

A Comparison of Human Activity Recognition [HAR] Based on Machine Learning Classifiers

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Abstract: Today's most challenging issue faced by the world is the COVID-19 pandemic, it is essential to track or observe the daily activities of people who living alone or taking individual isolation. So ADL (Activity Daily Living) is an essential thing, especially activity recognition plays a significant role in the medical field. In this paper, human activity recognition (HAR) can be detected with the help of web applications based on the various machine learning classifiers. Along with the activity detection a detailed study is carried to learn about the accurate prediction of each classifier during the training process. Activity detection is done by these processes mainly collecting data, feature extraction, matrix creation, testing, and training process. After that a comparison in the accuracy, precision can be done. The machine learning classifier used to compare is MLP, random forest, SVM, logistic regression, naïve Bayes, and KNN classifier. By using this web app easily detect human activity and monitoring the daily living of a person.

Keywords: accuracy, activity recognition, machine learning classifiers, web application.

1. Introduction

Human activity recognition (HAR) is the field of identifying the certain movement or activities of a person based on the data. Here supervised learning technique is used. However, human activity recognition (HAR) is mainly used in the medical field or health care as well as in eldercare and it is the most challenging problem that occurs in all medical sections due to conditions of the pandemic situation etc. Activities of daily living [ADL]is used to monitoring the health care of peoples, so its plays important role. In all the Previous study of activity recognition based on sensor technologies by using a single machine learning classifier that is wearable sensors. Here also using the supervised classification techniques namely kernel discriminant analysis, but all these algorithm shows accuracy of the data will be less and given it can be computationally expensive. In previous many studies the accelerometer sensor embedded in the smartphone detects the activity and by using the machine learning classifier using multilayer perceptron algorithm. Multilayer perceptron having three layers. It is also a supervised learning technique. Here using the multiple layers are used. The main disadvantage of using multilayer perceptron

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is, it has too many parameters are used and is fully connected. And it gives low performance. But these algorithms are not so effective today. The studies prove that the MLP causes inefficiency and the multilayer perceptron is very sensitive to feature scaling. Activity recognition also plays a major role in health care as health monitoring. But recent researches are found to be lot of problems such as security issues too. An effective solution to increase the performance of existing system using various machine learning classifiers which giving the best accuracy result. By using the web application, the activity recognition is more easier than before. In the proposed system using a web application the user can entering by using a user id and the file can be uploaded by the user. Here the training process can be done by classifiers other than MLP. The classifiers used are the SVM, logistic regression, random forest classifier, Naïve Bayes, KNN etc. There by the web app can detect the entire activity by the user. In this paper a novel study on activity recognition based on machine learning classifier using a web application and the main objective is to explore the limitation of the accuracy. In this paper activity can be detected by mainly three process that is model training, model testing and the activity detection.

2. Literature Review

Recently there is a lot of studies applying activity recognition using machine learning classifiers.

Adul Zukor, A Zakaria, [1] applied an accelerometer sensor for human activity recognition by using an artificial neural network called multilayer perceptron. Here using multilayer perceptron which having input layer, hidden layer, and an output layer which has been detected the accuracy and the accelerometer sensor is detected the activity. In the training process, the accuracy of the map is around 60%, and the maximum upper limit of 70%.

Saisakul, Anthony S Atkins, Hongnian [2] have proposed a system that is home equipped with smart technologies providing services that enhance the human way of living, sensor technologies that are used in the smart home. Activities of daily (ADL) to monitor the routine tasks of people. Especially in the care of old people, their (ADL) is very important.

F. Attal, S. Mohammed, M. Dedabrishvili [3] proposed human activity recognition by using wearable sensors. But it also shows low performance when compared to others.

Wendong Xiao and Yingjie Lu [4] present an innovative in activity recognition. Here the nonlinear kernel discriminant analysis (KDA) Scheme is used but the kernel parameters are optimized for the trained data, not for the distributions and they are computationally expensive.

D. Riboni and C. Bettini, [5] had presented an innovative idea model for detecting emergencies performed using a stochastic context-free grammar with a domain activity ontology.

I. Farkas and Dora, [6] in this the activity can be recognized. Here only perform activity labeling and prediction at each sampling point.

T. Sztyler, [7] here activity recognition in on body localization by wearable sensors, here a single acceleration sensor is used.

L. Chen, C. Nugent, and G. Okeyo [8] also an approach towards activity recognition based on smart home technology.

Even though the above research has improved the performance using machine learning classifiers but further improvement is still possible. This paper proposes an approach to activity recognition by using different machine learning classifiers are used in this, which are MLP, Naïve Bayes, Random forest classifier, Logistic regression, and, Support vector machine.it improves the performance by increasing the accuracy more than the existing systems.

3. System Model

The proposed system shown in fig. 1 has a web page that contains a login option and password. Initially, a user or client entered the webpage by login and after that, a webpage is open for activity recognition having an option for file uploading. The file that is uploading containing the input data, by the testing and training data set, the activity can be done. During the training process here using additional machine learning classifiers which giving the best accuracy during training thereby improving the performance.



Fig. 2. Block diagram of proposed system

A. Data collection

This study using a data set contain three types of activity daily living (ADL). The data set are sitting, walking, standing which are stored as x, y, z values. These activities are used because they are the most commonly used activities daily. They are stored in arrays.

B. Feature extraction

Feature extraction is the process by which characteristics getting from the data. The features that are extracted are the minimum value, maximum value, mean value, signal vector magnitude, signal magnitude area.

C. Training process



Fig. 3. Block diagram of proposed system (Training)

During the training process different machine learning classifiers are used. These are MLP classifier, KNN, SVM, Naïve Bayes, in addition to these add logistic regression, and random forest classifier. Random Forest Classifier can be defined as the single data set that can be divide into a random dataset and build decision trees for each of them, having every tree's output, taking the majority, and moved into the final decision. According to logistic regression, binary classification is done, and the output is taken as either 1 or 0. support vector machine can be defined as we can separate an n-dimensional data space by n-1 hyperplane. Here support vectors are used that are closest data points. Naive Bayes classifiers are called probabilistic classifier. MLP is a multilayer perceptron having three layers. KNN classifier is the k-nearest neighbor algorithm. During the training process accuracy of each of the classifiers can be predicted.





Fig. 4. Block diagram of proposed system (Testing)

During the testing process remaining 30% of the data can be used. After that here also feature can be classified and a feature matrix is created and reshaped. These feature outputs can be given to the input of each classifier. Then mapping is done and activity can be detected.

E. Web application

Here using a web-based application, because a user can

access anywhere by an internet connection and a browser. User can be entered into the webpage by login by id and password so that a website can be open as named 'Activity Recognition'. There is an option for file uploading. and the activity detected by the corresponding classifier.



Fig. 5. Login page



Fig. 6. Web page for file uploading

4. Experiments and Results

During the training process, accuracy, precision, F1 score, recall can be detected. Accuracy is defined as the ratio of no predictions to the total no of predictions. Precision can be defined as the no: of correct positive predictions that can be made. F1 Score is the weighted average of precision and recall. The recall is the ability for finding data points.

- Accuracy =No. of predictions/Total No. of predictions
- Precision = True positive/(true positive + false positive)
- F1score=2*(precision *recall)/(recall +precision)
- Recall =True positives/(true positives +false negatives)
- Recall =True positives/(true positives +false negatives)

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Fig. 7. Training result of Naïve Bayes and Random Forest

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Accuracy: 0.9523809523809523 Fig. 9. Training result of MLP classifier

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Fig. 12. Activity detection in web app

Table 1 Comparison Result

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S. No.	Classifiers used	Accuracy (%)
1	Multi-layer perceptron	95
2	Support vector machine	100
3	KNN	100
4	Random Forest classifier	100
5	Logistic regression	100
6	Naïve bayes	95.23

5. Conclusion

The objective of the paper is human activity recognition using web application based on various machine learning classifiers. And comparing the accuracy of each classifier used. The system shows better performances than the existing system because the system can use additional machine learning classifiers with high accuracy. The system can access every user through using a web-based application easily and it is secure too. By comparing the accuracy of each classifier here SVM, random forest and logistic regression classifier and KNN attain 100% accuracy. When compared with other classifiers used. The paper performs better performance when compared with the existing system by increasing the accuracy and system performance.

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