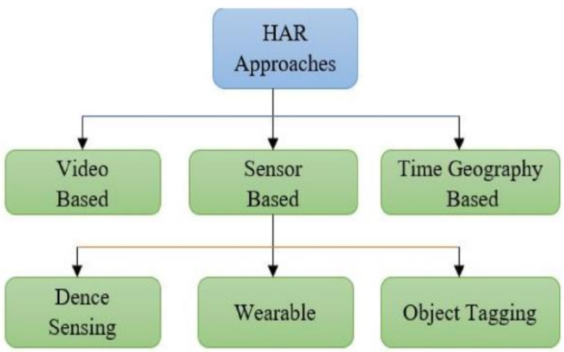

Figure 1.1: Classification of HAR system based on their approaches [4].

Innovations that emerge exclusively in the field of wearable sensors and IoT devices have made the life of people more comfortable. A variety of attempts must be taken to ensure that the population understands what they are doing and how a technique can assist them in completing their assignment, but this can be achieved. Smart watches, smartphones, and fitness trackers that have multiple sensors can be used for HAR, according to research [9]. It has been observed that HAR has a great potential to play a significant part in strengthening the progress of the human quality of life. HAR based on sensors focuses on predicting the activities based on low-level sensor data. Our study estimates the participant's activity using the WISDM dataset [10] and the signal information obtained from these sensors. In general, HAR can be thought of as a traditional Pattern Recognition (PR) problem, a common IoT application that can be used for good observational multiple body movement for human action recognition. The importance of HAR based on intelligent sensors is evident because it is used to detect and track numerous everyday activities such as eating, drinking, cleaning teeth, and detecting bedtime anomalies, which are not limited to aerobic activities. Simple and complex behaviour can be found in HAR. Studies on the recognition of complex human activities, such as brushing teeth or moving away from a ball, are rare. Accelerometers are used to detect moving objects by measuring accelerations along a reference axis. This allows the accelerometers to identify the velocity of the objects. Running and resting are particularly well-suited to tracking by these devices because they include a lot of body movement [11]. The accelerometer's measurements can be utilized to detect abrupt changes in motion. The gyroscope, which employs gravity to compute orientation, is another sensor that has proven popular in smart-wearable devices. The signal data from the gyroscope can be studied to identify the device's placement and alignment [12]. There has been a significant amount of research on SHA recognition, but relatively little on CHA recognition. To be viable, both domains must address a wide range of essential challenges (identity accuracy, privacy, energy consumption, computing cost, mobility).

Machine learning's HAR with annotated data is a different kind of time series categorization and supervised training than other approaches. Several studies have been conducted to explore the task of recognition and classification utilizing different algorithms such as XGBoost, Random Forest, SVM, and others and quasi-deep learning methods such as LSTM, CNN, ANN, RNN, and others. Existing approaches have the drawback of requiring a substantial amount of time-consuming extraction of features and manual feature engineering. On the other hand, deep learning techniques can immediately recognize features from data and are better suited to trying to identify complex human activities.

II. LITERATURE SURVEY

In recent years, HAR has gained a significant amount of attention from many researchers due to its wide area of applications in different fields such as continuous healthcare monitoring, human-computer interaction, learning behavior recognition, functional diagnosis and assessing outcomes. It is also an important indicator of lifestyle and quality of life. In the work, Hassan et al. developed a robust system for HAR using smartphone sensor and Deep Belief Network (DBN). For data collection, Hassan et al. used a Smartphone's accelerometer and gyroscopic sensory data. To make the features more robust, they utilized Kernel Principal Component Analysis (KPCA) and Linear Discriminant Analysis (LDA). The proposed approach showed better results as compared to traditional methods. They achieved an overall accuracy of 95.85% [13]. In contrast, the HAR method proposed by Sikder et al. based on a two channel CNN achieved a classification accuracy of 95.25% on the UCI HAR dataset.

In another work, Lee et al. proposed a method for HAR based on 1D CNN using Smartphone's accelerometer sensor. They collected sensor data for three activities such as walking, running and staying still. The gathered tri-axis accelerometer data then fed to the 1D-CNN to analyse the performance. They reported maximum accuracy of 92.71% [14].

Saha et al reported a method for HAR using smartphone sensor. They collected accelerometer data from smartphone for six common human activities and processed them through different supervised learning algorithms. They achieved a maximum accuracy of 95.99% with logistic regression [15]. Dogan et al. presented a study for HAR using traditional CNN. They used the Sussex-Huawei Locomotion (SHL) Dataset for recognizing human activities through the proposed CNN model, achieving an accuracy of 79.33% on the test set.

Wearable sensors have been applied in People's Daily life. For example, the current sports apps in various mobile phones use the accelerometer in mobile phones to monitor the dynamic activity of human bodies [16]. However, these applications still fall short in terms of the types of activity that can be easily monitored. Through this software, people can obtain daily activity data, which is the number of steps in the activity, without information describing the details of the activity.

The process of human activity recognition based on sensors mainly includes the following stages: data acquisition, data preprocessing, feature extraction and the recognition model design. Human activity data is acquired through wearable sensors, and in order to make the data collected by sensors better used for training the identification model, data pretreatment including outlier processing, data smoothing, data segmentation, data standardization, data normalization and equalization is needed. Anindya [17] analysed the problem of data segmentation in the process of human activity recognition. The window size of segmentation needs to be determined according to the duration of activity occurrence. Meanwhile, overlapping windows of fixed length can be adopted for adjacent segments to improve the recognition rate. In the feature extraction stage, the characteristics of the required recognition activity and the requirements of the selected recognition model should be considered to extract the data features suitable for training. Orlov [18] used Relief-F feature selection method for feature extraction. Traditional machine learning methods can recognize simple activity well, but it requires specific domain knowledge for feature extraction, and has low recognition ability for complex activities. The deep learning model can automatically extract features from the original data, and the special network structure can extract deeper features and achieve good recognition effect for more complex activity. Jiang [19] used convolutional neural network to identify six activities. Almaslukh [20] used automatic coding machine to identify six activities. And Saied [21] used the hybrid model of convolutional neural network and recurrent neural network to identify the six activities.

A major progression in sensor-based technologies has resulted in a fast evolution of the Internet of Things (IoT) applications for developing any real-time monitoring systems. Nowadays, an increasing number of aged people living alone dispersed worldwide, and tracking the status of their health function or activity is necessary. In this paper [22], an IoT-based human activity monitoring model is proposed to continuously check the activities of aged people via smart sensor-based technologies. In this model, vital data are collected by smart sensors or IoT-based devices, and analysis of that data is done by using different machine learning algorithms for detecting any risk in human activity behavior. After evaluating the proposed model, the SVM has attained the highest accuracy of 98.03% which is highly effective for our purpose. SVM outperformed all machine learning algorithms used for analysis purposes.

Human Activity recognition (HAR) is an important area of research in ubiquitous computing and Human Computer Interaction. To recognize activities using mobile or wearable sensor, data are collected using appropriate sensors, segmented, needed features extracted and activities categories using discriminative models (SVM, HMM, MLP etc.). Feature extraction is an important stage as it helps to reduce computation time and ensure enhanced recognition accuracy. Earlier researches have used statistical features which require domain expert and handcrafted features. However, the advent of deep learning that extracts salient features from raw sensor data and has provided high performance in computer vision, speech and image recognition. Based on the recent advances recorded in deep learning for human activity recognition, [23] briefly reviewed the different deep learning methods for human activities implemented recently and then propose conceptual deep learning frameworks that can be used to extract global features that model the temporal dependencies using Gated Recurrent Units. The framework when implemented would comprise of seven convolutional layer, two Gated recurrent unit and Support Vector Machine (SVM) layer for classification of activity details. The proposed technique is still under development and will be evaluated with benchmarked datasets and compared with other baseline deep learning algorithms.

Currently, autumn aims to meet wearable devices, environmental sensors and computer vision that must be worn or used as equipment. However, they have limitations and can affect the daily life of the elderly. Based on indoor propagation of wireless signals, this article presents a proof-of-concept for analyzing human loss behavior using wi-fi signals. This model can detect falling without violating privacy or affecting people's comfort, and has the advantages of no interference, powerful, universal and low cost. This model combines digital signal processing and machine learning techniques.

In paper [24], the state information (csi) information of the wireless signal is analyzed and processed, and the local outlier algorithm is used to find the abnormal csi. Support vector machine and cloud gradient boosting algorithms are used for classification, analysis and comparative research. Experimental results show that the average accuracy of fall detection based on wireless recognition is more than 90%. This work is important to ensure the safety of the elderly in society.

Human activity recognition (HAR) is one of the research areas in deep learning and machine learning. Since the daily activities we do are ubiquitous (everywhere), it would be helpful if models could predict activities. Many unsupervised techniques have been used before, but with the advent of deep learning and neural networks, we can train and test data more easily. A neural network (RNN) will be used as we will be dealing with real time data. RNNs use the time back propagation (BPTT) algorithm.

The long short term memory (lstm) model combined with the output technique solves the problem of gradient shift and overfitting of the model. LSTMs have cells used to store and forget, while automatically releasing some states and allowing other states to join and train data. A better strategy was considered in this work that is easier to use than the existing deep learning models featured here. The method in [25] achieves an accuracy of 92.67% of the test data.

Human activity recognition is the wide range of field of research and challenging task to identify the actions of the human in period of time based on received signal strength data in wireless sensor network. It is important to monitor activity of a person for numerous reasons. Recently, Machine Learning approach shows capable of classifying the actions of the human by automatically using the raw sensor data. In this work, the dataset consists of received signal strength of seven activities using three sensor nodes that are trained by using supervised machine learning algorithms to recognize the actions and random activities are monitored to identify the strange action of the person using unsupervised machine learning. The proposed [26] machine learning based human activity recognition model are evaluated and predict the seven human activities by achieving 90% of accuracy. The model is later improved to recognize the random actions of the human.

Execution of unsupervised operations using Doppler radar data has not received much attention, although it is important in real-world or anonymous situations. This work presents two non-invasive methods for monitoring human activity using Doppler flow. These include local discrete cosine transform (dct) based extraction techniques and local entropy based extraction techniques. In addition, a new dynamic variable autoencoder (CVAE) [27] feature extraction application is used for the first time on Doppler radar data. Our feature extraction architectures are compared to previously use convolutional autoencoders (CAE) and linear feature extraction based on fundamental principle analysis (PCA) and 2dpca. All three methods perform better when applied to encoded CVAE features.

In the development of a high-performance system that can manage multiple environments, the main problems are the problem of large and diverse data and different types of assets. Human recognition studies in the field of environmental protection have increased exponentially recently. In the development of a high-performance system that can manage multiple environments, the main problems are the problem of large and diverse data and different types of assets. The training methods of tracking algorithms are still limited as the available data usually does not have a working log file. This work [28] describes the distribution of data for dataset.

III. PROPOSED WORK

3.1 Following data cleaning steps are applied:

1. Check for duplicate and Null Values.
2. Check for data imbalance.
3. Apply t-SNE feature selection on the data.

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.
- 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.

3.2 Proposed Algorithm

Algorithm for Human activity detection:

Step 1: Read the dataset from various sensors.
Step 2: Apply preprocessing on dataset.
Step 3: Split the dataset into train and test data.
Step 4: Detect and classify the activities using Base classifiers and Proposed MLP classifier.
Step5: Evaluate the results.
Step 6: Apply Clustering on train and test data.
Step 7: Remove outliers by using LOF, ABOD and Isolation Forest.
Step 8: Detect and classify the activities using Base classifiers and Proposed MLP classifier.
Step 9: Evaluate the results.
Step 10: apply PCA on cleaned data.
Step 11: Detect and classify the activities using Base classifiers and Proposed MLP classifier.
Step 12: Compare the results.
Step 13: End of algorithm.

IV. RESULTS

In this section we are going to compare the results of existing methods as well as proposed methods. The parameters for comparing the results are accuracy, precision, recall and F1-score. The results are calculated on the original dataset obtained from the kaggle websites. The results are compared in three different tables. Table 4.1 is the accuracy comparison without applying preprocessing methods. Table 6.2 is the accuracy comparison with applying outlier's removal techniques and table 6.3 is the comparison for the results with PCA and removal of outliers. In all the three cases the proposed MLP classifier outperforms the other classifiers.

Table 6.1: Accuracy Comparison without preprocssing.

Implemented Algorithm (Without Preprocessing)	Accuracy in %
Decision Tree	85.95
Random forest	92.09
Extra Tree Classifier	94.02
Bagging classifier	89.17
KNN	90.43
MLP Classifier (Proposed)	94.74

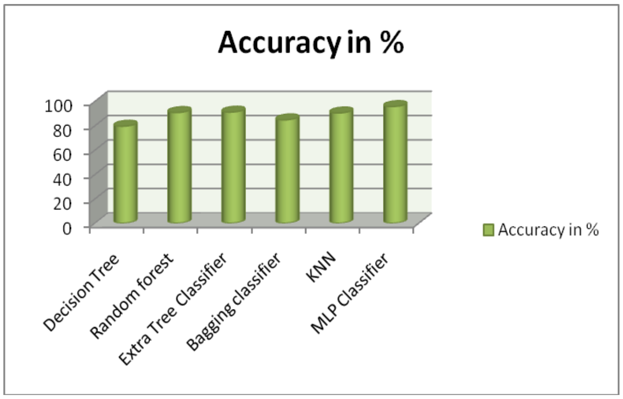

Figure 6.38: Graph Chart for accuracy Comparison.

Table 6.2: Accuracy Comparison without preprocssing.

Implemented Algorithm (With Preprocessing)	Accuracy in %
Decision Tree	85.57
Random forest	92.98
Extra Tree Classifier	94.19
Bagging classifier	88.90
KNN	90.43
MLP Classifier (Proposed)	95.96

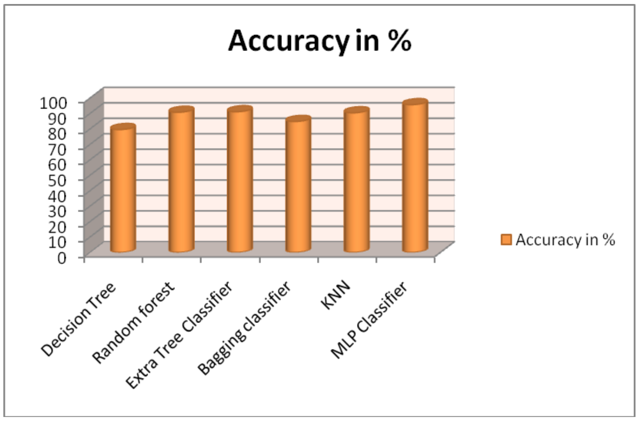

Figure 6.39: Graph Chart for accuracy Comparison with preprocessing.

V. CONCLUSION

Human activity recognition (HAR) is a rapidly growing field of study within computer science and engineering that aims to develop systems that can accurately recognize and interpret human movements in real-time. The field of HAR has its roots in computer vision and pattern recognition, but has since grown to include other areas such as machine learning, signal processing, and bio informatics. The goal of HAR research is to develop systems that can be used in a variety of applications, including healthcare, sports, and human-computer interaction.

The development of HAR systems typically involves the use of sensors to collect data on human movement, such as accelerometer and gyroscopes, which is then processed and analyzed using machine learning algorithms to identify patterns and recognize specific activities. The use of deep learning techniques has been found to be especially effective in HAR, as these techniques can learn to recognize complex patterns in large amounts of data.

KNN and SVM are some of the popular machine learning algorithms that have been used in many studies on HAR, which can achieve high accuracy rates (96% and 98% respectively). Both algorithms are powerful and robust, and can be improved by fine-tuning the model, feature selection, and hyper parameter tuning. However, the choice of algorithm will depend on the specific requirements of the thesis, the available data and computational resources.

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