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A Comparative Analysis of Different Approaches for Recognizing Human Activity

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Abstract: This research paper is based on study of existing methods for identification and analyzing the human activities. Many scholars have done their work with respect to the understanding of human behavior. Literature survey and comparative examination of identification of human behavior provide a schematic review of the various methods available for choosing the correct approach under a given situation Data Mining can be employed for extracting knowledge for recognizing human activity effectively.

Keywords: Human Activity Analysis, Data Mining, Machine learning techniques, Comprehensive Review.

I. INTRODUCTION

Human Activity Recognition (HAR) [1, 2] is a protesting research territory with mass applications in homeland security, entertainment, sports, smart environment and healthcare. Human Activity [3] is the origin of universal sensing, an effective investigation field with the determination of mining knowledge from the collected data. In the real-life project, Literature survey [4, 5] provides a framework of related research and suitable approaches and the reported result of the research is higher than the existing recognition system. The achievement of the activity recognition system build upon the data quality, algorithms, extracted features, activity set.

HAR is a junction between the data recovery and applications of data mining. By the reason of the growth in the detectors industry, devices are appearing in less power consumption, limited in content, cost effective, more accurate and high computing power. There are many categories of activities in HAR like as running, walking, eating, watching TV, medications etc.

Human Activity Recognition may be classified into groups and that groups are based on the different type of activities. Labrador and Lara [4] classify Human Activity Recognition in several groups these groups are based on different kind of activities. These groups are as-

1) *Peripatetic activities:* climbing stairs, travelling, running, riding elevator.
2) *Fitness activities:* lifting weights, spinning, pushups.
3) *Transportation activities:* driving, riding a car, cycling.
4) *Daily living activities:* reading, watching TV, eating, drinking, etc.
5) *Military activities:* kneeling, crawling, etc.
6) *Phones handle activities:* texting, call making.
7) *Upper body activities:* speaking, chewing, talking, etc.

Our aim is different from existing studies as follows. First, we don't want to use sensory data as used in previous works and also obtain a comparable accuracy. Second, we use samples of falls and samples of activities of daily living (ADL). Wearable sensors are drifting with the benefit of the customers.

In [6], the study links a Radio Frequency Identification (RFID) to the human for reorganization of the activities of daily living or lives (ADL). T

here are many sensors that have been published on the HAR like as ([7],[4],[8]). In [7], the survey on the detection of activities including a wearable devices like camera. In [4] the survey including physiological motion and passion sensors like as body temperature devices. Whereas, in [8], this survey includes smart phones as online HAR.
The general procedure of Human Action surveillance-

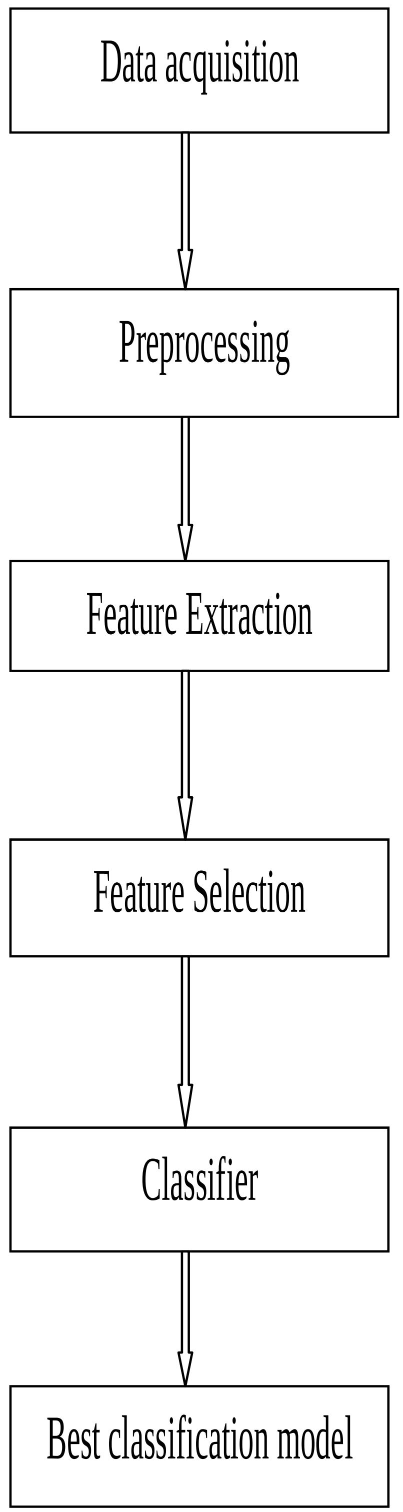

Figure 1. General Procedure for Human Activity Recognition (HAR)

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Human Activity Recognitions (HAR) is starting with data acquisition. Data is acquired for features extraction and selection of relevant data from the raw data is done in the feature selection phase. After that extracted features are used as an input data for each classifier that basically output the HAR model [21].

Framework for Human Activities Recognition (HAR) is given below in figure 2. In this framework, process done in three levels. In lower level, feature extraction, detection process is done and action or activities is recognizing in the middle level. After the recognition of action it is given in to the higher level [23].

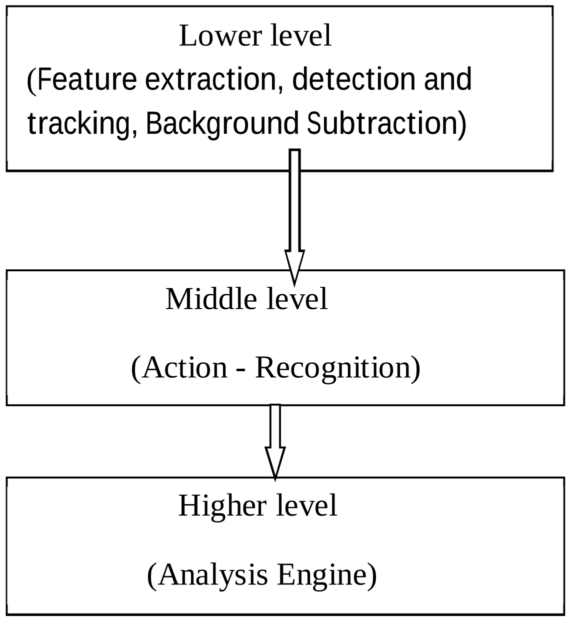

Figure 2. Framework for Human Activity Recognition (HAR)

II. BACKGROUND & METHODOLOGY

Most of the work on human activity reconnaissance targets for sensor and accelerometer operation. Lester et al.[2], suggested a realistic technique for physical activity recognition, in which the author comment on some questions about how to boost the accuracy in human activity classification and where the sensors have been placed to a person and which are the good methods for activity recognition. Author reach the consequence about questions is that it does not have problem where the human or person places the sensors and the good methods for recognition of human activity are accelerometers and microphones.

Casale et al. [9], proposed the knowledge of human behavior from accelerator data using tracking devices or sensors, in which the test on the features that is capable of classifying the operations. The Random-Forest (RF) classifier can be used to figure out the estimate of the new group of elements. Result shows that the new group of elements represents descriptive groups of features for recognition of activities with 94% of accuracy.

Mannini and Sabitini [10], proposed a classification method of wavelet-based activities using one or more accelerometers, in which the changing action components is separate out from the gravity components. The author classifies 7 basic acts or behaviors and conversion between the activities from the laboratory data and achieving 98.4% of accuracy.

A. Bayat et al. [11] study on human activity analysis using accelerometer data from devices like Smartphone, in which classifiers themselves and the combination of classifiers are used to increase accuracy of human activity recognition. Author select 18 relevant features like Mean, Min-Max, Average-Peak-Frequency (APF), Root-Mean-Square (RMS), Standard-Deviation (STD) according to dimensions (x-axis, y-axis, z-axis) and group of features was taken for evaluating recognition performance. The result shows 91.15% accuracy.

Jayabalan et al.[12] proposed a convolution-neural-network (CNN) model for provisionally standardized cooperative region data for dynamic motion recognitions, in which CNN model can anticipate the human activities using the cooperative data and utilize the advantages of lower aspects of the cooperative data features by the representation of videos or image. So the CN-Network architecture is quicker and simpler than the RN-Network. A 6 layer CNN were organized, which cut downs the particular input features vector and gives the predicted activities and with low practice data, the efficiency of the CNN model can be reached

Parka et al.[13] suggested scope of camera-based human activity recognition along with deep learning Recurrent Neural Networks (RNN) for social care and health assistance, in which human silhouette is taken as input and implemented a human activity recognition system by the use of Recurrent Neural Network (RNN) experienced using spatio-sensual features matrix. 28 elements of cooperative intersection that corresponds to 14 keys human body parts excerpted from silhouette of humans.

Li et al.[14] proposed a convolutional neural network (CNN) for home activity recognition of human using Ubisense Systems, in which motion feature and frequency features are taken as input that pre-process the basic dimensional position statistics and translate them into specified features or elements input into Convolutional Neural Network to perform analysis of local features. Output components are measured by classifier name SOFTMAX to recognize six activities like as walking, sitting and lying, standing, jumping and jogging. The Convolutional neural network-based approach outruns the BP Neural Network.

Bagautdinov et al. [22] offers an overview of the social scene End-to - end multi-person action position and group behavior identification, in which suggested model associate different individuals, deduce their social motions and measures the collective motions that are passes over the neural networks. The architecture is experienced point-to-point to produced opaque recommended maps. The temporal flexibility is directed by a human like Recurrent-Neural-Network (RNN). It does not desire any external tracks for multi-person scene detection and understand.

III. COMPARATIVE STUDIES

In this study, comparison of techniques and accuracy and also the comparison of various methodologies used for Human Activity Recognition are shown below:

Table1. Comparison table of techniques and Accuracy

S. No	Year	Author	Technique	Accuracy
1.	2014	A. Bayat, Marc Pomplun	Random Forest, Support Vector Machine, Multilayer perceptron	91.15%
2.	2016	C. Ranao and S. Cho	Deep convolutional neural network	94.79%
3.	2011	Pierluigi Casale et al	Random Forest	94%
4.	2018	Efhan bulbul et al	Stacking Classifier (KNN)	98.6%

Table2. Comparison of various methodologies of activity recognition

Methodology	Advantages	Future scope
Physical model- based [15]	Progressive features are figure out and by use of these features movement ranks are categories in terms twist.	Apply progressive features to human–motion recognition.
Kinematics model-based[16]	Proposed the adaptive (compatible) perception- based human motion recognition method.	Adaptive (compatible) learning shall be correlated to another yardstick cumulative training and regular transformation methods.
Sub space clustering approach[17]	It can stem multi-dimensional knowledge that cannot be feasible with the clustering technique.	Objective is to combine the large provisional details like as health or strength conditions, emotions.
SVM (multiple Instances)[18]	It improves activity recognition that are based on regional features by using progressive machine learning methods which are distinct from over tire features occupying representation.	Incorporation-temporal information and different descriptors.
K-model based (kinematics)[19]	It takes only the outstanding poses of humans that swiftness the knowledge or information and removes the remains.	Handles the similar action recognition.
Kinematics model-based[24]	It builds upon contour (curve) points for learning fundamentals.	This technique display great resistance to inter character deviation conducting of blockage and view-invariant.

Table3. Successes Rates of tested Models

Models	Success rates (%)
Binary Decision Tree (BDT)	53.1
Support Vector Machine (SVM)	99.4
k-Nearest Neighbor (k=3)	97.5
k-Nearest Neighbor (k=1)	97.1
Bagging	98.1
Stacking	98.6
Decision Tree (20)	91.7

Successes rates of models that are tested are given in the table 3 [22].

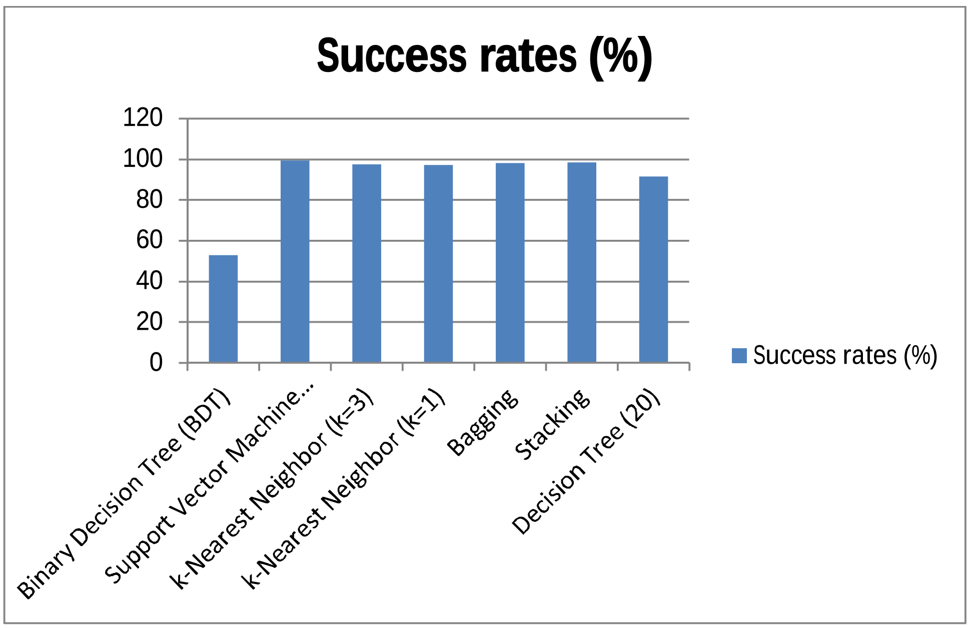

Figure 3**.** Graph compares the success rates of tested models.

This graph represents the comparison of different data mining technologies (Binary search tree (BT), support vector machine (SVM), decision tree and K-Nearest neighbor (KNN)) on the basis of different accuracies.

IV. CONCLUSION

This survey paper has been completed on 24 research papers published by using different data mining methods. Human activity data were tested and recognize by using data mining techniques like K-nearest neighbor, support vector machine (SVM) and artificial neural network. Best classification rate according to our survey is 99.4% which is achieved by support vector machine (SVM) and SVM is more accurate approach as compare to the other approaches. In this study, the comparison of different technologies and accuracy and also the comparison of different methods and their advantages which are helpful for recognition of daily live activities is done.

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