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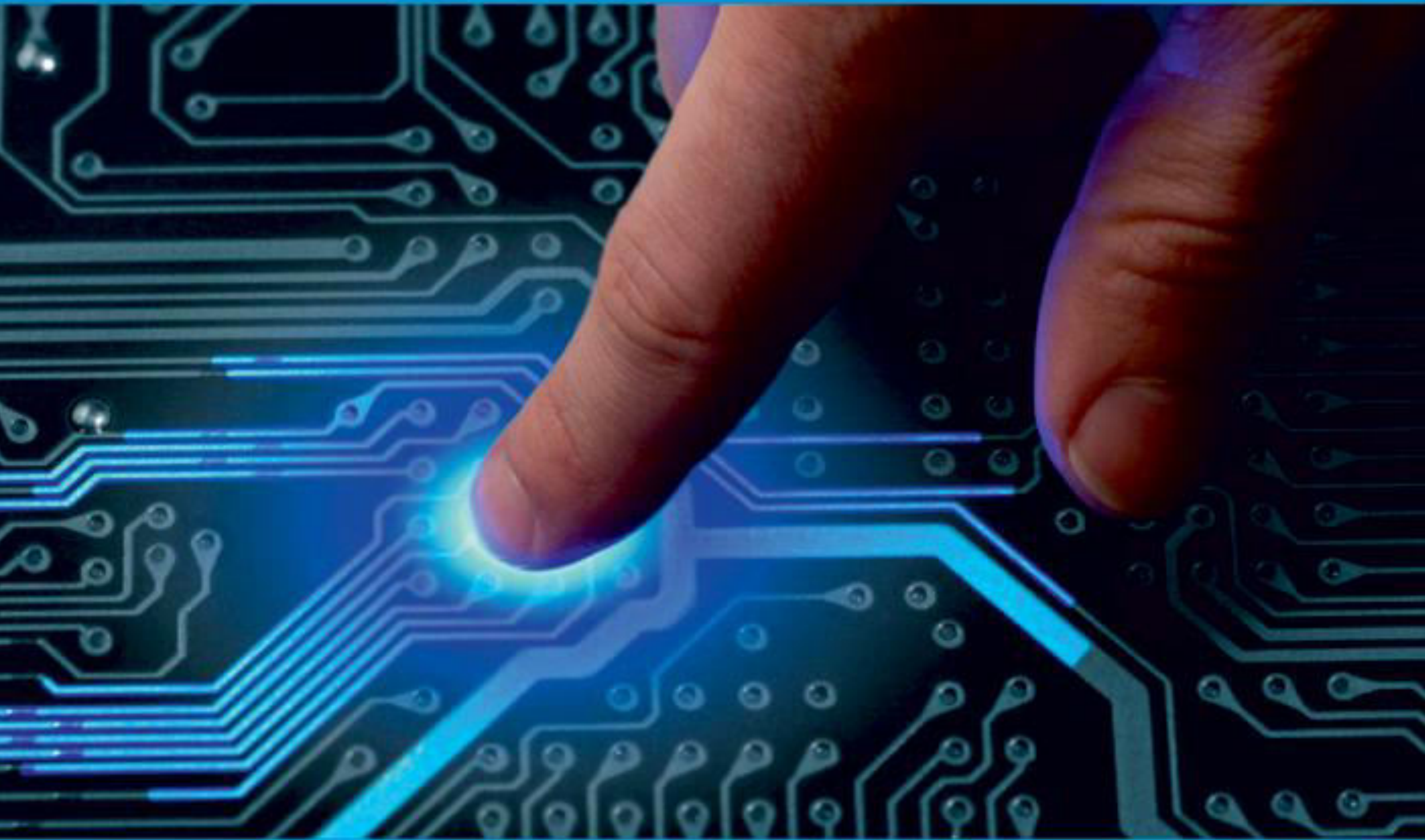

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Ensemble Classification for Human Activity Recognition with Feature Reduction

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ABSTRACT: The process to recognize the human action is effective approach in detecting, interpreting and recognizing the human actions and patterns. The complex task is to extract the information related to human activity. The main issue occurred before the systematic fields of computer vision and ML is the potential for recognizing the activities of another person. The human activity recognition technique is executed in diverse stages such as to pre-process the data, extract the features and classify the data. This work proposes a hybrid model in the human activity recognition which is the combination of K-mean clustering, PCA and of multiple classifiers which are merged through voting methodology. Python is executed to evaluate the presented framework and various metrics such as accuracy, precision and recall are considered to analyze the results.

KEYWORDS: HAR, K-means, PCA, Voting Classifier, Random Forest, ConvNet.

I. INTRODUCTION

The approach to recognize the human activity has garnered intensive research over the last few years and remains an active research hotspot. The actions are recognized and the activity patterns are investigated to understand the human activity. The initial aim is that the human activities are recognized at higher accuracy according to pre-determined activity systems. Consequently, the main goal of researcher of detecting action is to build an effective system, and then to construct an adaptable comprehensive system by applying the model. Activity pattern discovery, at the other side, involves the direct discovery of concealed patterns from sensor data of lower quality without any pre-determined systems or conventions. In this way, a researcher initially aims at building a complete architecture and a complete system and then discovering the activity patterns after analyzing the sensitive data. Despite the variances, both systems attempt on enhancing the efficacy of human action recognition [1].Typically, there are two main categories of HAR systems: camera-supported systems and wearable sensor supported systems. The camera supported system use 2D or 3D cameras as the main data acquisition device. Unlike camera-based human activity recognition systems, techniques based on wearable sensor focus on body-worn sensors which are able to provide sensitive data in virtual manner anywhere and anytime. Camera-supported systems may lack full coverage and may cause problems with recorded video. Later, unlike the immense video data, body-worn sensors are capable of creating the lightweight signals, and detecting the online HA and recognizing the mass. At last, sensor data is ineffective of exposing the identity of the user and are least susceptible to privacy issues.

In view of the above benefits, Human Activity Recognition based on sensor has drawn a lot of popularity and has become an emergent research domain with various crucial applications. For example, wearable sensors in healthcare sector are utilized for monitoring the regular human actions and can fruitfully trace irregular activities during events. The emergence and growing popularity of mobile technology has prompted smart wristbands and smart phones as a suitable mechanism to main record of people's day-to-day and fitness activities aims to compute the step and to monitor the heart rate. HAR is all about the detection, interpreting and recognizing human behavior, kinds of activities and patterns, either regular or irregular. Its potential applications in many fields such as smart home, medical, nursing and sports can help make people daily lives smarter, securer and more comfortable [2]. The general architecture to recognize the human activity has diverse phases in which, data acquisition is done, data is pre-processed, segmented, features are extracted and classification is done, as depicted in figure 1.

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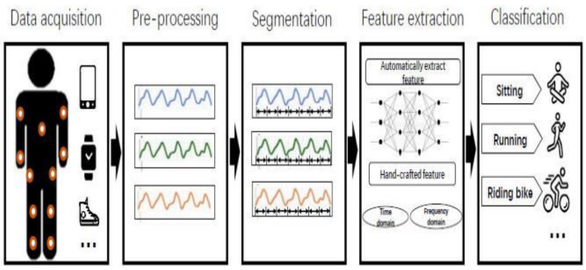

Figure 1: The processing flow of the human activity recognition system

Diverse phases to recognize the human actions are explained as:
a. Data Acquisition: This phase aims at collecting and storing the raw sub-II level smart phone measurements. The data that sensor network collect about the activities of human beings is in continuous stream, which includes many activities. Activities are of two kinds according to their duration: BA and TA. The first group includes activities of longer period and activities can be dynamic or stationary. The second group is represented by the activities of small duration, for example postural changes.

b. Pre-processing: This phase is executed to segment and split the image. Prior to execute the procedure to extract the attributes and the next procedure, the continuous data stream must be broken down into minor chunks. In essence, data is broken down into various action portions which are not relied on each other. Every portion has attributes which are useful to identify dissimilar actions. Sliding-window based methods are common technique for splitting the stream of activity data.

c. Feature Extraction: Small inertial sensors provide acceleration and gyroscopic data that are assisted in recognizing diverse activities. Generally, the partition of time series signals is done into windows with or without overlapping. Then, the process of extracting attributes is applied to the windowed data so that a feature vector is created to identify the action [3]. The sensor signals often support some statistical behavior. To keep periodic signals in human actions, DFT and DCT algorithm is utilized to transform the unprocessed sensor signals into the frequency domain, and various statistical features can be taken out, for example peak of Discrete Fourier Transform coefficients, signal power, etc. in different frequency bands.

d. Classification: The term activity classification focuses on making a link amid extracted attributes and a particular action type according to the classifier employed. The Human Activity Recognition methods, adopt basis algorithm to predict the data. It is used as a direct solution to measure the similarity between two streams of different lengths or speeds. Various existing classifiers in models of recognizing the human activity need some enhancements.

II. LITERATURE SURVEY

Hairui Jia etal. (2020) [7] designed a set-up based on categorial hierarchical composition and practice for recognizing individuals' activities. The new solution was the combination of a data-driven scheme and a knowledge-specific scheme. This approach delivered an appealing structure with the potential of connecting the identification of lower-level patterns and greater level of knowledge for perceptive and clarification.In particular, this solution built a categorical composition to represent the overall action by structuring actions and gestures of lower levels as per their semantic sense. The data related to video based on recognizing the human action is employed for quantifying the designed work. The designed set up was then converted into proper syntactically logical formulations and instructions according to the convolution oriented automatic reasoning to identify aggregate actions during the identified lower-level actions through ML techniques determined by data
Md Maruf Hossain Shuvo etal. (2020) [8] put forward the proposal of a flexible framework to identify individuals' actions. This work used a waist worn accelerometer and gyroscope sensing devices that identified and recorded human actions through a dual stage learning methodology. The primary stage involved the use of Random Forest (RF) binary classification framework to categorize the activities into fixed and stationary. The next stage identified the static and dynamic activities of human beings using SVM and one dimensional ConvNet respectively. This strategy increased the robustness of the designed framework and made it friendly.The new methodology displayed same robustness for various activity intensities and could successfully record changes in the similar motion. The ConvNet in the hybrid framework not only realized the local dependence of the motion indicators but also maintained the scale

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invariability.This work used six activity categories of the broadly acknowledged standard UCI-HAR dataset and yielded total accuracy of 97.71%.

MohanadBabiker etal. (2017) [9]constructed a smart framework for recognizing activities of different people. The new framework was implemented with a range of digital image processing techniques in its every step in the form of background retrieval, bifurcation, and morphological operations. Based on individuals' actions a powerful neural network was constructed through a database containing features. These features were derived from the series of frames. This work classified the actions modelled in the data suite using a MLFFP (multi-layer feed forward perceptron) network. The outcomes of classifier displayed outstanding performance at every step of training, testing and authentication. In conclusion, these outcomes yielded a satisfactory demonstration in action identification process.

Syed K. Bashar etal. (2020) [10] put up the proposal of a neural network framework for classifying people activities using activity-based hand-generated attributes. This work initially used a neighborhood component analysis determined feature selection to select a sub-suite of the significant attributes from the given time and frequency domain indices.Second, this work modelled a dense neural network made up of four hidden layers is modeled for classifying the input attributes into several classes. This work used an open-source UCI HAR data set consisting of six day-to-day actions for the framework evaluation. The accuracy of classification yielded by new methodology was counted 95.79%.in contrast to existent classic methodologies, the introduced framework outclassed the maximum methodologies with lesser number of attributes, and demonstrated the significance of appropriately selected features.
Yu-Liang Hsu etal. (2017) [11] constructed a body worn human action classifier architecture driven by inertial sensing along with a related action classification algorithmic scheme to accurately identify the day-to-day activities of people. The fabricated framework adopted two inertial sensor units which were attached to wrists and ankles of patients to gather activity signals of individuals actions. This work reduced the features' dimensionality and improved the classification level at the same time through the nonparametric weighted feature extraction (NWFE) algorithmic scheme. The body worn activity classifier framework and its action classification scheme showed their potential by identifying ten regular motions with 90.5% of classification accuracy in the test results.

Zhaosheng Shao etal. (2021) [12] developed a UCI dataset-based classifier framework called LightBGM to fix the issue of less accuracy of frequently adopted human activity identification methods. The new approach integrated the client and the nearby scenario with the machine, and interpreted the activities of individuals using smartphones. There was no need of superior sensors in this framework to gather activity information in various body positions. It merely made use of smart phones along inertial sensing devices to gather activity info, and performed classification and identification through testing on UCI data suites.The newly developed algorithmic scheme depicted a greater accuracy rate than its counterparts and was capable to recognize a wide range of activities in more accurate manner.

Sonia Perez-Gamboa etal. (2021) [13] devised a hybrid configuration consisting of multiple layers using ConvNets and LSTM (Long Short-Term Memory). This work constructed a frivolous and hybrid model containing multiple layers in order to enhance the identification performance through the integration of local attributes and scale-invariability with dependent actions by exploring various amalgamations consisting of multiple layers. The outcomes of tests depicted the effectiveness of the fabricated architecture which was able to yield 94.7% activity recognition rate over the standard dataset. This architecture outclassed its counterparts. Apart from this, the enforced architecture balanced the accuracy and effectiveness.

Congcong Liu etal. (2018) [14] initiated a methodology to identify irregular individuals' activities using monitored video footage. The methodology identified four motions, using Bayes classifiers and ConvNets. KTH dataset was fed into the Bayes Classifier and ConvNet as input. This work adopted Kalman Filter to identify mobile subjects in every frame and took out three features of the photo targeted. A number of features were taken out. In the meantime, ConvNet of irregular subject action identification was formed and trained. Experimentation revealed that the ConvNet architecture respectively obtained 92%, 96%, 100% and 100% accuracy per action while 88%, 92%, 92% and 100% was the identification rate yielded by Bayes classification framework respectively.

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IV. RESEARCH METHODOLOGY

Distinct stages of research methodology are discussed as: -

1.Data Set input and Pre-processing: - The dataset generated via Kaggle is utilized for input. Thirteen features are included to detect the human body organ so that image is pre-processed.

2.Feature Reduction and Clustering: - This stage is executed to employ the entire data as input and process this data further for mitigating the attributes of the dataset. PCA algorithm is considered to alleviate the dimensionality. Being a mathematical technique, Principal Component Analysis is utilized to convert a group of regularly interrelated features into a group of LD subsets in accordance with a conversion that lead to the dissimilar variables. In general, this algorithm is an orthogonal linear conversion to project the primary data set into another projection model. The major emphasize is on generating the biggest variance that predicts the 1st coordinate while the 2nd largest variance defines the forecasting of 2nd coordinate based on notion that it is perpendicular to the 1st component. Primarily, PCA is useful for discovering a linear conversion represented with $z = W_k^T x$, and $x \in R^d$, and $r < d$, for improving the data variance in the estimated space. A set of p-dimensional vectors of weights $W = \{w_1, w_2, \dots\dots\dots, w_p\}$, $w_p \in R^k$, whose matching is done with each x_i vector of X to a, is effective in representing the conversion when the data matrix is $X = \{x_1, x_2, \dots\dots\dots, x_i\}$, $x_i \in R^d$, $z \in R^r$ and $r < d$,

$$t_{k(i)} = W_{|(i)} T_{x_i}$$

The variance is maximized when the initial load W1 is utilized for satisfying the condition of the below expression as:

$$W_i = \arg max_{|w|} = \{\sum_i (x_i \cdot W)^2\}$$

The expansion of prior condition is further done as:

$$W_i = \arg max_{\|w\|=1} \{\|X.W\|^2\}$$
$$= \arg max_{\|w\|=1} \{W^T X^T X W\}$$

W is considered as a correlated Eigen vector; therefore, symmetric grid is inspected successful. For this, $X^T X$ subsequent to attaining the biggest eigenvalue of the matrix. When the W_1 is achieved, the projection of primary data matrix X is done onto the W_1 in the area extracted after the transformation for presenting the initial principal component. The deduction of novel components helps these lines to acquire more segments. The data is segmented into some segments using KMC algorithm. It is an extensive algorithm to cluster the data. Suppose there are N pixels in a picture and they are split into K sets at which the major task for user is that the value of K is transmitted. A group of pixels is contained in the clusters with regard to their values in the picture, without considering their place as it is a quantified trait.

If $X = x_1, \dots\dots x_N\}$ is used to denote a group of N pixels of image, and assume $V(x_i)$ as a feature vector concerning pixel x_i. KMC algorithm is executed in diverse phases:

i. Initializing parameters: The means of all K groups are initialized to the values of the possible property vectors. The standard KMC is responsible to randomly select the value of every component belonging to the property vector from the suite of feasible values for that object. For instance, the HSV form of property vector leads to select the initial component H randomly from all possible hues.
ii. Hard Assignment of Pixels to Clusters: The involvement of a mean μ_k in each cluster among K clusters results in assigning every pixel x_i to the cluster having the closest mean via a distance function. This function is useful to compute the distance amid two property vectors. In this, every pixel x_i is associated with a single cluster C_k.
iii. Re-computing parameters: This metric is effective for re-computing the clusters with regard to the property vector values of overall pixels in each cluster. Thus, the computation of μ_k is done as the mean of $\{V(x_i) | x_i \in C_k\}$.

The iteration of Steps 2 and 3 is going on until the convergence is attained. This is happened in case of termination of moving of all pixels to other clusters in a certain iteration.

3.Classification: - The voting classifier is adopted for classifying data into some classes. In the voting classifier, different algorithms namely LR, RF and Support Vector Machine are integrated. Logistic Regression, involves extracting weighted features from the input, and obtaining logs which are further combined linearly. This means the multiplication of every attribute with a weight and addition later on. The Naïve Bayes and Logistic Regression are different in the manner that Logistic Regression and NB, respectively represent the class of discriminative and generative classification algorithms. This is a regression type which has potential for estimating the possibility of occurrence of an episode where the data shows robustness towards a logistic function. Like various forms of RA, LR makes use of a range of predictive variables that are present in numeric or categorical manner. The SF providing values in the range [0,1] has specific qualities. LR uses the following formula to calculate cost function:

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$$J(\theta)=\frac{1}{m}\sum_{i=1}^{m}[-y^{(i)}\log\left(h_{\theta}(x^{(i)})\right) - \left(1-y^{(i)}\right)\log\left(1-h_{\theta}(x^{(i)})\right)]$$

The minima of this cost function is discovered in Machine Learning. For this, a built-in function called $fmin\_bfgs^2$ is exploited which implies that the most optimal metric $\theta$is discovered to attain the CF of Logistic Regression, so that a fixed dataset having x and y as values in a dataset. Metrics indicate the initial values of the metrics which have to be optimized. The CF of this algorithm is evaluated using a special θ. The gradient is evaluated as θ for datasets which take x and y as values. The ultimate θ value is employed for plotting the decision boundary of data utilized to train the system. The Support Vector Machine algorithm is effective for recognizing the arithmetic design with uses in various issues regarding engineering. This algorithm makes the deployment of a hyperplane for separating 2 classes. The normal vector and bias term is employed to represent this hyperplane. The augmentation of distance from the hyperplane to the closest objects of two kinds is done on the basis of the optimum separating hyperplane. Kernel functions are considered with SVM algorithm to obtain the non-linear decision boundaries. This indicates that a kernel function k is the major reason of the nonlinearity while performing the classification. The process to compute this algorithm is discussed and this algorithm is useful to generate decision functions having more accuracy. The formulation is expressed as:

$$w.\Phi(x)+b=0,$$

It is utilized to acquire the corresponding decision function as:

$$f(x)=y^{*}=sgn(\langle w.\Phi(x)\rangle+b)$$

In this equation,$y^{*}=+1$ if x comes under from the matching class or else $y^{*}=-1$.

The kernel techniques are implemented after presenting the additional simplification which assists in replacing the hard margins using soft margins. For this, alleged slack-variables ζ_i are deployed with the objective of ensuring the inseparability, relaxing the constraints and handling the noisy data. Furthermore, though the standard Support Vector Machine paradigm was suggested to deal with the issues related to accomplish the binary classification, yet its re-construction is done to tackle the multiclass problems. The RF is an EL method which is helpful in classification and regression tasks. The Decision Tree algorithm is considered to develop this algorithm according to the supervised rule to make decisions and to generate their possible outcomes as a tree, a graph or a flowchart. The images are classified using the training data. Moreover, a set of rules is derived from the Decision Tree algorithm in order to differentiate the data. In addition, this algorithm helps in generating a tree relied on discriminative attributes. These features are chosen for every level of a tree. Afterward, these rules are adopted to predict the unseen information. Various DTs are composed to construct a RF algorithm which has 2 phases. The major intend of initial stage is to develop a RF and this procedure is utilized to select $k$attributes from n number of components at random for its initialization. Subsequent stage aims to formulate a current tree. This stage is executed to select the finest attribute as a root mote and take the rest of the $k-1$ attributes as the child motes. In this, tree ends at leaf nodes using which the target classes are illustrated. This procedure is going on to produce m random trees. In the end, the development of RF is done. This procedure is known as majority voting technique for predicting the classes in such algorithm. Random Forest is an extensive algorithm of predictive aggregation methods in EL.

V. RESULT AND DISCUSSION

To recognize the movements of people, the database has been created using recorded data from 30 subjects under analysis while performing day-to-day activities wearing a smartphone at the waist and connected to inertial sensing devices. Its purpose is to classify tasks into one of six done tasks. The experiment is conducted on a group of 30 volunteers between the ages of 19-48. Every volunteer conducted six actions (WALKING, WALKINGUPSTAIRS, WALKINGDOWNSTAIRS, SITTING, STANDING, LAYING) by mounting a smartphone (Samsung Galaxy S II) on the waist. This work used three performance measures called accuracy, recall and precision to evaluate the developed architecture.

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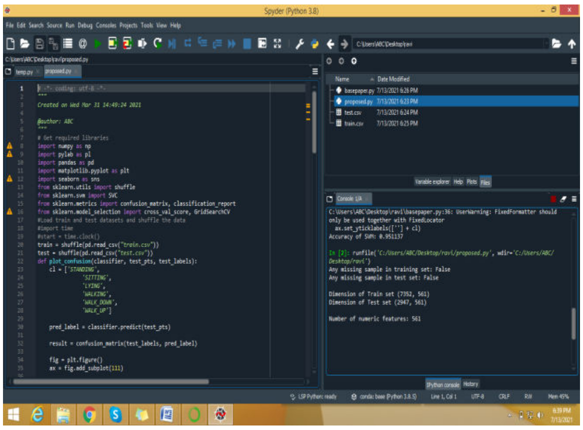

Figure 2. Execution of proposed model

Figure 2 displays the task of recognizing human activities. The input used is the dataset which is further processed for the classification. The designed architecture consists of several classification frameworks namely LR, RF and GNB. A voting methodology is developed through the integration of above-mentioned classifiers.

Table 1: Performance Analysis

Parameter	Logistic Regression	Hybrid Classifier
Accuracy	87.56 percent	93.45 percent
Precision	86.78 percent	92.89 percent
Recall	87.20 percent	91.23 percent

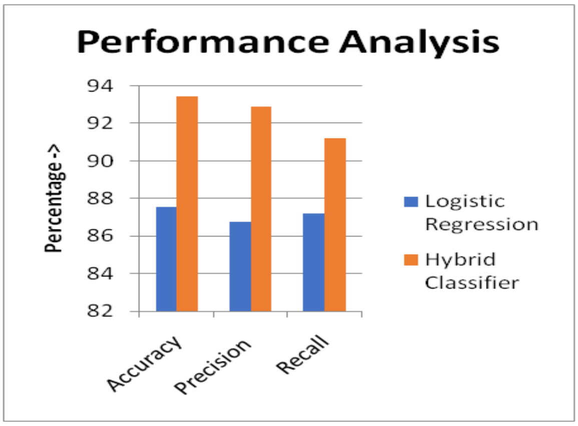

Figure 3: Performance Analysis

Figure 3 depicts the analysis of the performance of developed hybrid framework in the context of accuracy, precision and recall. The newly designed framework is compared with the existent LR based for identifying the activities of people. The improvement of 4 to 5% is noticed in the results obtained with the use of new methodology.

VI. CONCLUSION

The conclusion drawn from this work is that human activity recognition (HAR) involves identifying, understanding and distinguishing individuals' behavior, types and patterns of movements, whether normal or abnormal. The techniques introduced in this work depends on PCA, K-means and voting classifier. The purpose of PCA algorithm is to reduce the dimensionality of features. The K-means algorithm aims at clustering features of same nature. Voting classifier is the amalgamation of several classifiers namely, naïve bayes, Logistic Regression, Random Forest. This work implements

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new framework in python software and obtains approximately 5% of hike in results in the context of universal performance measures

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