World Journal of Innovative Research (WJIR)
ISSN: 2454-8236, Volume-12, Issue-1, January 2022 Pages 37-39

A Review on Human Activity Recognition Techniques and Comparative Performance Analysis

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***Abstract*— In this paper, we discussed about the several machine learning algorithms and its use in recognition of human activity .Human activity recognition is an active field of research today that aims to understand human behavior by interpreting sensory information collected from humans and their living environment. Machine learning is an evolving branch of the computational algorithms that are designed to find the human intelligence by learning from the surrounding existing environment and it considered the working horse in the new era of the so-called big data also. The techniques based on machine learning have been applied successfully in diverse fields ranging from pattern recognition, computer vision as well on spacecraft engineering, finance, entertainment, and computational biology to biomedical and medical applications. These are few types of machine learning: supervised learning, unsupervised learning, and reinforcement learning. Machine learning have neural networks like ANN, RNN, CNN and algorithms classifier like first is Linear Models, Logistic Regression, Support Vector Machines.second is Non-linear Models. K-Nearest Neighbours. Kernel SVM. Naïve Bayes, Decision Tree Classification, Random Forest Classification. This paper shows the technology analysis of some recent existing human activity recognition techniques using different algorithm and neural networks. At end of this review paper compared results show the accuracy parameter of different algorithms.**

***Index Terms*—** Biomedical, Human Activity Recognition, Machine Learning.

I. Introduction

Human activity recognition is an active field of study today. This aims to understand human behavior through expounding sensory information collected from humans on their basic activities, using sensors like accelerometer or gyroscope. One of the methods for collecting user activity data is through portable sensors. Using portable sensors, you can easily and directly collect data which describe physiological signals, movement and position from the user. But these sensors have some drawbacks, which is being intrusive and restricting the movement of users. To overcome from this drawback and smooth sensing operation, we can use smart phones for portable sensing operation. Also the smart phone has following advantages I) Smartphone have embedded sensors like motion sensors (accelerometers) gyroscope, magnetometer, GPS, etc. II.) In this advanced era of technology people are more familiar and comfortable with smart phones because they are constantly using these devices. In this work, we propose a new smart phone-based online HAR system for classifying activities using multi-class support vector machine (SVM) that performs activity probability estimation for each activity of user. When combined with the predictions from previous samples, these estimates are interpreted as activity probability signals, and eventually they are heuristically filtered to improve classification accuracy. Although various HAR datasets have been published, only a few publicly available HAR datasets include Smartphone supported data.

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This work can be used in health applications such as care and monitoring of the elderly. In recent years, with the rapid development of smart gadgets and technologies, the value of ubiquitous systems has become a major attraction for researchers. The automatic recognition of human activities in everyday life is of great importance in a wide range of applications related to robots, intelligent surveillance, network video exploration and traffic safety. Much research has been done in the field of HAR using vision-based or sensor-based methods. Due to certain difficulties, including background confusion, limited occlusion, changes in point of view and lighting, and camera movement, it is challenging to identify human activity from still images or video sequences. In addition, it is impossible to carry out ubiquitous field surveillance of human activities using static cameras. These challenges are addressed using small motion sensors for HAR, including body inertia sensors and Smartphone sensors. These sensors provide the ability to stay with humans throughout the day and provide universal monitoring of human activities. Therefore, sensor-based HAR has become crucial in detecting and identifying human activities in nature.

II. HUMAN ACTIVITY RECOGNITION

There are several surveys in the human activity recognition literature, like taking inspiration from inception and dense networks for human activity recognition using Inertial Sensors given by Hamza Ali Imran et al. [6]. Human Activity Recognition (HAR) is an imperative area of investigate because it provides huge applications such as health monitoring, sports, entertainment, effective human-machine interfaces, childcare, education and more There are many. The use of computer vision to recognize human activity has several limitations. Given the advantages of inertial sensors over traditional computer vision technology, it has become the norm to use inertial sensors (including accelerometers or gyroscope sensors) in HAR today. In this article, we propose an l-dimensional degradation neural network inspired by two advanced architectures proposed for image classification.

In Smartphone Based Human Activity Recognition with Feature Selection and Dense Neural Network given by Syed K. Bashar et.al [7], human activity recognition (HAR) based on smartphones has been very prevalent in healthcare, surveillance, human interaction, pattern recognition, etc. Due to its embedded sensors, so it has been preferred. In this article, a neural network model for classifying human activities using activity-driven manual functions. The feature selection derived from the neighborhood parts analysis will be used first to select a subset of imperative features from the available time domain and frequency domain parameters. The following model is a dense neural network with four hidden layers to organize input functions into dissimilar categories. The model is evaluated based on public UCI HAR dataset, which consists of six daily activities; our method achieves a classification accuracy of 95.79%. Our planned model exceeds most other methods when it uses features less than the current advanced methods and shows the importance of correcting the selection of functions.

By Kyoung-Soub Lee et al. [8] in optimal time-window derivation for human-activity recognition based on convolutional neural networks of repeated rehabilitation motions, the convolutional neural networks were used to examine time window required to achieve maximum accuracy in the classification of regular Convolutional Neural Networks (CNN). To classify real-time motion with HAR, the data must be segmented with time windows. Human activity recognition based on CNN must be used. Particularly for repeated rehabilitation tasks, relationship among repeated task period and the optimal size of time window must be investigated. In this research, a smart watch and smartphone collection system is used. Five different periods of upper limb exercises were measured to classify rehabilitation exercises with a specific time window. Use 5 times cross-validation to compare performance. The results show that the time window that maximizes the performance of CNN-based HAR affects the size or time period of samples used.

Soo Min Kwon et.al [9] introduces a hands-free human activity recognition framework leveraging millimeter-wave (mmWave) sensors. Compared to other existing approaches, this network protects user privacy and can remodel a human skeleton performing the activity. Moreover, It show that the network can be achieved in one architecture, and be further optimized to have higher accuracy than those that can only get singular results (i.e. only get pose estimation or activity recognition). To demonstrate the practicality and robustness of the model, It demonstrate model in different settings (i.e. facing different backgrounds) and effectively show the accuracy of the network.

III. CONCLUSION

The performance of the machine learning algorithm classifiers is compared in this section and found that random forest and naïve bayes has best performance.

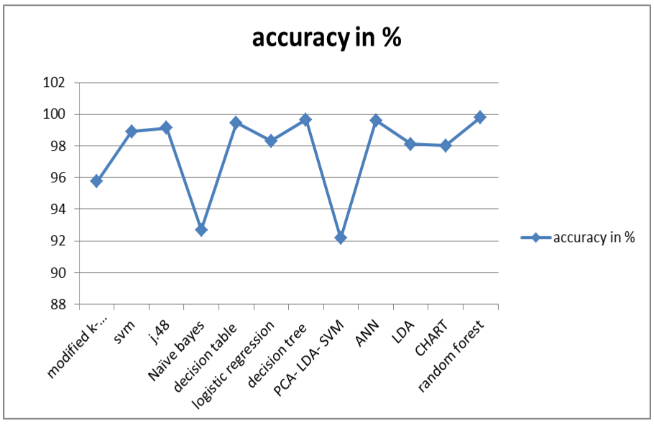

Figure 1.1: Performance Comparisons of various ML algorithms

S.No.	Researchers	Year	Method /Technology
1	Ya Min et.al	2020	Decision Tree, J48, JRIP, and Random Forest and Rule based algorithms Classifiers (Naive Bayes and AD1)
2	Hamza Ali Imran et.al.	2020	Machine Learning (ML) and Deep Neural Networks (DNN)
3	Syed K. Bashar et.al	2020	UCI HAR dataset, Dense Neural Network
4	Kyoung-Soub Lee et. al.	2019	Convolutional Neural Networks (CNN)
5	Soo Min Kwon et.al	2019	millimeter-wave (mm Wave) sensors, Dynamic Spectrum Access Networks

Table 1.1: Various ML algorithms

We illustrated that while keeping Smartphone in pocket, it is very easy to recognize activity of daily alive with the help of built-in sensors. We can further improve the accuracy by using suitable classifier and recognition rate can improve in most of the activities.

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