DESIGN AND IMPLEMENTATION OF IMPROVED ENSEMBLE CLASSIFICATION ALGORITHM FOR HUMAN ACTIVITY RECOGNITION (HAR)

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Abstract
To recognize the human activity is considered very essential in human-to-human interaction and interpersonal relations due to its nature of providing information regarding the identity of a people, their personality and psychological state. The extraction of this information is very challenging. The main operation occurred before the systematic fields of computer vision as well as ML is the potential for recognizing the activities of different person. The human activity recognition technique is executed in various stages such as to pre-process the data, extract the features and classifying the data. This work proposes a improved ensemble 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 get evaluated the presented framework and various metrics such as accuracy, precision and recall are considered to analyse the results. The major subject of study of the scientific and research areas of computer vision and ML is the potential of human for identifying the activities of particular person. A sequence of human body movements in which different body parts (head, hands, legs etc.) are engaged in concurrent manner is known as action.

Figure 1: HAR Problem and Performed Activities.

Keywords : HAR, Clustering, PCA, Voting Algorithm, Precision, ConvNet, RGB+D, HOG.

1.Introduction

The verge to recognize the human activity has garnered intensive research for the few years and remains an active research segment. The aim is that the human activities are recognized at maximum accuracy according to pre-determined activity systems. The goal of researcher of detecting action is to build an effective system. 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 aims at building a complete system and then discovering the activity patterns after analyzing the data. Despite the differences, all the systems attempt on enhancing the efficacy of human action recognition [1]. There are two main categories of HAR systems: camera-supported systems and wearable sensor supported systems. The camera supported system need 2D or 3D cameras as the main data acquisition device. The techniques based on wearable sensor focus on body-focused sensors which are able to provide sensitive data virtually- anywhere and anytime. Camera-supported systems may lack full coverage. Later, unlike the immense video data, body-worn sensors are capable of creating the lightweight signals, and detecting the online HA and recognizing the situation. The growing popularity of mobile technology has prompted smart wrist-bands and smart phones as a suitable mechanism to main record of peoples' day-to-day and fitness activities aims to compute the step and to monitor the heart rate. HAR mean the detection, interpreting and recognizing human behaviour, 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, the data acquisition is done, data is pre-processed, segmented, features are extracted and classification is done, as depicted in figure 2.

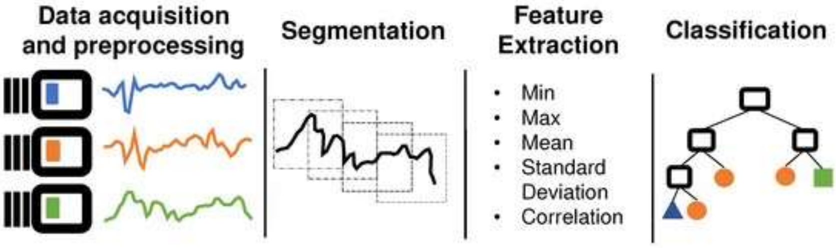

Figure 2: The processing flow of the human activity recognition system

Diverse phases to recognize the human actions are explained as:-

a. Data Acquisition and Pre-processing: 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. Pre-processing phase is executed to segment and split the image. Firstly, execute the procedure to extract the attributes and the next procedure, the continuous data stream must be broken into minor chunks. Data is broken down into various action portions which are not relied on each other. Every part has attributes that are useful to identify various actions.

b. Feature Extraction: Small inertial sensors provide acceleration and gyroscopic data that are assisted in recognizing activities. 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 sometimes support some statistical behaviour [4]. There is a need to select the exact value from those statistical behaviour. 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 such as peak of Discrete Fourier Transform coefficients, signal power, etc. in different frequency bands [5]. Discrete Fourier Transform (DFT), a popular approach of signal processing domain, aims at transforming a discrete signal from the time domain to the frequency domain. The DFT of the sequence for an N-bit finite number sequence can be expressed in the form of following equation:

$$x(n) = \frac{1}{N}\sum_{n=0}^{N-1} X(k)e^{j\frac{2\pi}{N}nk} \quad , n = 0,1,2 \ldots . N-1 \ldots .(1)$$

The inverse Fourier transform of DFT is:

$$x(n) = \frac{1}{N}\sum_{n=0}^{N-1} X(k)e^{-j\frac{2\pi}{N}nk} \quad , n = 0,1,2 \ldots . N-1 \ldots ..(2)$$

c. Classification: Classification focuses on creating 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 sections of different lengths or speeds. Various existing classifiers in models of recognizing the human activity may need some enhancements [6].

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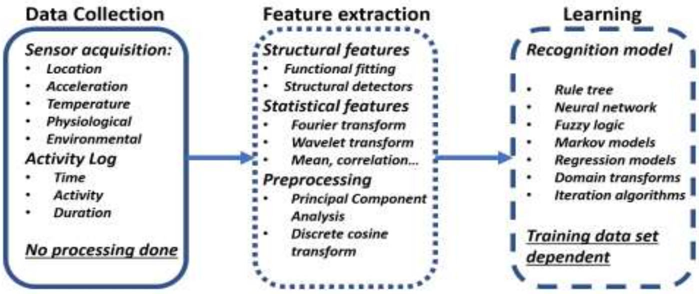

Figure 3: Learning Process of HAR System.

2. Literature Survey

Hairui Jia et al. (2020) [7] created a set-up based on hierarchical composition and practice for recognizing individuals' activities. The solution was the combination of a data-driven scheme and a knowledge-specific scheme. This resemble 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 the aggregate actions during the identified lower level actions through ML techniques.

Md Maruf Hossain Shuvo et al. (2020) [8] put the proposal of a flexible framework to differentiate 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. 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 of invariability. This work used six activity categories of the broadly acknowledged standard UCI-HAR dataset and yielded a total accuracy of 97.71%.

Mohanad Babiker et al. (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 et al. (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 neighbourhood 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 modelled for classifying the input attributes into several classes. This work used an open-source UCI HAR data set consisting of six day-today 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

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maximum methodologies with lesser number of attributes, and demonstrated the significance of appropriately selected features.

Yu-Liang Hsu et al. (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.

B Jagadeesh et al. [12] (2016) described that human actions were detected and recognized based on video on the KTH dataset and on videos of real-time. Initially, the extraction of 100 frames was completed from every video sequence and the optical flow was evaluated among the frames. The extracted was transformed into binary image. Subsequently, the feature vector was extracted from the binary images through the HOG descriptor.

Thien Huynh-The et al. [13] (2020) recommended a new hierarchical deep feature fusion model to recognize the human action based on three-dimensional skeleton. The CNNs were executed to provide the deep information that was employed to model the human appearance and action dynamic. A multi-stream Convolutional Neural Network algorithm assisted in extracting the deep attributes so that the concealed correlations were exposed in the spatial and temporal dimensions. The NTU RGB+D dataset was deployed for carrying out the experiment.
Zhaosheng Shao et al. (2021) [14] developed a UCI dataset-based classifier framework called Light BGM 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.
Chengwu Liang et al. (2020) [15] intended a segmental architecture so that the relation of sub-actions was associated with heterogeneous information fusion and CPPCR for multi-modal HAR. The suggested architecture was planned on the basis of normalized action motion energy. The long-range temporal structure was modelled over video sequences in the differentiation of the similar actions allowing sub-action sharing phenomenon. After that, the extraction and fusion of depth motion based on sub-action and attributes of skeleton had carried out. Additionally, the presented Class-privacy Preserved Collaborative Representation was proved useful in dealing with sub-action sharing phenomenon. The experimental outcomes obtained on 4 data sets validated that the intended technique.
Sonia Perez-Gamboa et al. (2021) [16] 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 in variability 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 et al. (2018) [17] 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

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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.

3. Research Methodology

The stages of research methodology are discussed as: -

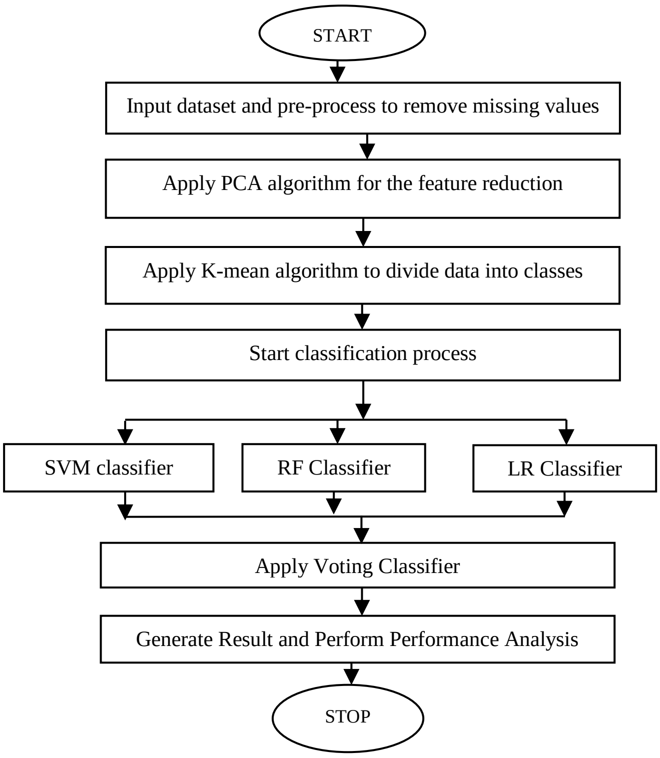

Figure 4: The working Flow-Chart.

1. Data Set Input and Pre-processing: - The data set generated is utilized for input. Thirteen features are included to detect the human body organ so that image is pre-processed. The dataset is collected from the different sources like Google dataset search, UCI Machine Learning Repository, Quandl etc. for the human activity detection. The missing values from the dataset are eliminated by performing pre-processing on it.

2. Feature Reduction and Clustering: - This part is generated to deploy the entire data as input and process this data for mitigating different attributes of the dataset. PCA algorithm is deliberate to alleviate the dimensionality. This algorithm is an orthogonal linear conversion to project the primary dataset into other projection models. The respectable emphasize is on generating the biggest variance that predicts the 1st co-ordinate while the 2nd largest variance sketches the forecasting of 2nd coordinate based on the notion that it is mostly perpendicular to the 1st component. Primarily, PCA is essential for discovering a linear conversion with $z = W_k^T x$, and $x \in R^d$, and $r < d$, for enhancing the data variance in the estimated space. The set of p-dimensional vectors of weights $W = \{w_1, w_2, \ldots \ldots .., w_p\}$, $w_p \in R^k$, whose matching is done by each x_i vector of X to a, is effective in representing the conversion when the data matrix is $X = \{x_1, x_2, \ldots \ldots .., x_i\}$, $x_i \in R^d$, $z \in R^r$ and then $r < d$,

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

The variance is maximized when there initial load with W1 is utilized for satisfying the general condition of the below expression as follows:-

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

The expansion of the prior condition of this system is done as follows:-

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

W is studied as a correlated Eigen vector, therefore, symmetric grid is inspected as successful. For this, $X^T X$ subsequent to attaining as the biggest Eigen value of the matrix. When $W_1$is achieved, the projection of the primary data matrix X is done onto the W_1 in the area extracted after the transformation for presenting initial principal component.

3. Classification:- Voting classifier is adopted for classifying the data into some various classes. In the voting classifier, different algorithms namely LR, RF and Support Vector Machine are integrated. Like various forms of RA, LR makes use of a range of predictive variables that are present in numeric or categorical manner. The SF is providing values in the range [0,1] has specific qualities. LR uses the following shown formula to calculate cost function as:-

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

The minima of this cost function is invented in Machine Learning (ML). A built-in function is called $fmin\_bfgs^2$ is exploited which indicates hugely the most optimal metric θ is discovered to attain the CF of Logistic Regression. A fixed dataset having x and y as values in a dataset. Metrics indicates the starting 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. Here the θ value is employed for plotting the decision boundary of data utilized to train the system. Here the Support Vector Machine (SVM) algorithm is essential for recognizing the arithmetic design with its uses in various issues regarding engineering. This algorithm makes the deployment of a hyperplane for separating 2 classes. 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 follows:-

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

Here is the utilization to acquire the corresponding decision function as follows:-

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

In this above equation, got that $y^* = +1$ if x comes under the significant matching class or else $y^* = -1$.

The kernel techniques are implemented after the presentation of the additional simplification which assists in replacing the hard margins using soft margins accordingly. For this purpose alleged slack-variables ζ_i are deployed with the reserved objectives of ensuring the inseparability, relaxing the constraints and maintaining the noisy data.

4. Performance Analysis: - In this phase the various parameters like accuracy, precision, recall, F-Measure as well as execution time is calculated for the performance analysis. The performance of proposed model which is hybrid model is tested with regard to accuracy. The comparison of performance is done with existing model that is based on logistic regression for the human activity recognition. The moto of this research is recognition of the human activity. The two models are implemented which logistic regression-based model and second one is hybrid model. The hybrid model is the is developed by combining PCA, K-mean and voting classifier. The precision and recall etc. are considered to compute the performance of the hybrid approach. The performance of hybrid model is compared with existing model which Logistic Regression (LR) model for the human activity recognition.

4. HAR-IoT and Sensors

The Internet of Things (IoT) in recent years has gained significant importance in daily life. The IoT combines sensors, actuators, and communication networks to allow sensing and collecting information

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from the environment and human body for further computing and processing. The proliferation and changing trends of smartness in every physical object enables humancentric pervasive application development to facilitate people's daily lives. Diverse and powerful embedded sensors make a ubiquitous platform to acquire and analyse data. This provides greater potential for efficient resource management and utilization, and for the ability to monitor human activities for health and wellness. The lightweight and miniature size of devices allow them to be worn and carried on the move. In recent years, wearable sensors have emerged in various fields, such as entertainment, medicine, and security, changing the IoT trend to the wearable IoT (WIoT).

5. HAR-Devices and Networking

IoT Network refers to the communication technologies used by Internet of Things (IoT) devices to share or spread the data to other device or interfaces available within reachable distance. There are various types of IoT networks available for IoT devices / IoT sensors to communicate. Mobile, wearable, and IoT devices provide a large amount of important personal data and help elucidate the context of the user. Wearable sensors provide reliable and accurate information on human activities and behaviour to ensure a sound and safe living environment. The WIoT permits observing, tracking, and measuring individual functions in daily life. HAR-IoT system can quantify physical variables. This framework includes an HAR unit working accordingly the sensor data. It deploys a cloud framework to store data and to monitor a patient's condition from remote station. It is also possible to do programming of smart alarms based on various levels so as to meet the hospital demands.

6. Result and Discussion

Every person or volunteer are here conducted six actions. They are: WALKING, WALKINGUPSTAIRS, WALKINGDOWNSTAIRS, SITTING, STANDING and LAYING by mounting a smartphone (Samsung Galaxy S5) on the pocket. This work used five performance measures called as Accuracy, Recall, Precision, F-Measure and Execution Time to evaluate the developed architecture.

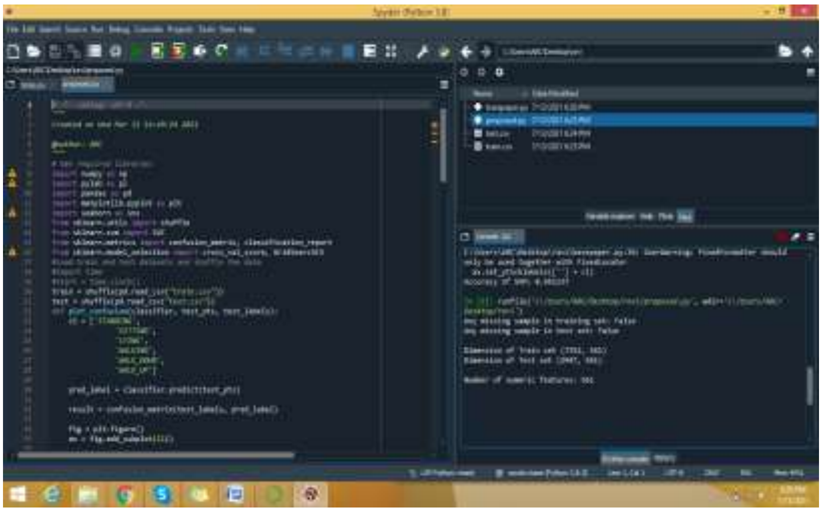

Figure 5: Execution of proposed model.

Figure 5 displays the task of recognizing human activities and the execution of the proposed model. The input here used is the dataset which is further processed for the classification. The designed architecture consists of several classification frameworks they are LR, RF and GNB. The voting methodology is developed through the integration of the mentioned algorithms.

Table 1: Performance Analysis

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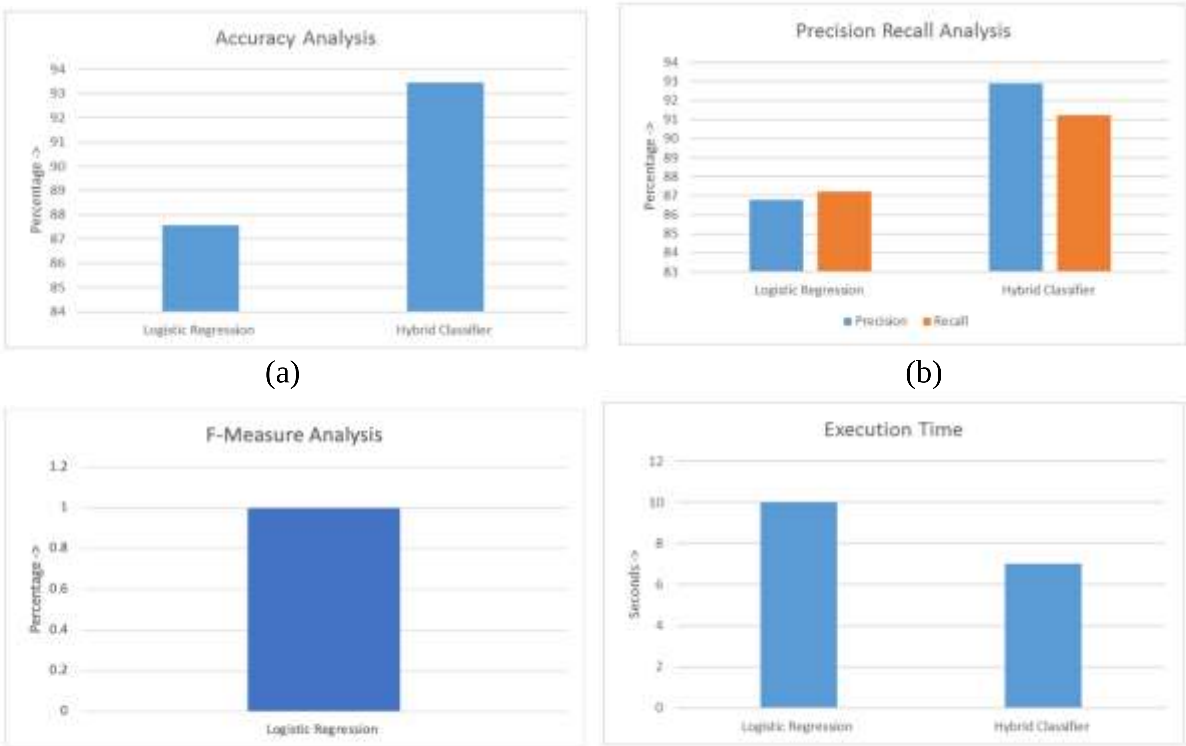
Parameter	Logistic Regression	Hybrid Classifier
Accuracy	87.56 percent	93.45 percent
Precision	86.78 percent	92.89 percent
Recall	87.20 percent	91.23 percent
F-Measure	88 percent	91 percent
Execution Time	10 Second	7 Second



(a) (b) (c) (d)

Figure 6: Performance Analysis: (a) Accuracy Analysis (b) Precision and Recall analysis (c) F-Measure Analysis and (d) Execution Time.

Here, Figure 6 depicts the analysis of the performance of a developed hybrid framework in the context of accuracy, precision and recall. The newly designed framework is then compared with the existent LR based framework for identifying the activities of people. The improvement of 4% to 5% is noticed in here obtained with the use of new methodology.

- **(a) Accuracy Analysis:** The performance of proposed model which is hybrid model is tested with regard to accuracy. The comparison of performance is done with existing model that is based on logistic regression for the human activity recognition. It is analyzed that results are improved up to 4 to 5 percent.
- **(b) Precision and Recall analysis:** The performance of proposed model which is hybrid model is tested with regard to precision and recall. The comparison of performance is done with existing model that is based on logistic regression for the human activity recognition.
- **(c) F-Measure Analysis:** the performance of proposed model which is hybrid model is tested with regard to F-measure. The comparison of performance is done with existing model that is based on logistic regression for the human activity recognition.
- **(d) Execution Time:** The performance of proposed model which is hybrid model is tested with regard to execution time. The comparison of performance is done with existing model that is based on logistic regression for the human activity recognition.

7. Conclusion

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Actually human activity recognition (HAR) involves for identifying, understanding and distinguishing individuals' behaviour, types and patterns of human body parts movements, whether it can be normal or abnormal. The techniques introduced in this work depends on some algorithms. Such as PCA, K-means as well as voting together classifier. The purpose of using of PCA algorithm is reducing the dimensionality of features. The K-means algorithm aims here at clustering features of the same characteristics. Voting classifier is the amalgamation of several classifiers namely, naïve bayes, Logistic Regression (LR) and Random Forest (RF). The work introduces new framework in python software and obtains approximately 5% of boost in results in the context of universal performance measures. The resultant performance estimation has shown that the proposed method provides quite significant results over the available methods.

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The above contents and survey we mentioned is true to my knowledge.

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Md. Abrar Jaheen Tahmid, A Research Scholar in Department of CSE from Golden College of Engineering and Technology. Participated to complete this Research in the year of 2022. With the thesis title "Design and Implementation of Improved Ensemble Classification Algorithm for Human Activity Recognition (HAR)".This article research specialization is in Data Mining. His Areas of Interest are AI, Machine Learning, and Data Mining.

Er. Suraj Pal, Head of Department, Computer Science and Engineering (CSE) from Golden College of Engineering and Technology guided to complete this Research in time. He is thankful for this article. His Areas of Interest are AI, Machine Learning and Networking.

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