# Human Activity Recognition using Smartphone Sensor Dataset

**V Arun, Hariharan T A, K V Srihari, M Abhijeet Sriram**

***Abstract*: Human activity recognition is an intensive space of a machine learning analysis owing to its applications in health care, smart environments, Homeland Security, Research, etc. Study for human action recognition observes that researchers have an interest largely within the daily activities of the human. The identification process can be done by manipulating the information obtained from the surrounding environment or from sensors attached to human body. This paper introduces a deliberate act investigation of movement sensor conduct for human action acknowledgment by means of cell phones. Tangible data arrangements are gathered by means of cell phones once members perform run of the mill and every day human exercises. Exploratory outcomes on a freely accessible data-set demonstrate that combination of both accelerometer and gyroscope information adds to get preferred acknowledgment execution over that of utilizing single source information.***

***Keywords*—-Human Activity Recognition (HAR), Machine Learning, Data Science, Smartphone and wearable sensors.**

## I. INTRODUCTION

With the improvement of sensor and sensor arrange innovation, an assortment of cutting-edge applications is rising in countless, going from inescapable figuring, security and reconnaissance to vehicle system and social insurance. Because of the colossal development of registering and detecting power, numerous applications like wellbeing screen, amusement, sports following, can be executed on cell phones. As a ubiquitous registering and information gathering stage, cell phone has roused numerous looks into on indoor person on foot following, human movement acknowledgment, verification dependent on organic attributes and so on. Tactile information (basically including accelerometer and spinner sensors) were gathered when members play out some ordinary and every day human exercises: slipping stairs, climbing stairs, strolling, running and bouncing. We at that point extricated each and every development unit from the durable information grouping by utilizing cycle recognition calculation, and after that we got time, recurrence, and wavelet-area highlights from the fragmented information. Contrasted with different past takes a shot at cell phone-based action acknowledgment, our action dataset is increasingly various and opened, for example included obscure exercises. Numerous individuals are experiencing ailment like Alzheimer, Diffuse Lewy Body Disease, Frontotemporal Dementia (otherwise called Pick's illness), Vascular (Multi-infarct) dementia, Depression, Parkinson's sickness, Normal Pressure Hydrocephalus, or the individuals who have broken their leg to have a serene existence. So, to improve their way of living this project has been implemented with which one can monitor their day to day activities like ascending or descending stairs, walking, running, etc. using sensors available in the smartphone like gyroscope and accelerometer. Gyroscope sensor is used to detect the direction of motion and accelerometer is used to measure linear acceleration. All these data are monitored from time to time and a data cyclic algorithm is used to check for any abnormal activities, and if any then the concerned person is informed. This makes sure the person with difficulties are carefully monitored.

## II. BACKGROUND AND RELATED WORK

In this section, we briefly discuss researches on human activity recognition. We also focus on applying smartphone sensor data to recognize the activities. Human activity recognition is a simple way of using the data of few sample cases and then using their ideas in the presentation of the upcoming statistical analysis and to bring out the best outcome of the data that were collected from the user. The data for the calculating, evaluation process needs to be collected with the help of the sensors and some other ways to detect the human activity, the sensors that were meant to be used are inertial sensor, accelerometer. Since the 80s the development and the interest for the development to understand human emotions and the need to use them to improve the interests of the people, such trials have been made and are being developed till date. These can now be used for a wide range of applications that might include fields such as medicine, and the use to recognize human interactions with computer, psychology and even sociology. By monitoring people having human activities, one can make ways easy for rehabilitation for the patients for him to undergo brain surgery. The aim of the human activity recognition is to study the varying physical patterns based on the movement, activities of the person that are being monitored the various sensors. Human activity recognition also has several applications, which apart from monitoring human activity (e.g., fall-down detection, health-care), can also help to understand human activity (e.g., surveillance environments, which can automatically detect abnormal activities).

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* Correspondence Author (s)
**V Arun**, Assistant Professor, SRM Institute of Science and Technology, Ramapuram, Chennai – 600089
**Hariharan T A**, UG Scholars SRM Institute of Science and Technology, Ramapuram, Chennai – 600089
**K V Srihari**, UG Scholars SRM Institute of Science and Technology, Ramapuram, Chennai – 600089
**M Abhijeeth Sriram,** UG Scholars SRM Institute of Science and Technology, Ramapuram, Chennai – 600089

The action acknowledgment strategy can be principally delegated two classifications: cell phone based and wearable-based. Smartphone based technique appeared before the wearable-based technique. The processes that were included in this technique were data pre- processing, segmentation, extraction of features and implementation. Though many efficient techniques were proposed in the past few decades, Smartphone-based Human Activity Recognition still remains challenging. The exact movement or the direction of the movement cannot be extracted efficiently. Moreover, the Smartphone-based HAR cannot calculate the Blood pressure, Calories and other important data will can be used for the further research. With the advent in the MEMS (Microelectromechanical Systems), the size of sensors became small, light, less expensive and yielded accurate results. Nowadays, mostly smartphone and smart wearable devices are equipped with many sensors like barometer, accelerometer and gyroscope making their usage handy. In this way, sensor-based movement acknowledgment is progressively beneficial in making considerations as of late. Past studies have used one or almost two sensors at the maximum and thus were not that much accurate in bringing out the results to recognize human activities. One of the methods is Farringdon et al. This study used namely the sensor jacket that consisted of many accelerometers to study by detecting the difference in the(static)- sitting, standing, (dynamic)- walking and running styles of different persons. Another study, Matijevic el al. used two level accelerometers at both the hands and thus above the hip and they were to monitor the walking up, walking down, opening doors etc. Some researchers used only single sensor for the same and got varied level of accurate results. Besides, features and classification algorithms are also varied. For the most part, highlights can be separated into two gatherings: time-space and recurrence area. The mostly classifiers are Support Vector Machines, Neural Network, K-Nearest-Neighbor and Hidden Markov Mode. In recent times, the advent of smart phones has majorly replaced the separate need to use sensors to manipulate data as they are very much capable of computing the values of the sensors in them and giving end result. So it is quite easy to monitor the dataset at regular intervals and the need to use them when needed. In this paper, we mainly focus on two motion sensors: accelerometer and gyroscope. In comparison with the handy wearables, the smartphone-based sensors are facing many issues and challenges. The problems are the placement of the phones in varied areas like the data should not change and should give same results when held in hand and when also kept in pocket .Another major drawback is that sensing of the multiple tasks being performed at the same time ,placement of the sensors, size of the sensors and there is also an important issue that the sensors should not be observing or monitoring the user all the time thus indulging in his private life too. Without the auxiliary sensors the motion in the body movement and certain actions can’t be monitored. Thus, on limiting the cost one must make sure to take into consideration of the above factors for the research to undergo in a smooth go.

The acquired data are to be mixed with noise. To make their approaches accurate and perfect, researches focused on de-nosing, feature construction, selection of carrying position and sensors, and detector implementation. Tomas *et al*. provided a way of primary activity recognition for the HAR using smartphone devices. The training was given and the person had to adjust himself according to the processes that he was meant to do. The location was monitored whether the phone was in the pocket, near the chest, in hand and around him. Work covered 6 daily activities, and a k-NN classifier was implemented. The recognition algorithm results in providing highest accuracy 90%, and the lowest achieved 70%. Apiwat *et al*. placed smartphones at different locations and based on varied orientations their calculations were done. The calculations were done for different individuals. For some the phones were placed at waist and for they were placed in pockets and in trouser pockets. The orientations with respect to the motion of the accelerometer and the gyroscope’s signals changed and thus the results also differed and thus accurate results were brought up to 90%. Lin et al, utilized an accelerometer to recognize 7 physical exercises directed by individuals consistently. Additionally, this paper indicated 6 stash positions. telephone was conveyed in subjects' leg pocket of front jeans. The highlights extricated in this paper were measurement esteems in time area. At long last, they develop 4 classifiers, and demonstrated a high precision over 90% for generally exercises. Jennifer et al. gathered accelerometer information from 29 volunteers, leading 5 day by day exercises. The Compared with previous two investigations, this paper understood more highlights from information gathered from 7 subjects, including time-space includes as well as recurrence area highlights, and after that it executed SVM classifier. With realized pocket position, the general F-score could achieve 94.8%. We can see that the accelerometer has gotten the most consideration in past human movement acknowledgment think about. Be that as it may, as of late, different sensors like spinner have pulled in specialists' core interest.. Wanmin et al. proposed an action recognition approach utilizing accelerometer and gyroscope information for 16 members on 13 exercises. Seven classifiers had been implemented and the outcome demonstrated that the accuracy was higher than exclusively on accelerometer. Muhammad et al. made a far-reaching study on effect of position to convey the telephone, blend of sensors and the execution for various classifiers, and they developed summed up model and customized model to explore the impact of client space. These past examinations have demonstrated that HAR is an intricate undertaking, where numerous variables would all influence the precision of HAR, and their methodology structures and assessment systems are unique. methodology structures and assessment systems are unique. As far as anyone is concerned, there are many methodical researches like for smart phone sensor-based action recognition, and a couple of explores present a precise act assessment in this field.

In this way, in our study, we attempt to give a point by point action recognition approach, from information obtaining, information preprocessing, including development, classifier execution to action separation. Also, we make a full-scale act assessment with broad outcomes, with the expectation that our decisions can add to improve the movement acknowledgment innovation.


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## III. ACQUISITION OF DATA AND PRE-PROCESSING

In this section we discuss about how the data is collected from the sensors and how the pre-processing is done.

### A. *Data from Wearable devices*

Wearable devices are popularly used now, they are mostly attached to the wrist. Wearable gadgets are capable of measuring Body temperature, heart-rate, calorie, Global Positioning System (GPS) location and body movements. Most of smart wearable devices cannot function on their own, they need a smartphone as a base system which makes easy for the device to store the data and process them. Wearable devices are considered to be more accurate than the smartphone sensors which is an added advantage for those who use a smart device.

**Figure 1. Wearable device and a smartphone**

### B. *Data from Smartphone sensors*

Smartphones incorporate various sensors such as Accelerometer, Gyroscope, barometer, proximity sensor, etc. and most of them remains unnoticed by the users. So, it is one of the important and popular devices to recognize human activity. The activities can be recognized accurately with the varying phone location and the accelerometer. CenceMe was developed using the sensor enabled mobile phones using data from the sensors such as microphone, camera, GPS and accelerometer. Straightforward activities can be effectively perceived with advanced mobile phone sensors with regards to complex exercises, such as ascending and descending stairs can be hard to perceive and separate between them.

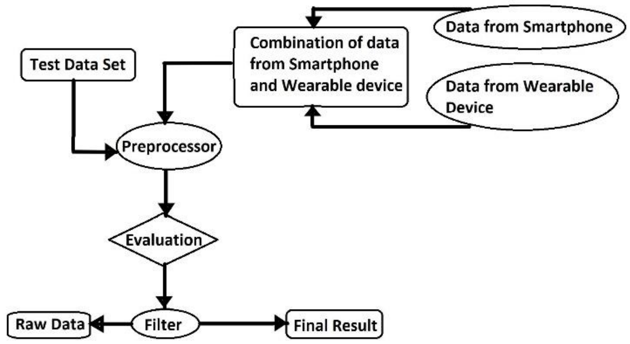


**Figure 2. Architecture Diagram**

### C. *Combination of Smartphone and Wearable device data*

The data collected from both smartphone and the wearable device are first stored as plain data. The mean between the smartphone data and the wearable device data are then produced to form a better and accurate data set. Only the required attributes are used for the activity recognition the unwanted attributes are stored as a raw data for future use. In some cases where in heart rate and calories are taken in the account, these sensors are not present in the smartphone in this case we need to totally rely upon the shrewd wearable gadget for the information extraction. At the point when this is executed in an application, for the decision of classifier, one can utilize either transient classifiers or non-fleeting ones. If there should be an occurrence of nontemporal classifiers like Decision Tree, Artificial Neural Network, k-Nearest Neighbor, K-Mean and so on., one can't give the crude information as information straightforwardly to the classifier. Initial, one needs to separate a few highlights from the crude information and afterward pass these highlights to the classifier. In this way, there is a preprocessing on the crude information before sending it to classifier. For this situation, the highlights that are for the most part utilized are the accompanying:

- Arithmetic Mean
- Standard Deviation
- Max, Min
- Median Absolute Deviation
- Frequency Signal Weighted

From Table I, we can see that, to acquire higher exactness rate for perceiving Human Activities, Multi-model frameworks are more proficient than others. Normal in the event of fleeting classifiers like AR and DTW, and so forth., there is no requirement for highlight extraction. These calculations accept contribution of information as a period arrangement. Additionally, one can without much of a stretch plot the accelerometer and whirligig information obtained from the advanced mobile phone into a period arrangement. Henceforth, a transient classifier is a superior decision for ordering exercises utilizing the information gained from advanced cell sensors. As DTW works best on time arrangement information, this makes DTW a solid match for our motivation.


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| Sensors | Machine Learning Algorithm | Accuracy |
|---|---|---|
| Accelerometer, Gyroscope, Planter Pressure Sensor | Decision Tree | 94.37 - 99.53% |
| Accelerometer Gyroscope | Support Vector Machine | 89.3% |
| Accelerometer, Gyroscope | k-NN | 90.2% |
| Accelerometer, Gyroscope | Decision Tree, Logistic Regression, Multilayer N | 91.7% |
| 2D-Accelerometer (Wearable) | NB, DT, kNN, ANN, GMM, cHMM | 92.2 - 98.5% |

**Table 1. ML Algorithms and Accuracy**

## IV. OUR APPROACH

From the writing survey, it is plainly seen that less complex motion exercises can be identified effectively yet comparative sorts of exercises are hard to separate. We are especially keen on separating these comparable exercises effectively. As DTW calculation has never been utilized in HAR examines however it appears to be especially appropriate for the reason, we propose to apply DTW calculation for arrangement reason. We additionally present setting sifting strategies in HAR to channel the information for accomplishing an increasingly exact outcome. Clarification of the setting separating is given underneath. We develop a multi-modular framework that takes client's advanced cell accelerometer and gyrator esteem as info. It additionally simultaneously records the difference in elevation of the advanced mobile phone utilizing its gauge sensor and the client's pulse utilizing a pulse screen amid the period. Accelerometer and whirligig esteems are utilized by the classifier to arrange the information. The elevation and pulse perception are then utilized as a setting channel. Thus, when classifier produces an outcome, it is gone through setting channel and the yield from the setting channel is the last outcome. From foundation think about, we have demonstrated that it is troublesome for classifiers to group comparable exercises like going upstairs and going ground floor, quick strolling and moderate running and so forth. The most noteworthy exactness for identifying climbing and sliding stairs is around 55-60%. The possibility of setting channel is especially pertinent here and it will almost certainly separate these comparable exercises utilizing the recognition on height and pulse esteems and produce a progressively precise outcome. Usually hard to separate between these comparable exercises by just utilizing accelerometer and gyrator. Be that as it may, in the event that we use indicator sensor here, this may improve the outcome. From the indicator sensor, we get the height. So while strolling on the off chance that the height of the individual is expanding, at that point we can accept that the individual is going upstairs. In the event that it is diminishing, at that point we can say the individual is going first floor. Furthermore, on the off chance that the height is steady, at that point we can expect the individual is simply strolling. Along these lines, by normalizing the gauge and pulse sensor esteems and afterward setting up guidelines relating with those, we can setup the Context Filter. Setting channel may not make an effect on the ordered outcomes immediately in light of the fact that the pulse and the elevation esteems don't increment or diminishing quickly. For instance, when someone begins running, his pulse remains ordinary in the first place however after a timeframe, it begins expanding step by step. So our setting channel will dependably be watching the elevation and pulse estimations of the close past and will endeavor to discover a window containing discernible variance. When it will discover it, it will again channel the outcomes. This time it will channel with the new window for better streamlining of the outcome.

## V. METHODOLOGY

Information from the Heart rate screen and inertial sensor's information from Smartphone have been gathered by an Android telephone. In the wake of gathering information in the Android telephone, it is then prepared and put away in the cellphone. The Ninth International Conference on Advances in Computer-Human Interactions processed by an offline data processing system. The arrangement of the information is done in the server. Figure 2 portrays the framework engineering for our framework. For our examination, we required an advanced cell which joins tri-hub Accelerometer, Gyroscope, and Barometric sensor. It must be ANT+ upheld as we use Garmin Heart Rate Monitor as our sensor for acquiring pulse information. A Samsung Galaxy S4 (I9505) advanced mobile phone was utilized in our examination as it meets every one of the prerequisites. Around 25 people of various ages were picked arbitrarily for our information gathering process. They were likewise unique in physical fabricated, tallness and weight. For building up the framework, we manufactured the Android application. This advanced cell application was assembled utilizing Android Development Tools (ADT) group which coordinates an accumulation of the accompanying projects: -

Eclipse: an incorporated


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domain for the improvement of programming ventures with multi-language support. - ADT module: the toolset for Eclipse intended to permit the advancement of Android Apps. - Android Software Development Kit (SDK): gives the API libraries and designer apparatuses required to manufacture applications for Android. - ANT + SDK: gives the API libraries to utilize the ANT+ sensors. From the Android App All information is passed to server through remote medium.

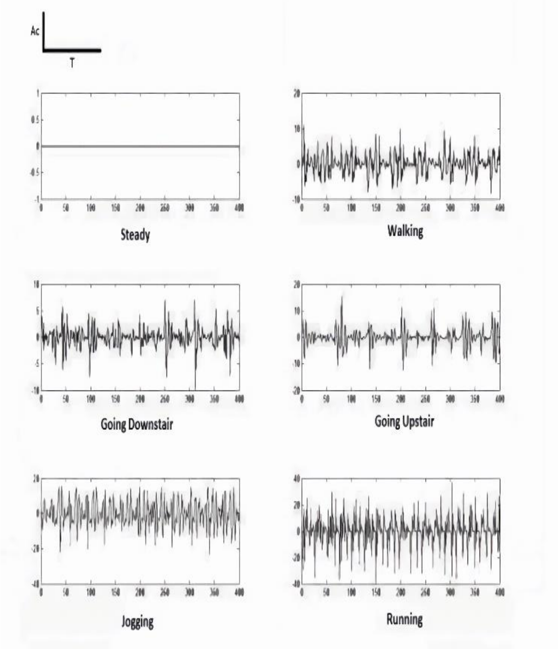


**Figure 3. Accelerometer value for different activities**

At that point, on the server side all estimation is finished. We take tests at a rate of 50 tests/second. The length of every movement test is 8 seconds. We additionally compute twist way by applying DTW calculation. Twist way is determined of each test information by taking the separation from the enduring state. DTW works in just a single measurement, however both the accelerometer and the whirligig have three components of information. Along these lines, we determined the separation for each measurement and consolidated them to a solitary esteem which is our twist way utilizing (1) and (2).

$$Ta=\sqrt{(dtw(Xa)^2+dtw(Ya)^2+dtw(Za)^2)}$$

$$Tg=\sqrt{(dtw(Xg)^2+dtw(Yg)^2+dtw(Zg)^2)}$$

Here Ta and Tg is the warp path for accelerometer and gyroscope, respectively. For each template, each test data produced a warp distance indicating the difference from the steady state. Different kinds of activities produce different kinds of distances. So using this distance we can train a classifier which will take the warp path distance as input and then classify it to a class of activity.

Da or Dg = DTW (Test Data)

Output = Classifier (Da or Dg)

On the off chance that we watch the accelerometer x-pivot esteems for various exercises from Figure 4, at that point we will see that every one of the exercises has a particular example of speeding up plenteousness levels amid the movement. For instance, in the event of strolling it is between 10 to - 10, for running it is 20 to - 20 and for running it is 40 to - 40. Be that as it may, the range is an incredible same for strolling, going upstairs and first floor. Every one of these attributes stay steady for the other accelerometer pivot too. In this way, on the off chance that we think about these time, arrangement of the diverse exercises regarding a relentless state then the yield will be very comparative for strolling, going first floor and going upstairs however extraordinary for running and running. There are three hubs in accelerometer and DTW can be connected to just a single time arrangement at any given moment. Along these lines, the twist way to remove for every hub concerning unfaltering state must be estimated independently and after that joined to get a solitary esteem. Thus, we have determined the DTW twist way remove for every pivot and joined them to a solitary esteem utilizing the methodology outlined in Figure 4.

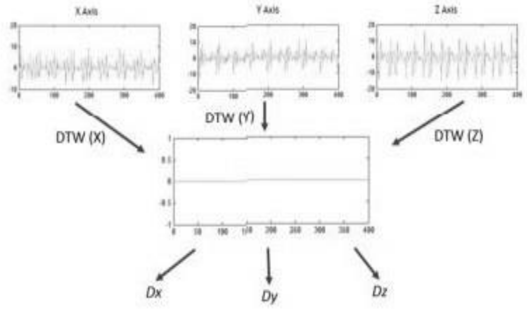


**Figure 4. Applying DTW with respect to Steady State**

We have just observed that the sufficiency of increasing speed contrasts for various types of exercises. Be that as it may, for strolling, going first floor and upstairs, the qualities are very comparable. That is the reason the all-out twist way remove (Da) estimated utilizing DTW calculation as for the Steady State is an incredible same for these exercises however unique for running and running. Figure 4 demonstrates the different twist way remove esteems for five unique exercises. It is obvious from the figure 4 that running and running has its different zone however strolling, going first floor and going ground floor are in a similar zone. So in the event that we think about strolling, going ground floor and going upstairs as a solitary class (Combined Class) at that point utilizing the absolute twist way separation of an action with a classifier, we can separate between the joined class, running and running. Utilizing this trademark, we have prepared a k-NN classifier which takes the complete twist way remove (Da) of a movement as info and groups into the consolidated class or running and running Though the fundamental order can be practiced by the previously mentioned technique, still the disarray stays as we don't have the foggiest idea about the genuine class of an action when it is arranged to the Combined Class. So here we are applying our setting separating approach which utilizes gauge sensor esteems to separate them. At the point when an information is delegated Combined Class, we are again sifting the choice utilizing Context Filtering. In the event that we take the distinctions of the height of the advanced cell from beginning to consummation purpose of joined class exercises, for example dA = Altitude of completion point – Altitude of beginning stage and plot them on a chart, it will look as portrayed in Figure 7.



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So in the event that we use dA of a consolidated class action, we can without much of a stretch separate them as every one of strolling, going ground floor and going upstairs has their very own different zone and it is effectively classifiable. We have utilized another k-NN classifier here which utilizes dA of a joined class action to recognize the genuine class. This is the manner by which a movement can be characterized into one of the five classes by diminishing the disarrays.

## VI. RESULTS

Figures **5**, **6** and **7** show the accuracy of detecting the five activities, respectively, using only accelerometer, only gyroscope and a combination of both sensors. On the basis of the different accuracy level of the different cases, it is clear that using only accelerometer in DTW produces better result in our approach. The computational complexity is also decreased as only the accelerometer is enough to detect the basic activity. More importantly, the accuracy level for detecting similar activities like going downstairs and going upstairs has also been increased with respect to previous studies. For these two specific cases, we got precision of 92.85% and 100% separately while in past examinations [5], the exactness was 59.3% and 55.5%.

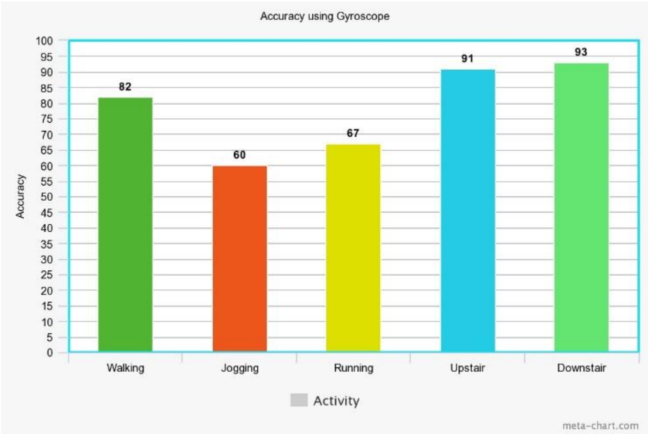


**Figure 5. Accuracy using only Gyroscope**

Action acknowledgment achievement rate can again be expanded for individuals of various classification in the event that we utilize just the information of that classification as preparing tests. As people of different categories were chosen for our data collection process, the result we have acquired is quite for a general case.

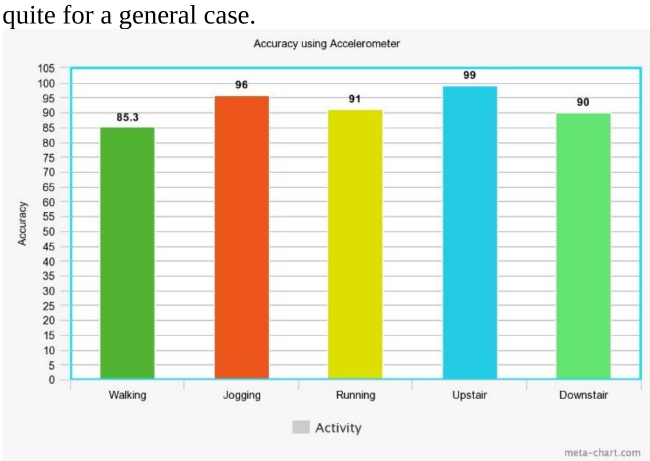


**Figure 6. Accuracy using only Accelerometer**

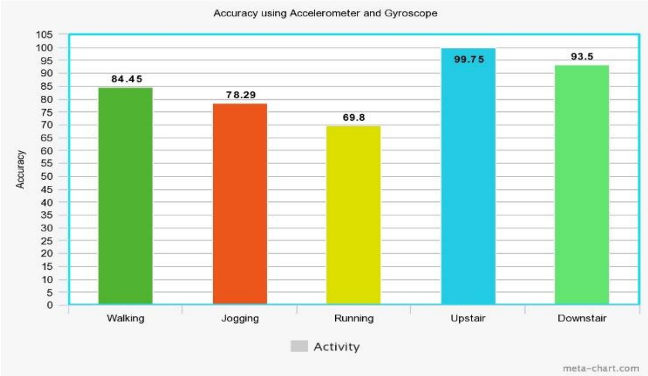


**Figure 7. Accuracy using both Accelerometer and Gyroscope**

## VII. CONCLUSION

In this paper, we address some basic difficulties of Activity Recognition with Mobile telephones. DTW is a costly calculation as for time. May be this is the motivation behind why this calculation has not yet been utilized in this examination field previously, feeling that it may not be appropriate for constant acknowledgment. But instead utilizing DTW for customary format coordinating concerning standard layouts of every sort of movement, we are utilizing it just once as for the unfaltering state, decreasing the example number. We have likewise separated between comparable exercises like going upstairs and going ground floor. We as a whole realize that cell phones have constrained power limit. So we have run our action acknowledgment classifier on our server rather on cell phones to diminish the utilization of versatile battery. In the past investigations of human movement acknowledgment, we have seen that the introduction and area of the advanced mobile phone was fixed to a specific piece of a human body, for the most part the abdomen. Yet, we have put the telephone in the correct pocket of the gasp. Thus, it is more easy to use than the past ones. We additionally gathered pulse information amid a movement. Nonetheless, pulse is for the most part individual ward. Every individual has a particular example of pulse trademark amid an action. So it is very hard to extricate a general component from the pulse estimations of a gathering of individuals. That is the reason we couldn't utilize the pulse information to improve the order result. Be that as it may, as pulse is individual ward, if there should be an occurrence of client subordinate characterization, it might have some effect. This would be our future examination to utilize pulse for client subordinate action acknowledgment learning. Acknowledgment of semi-mind boggling and complex exercises like cooking, moving, and going in transport and so on still remains a test. So alongside movement exercises, we will likewise attempt to perceive these complex and semi complex exercises consolidating advanced cell sensors and the information we gain from our present work.

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## AUTHORS PROFILE

**V Arun** is an Assistant Professor at SRM Institute of Science & Technology. He has over 10 years of experience in teaching. He got his Bachelor's Degree in Computer Science & Engineering from SA Engineering College and Master's degree from Rajalakshmi Engineering College. Main area of research interest is Big Data and Data Mining.

**HARIHARAN TA** is an Undergraduate Student in SRM Institute of Science and Technology, Ramapuram in the B.Tech Computer Science and Engineering Department. He has previously published 2 papers – "Brain Controlled Wheel Chair Using Brain Computer Interface (BCI)" and "Automatic Device Brightness Control by Analysing Face to Screen Distance".

**KV SRIHARI** is an Undergraduate Student in SRM Institute of Science and Technology, Ramapuram in the B.Tech Computer Science and Engineering Department. He has previously published 2 papers – "Brain Controlled Wheel Chair Using Brain Computer Interface (BCI)" and "Automatic Device Brightness Control by Analysing Face to Screen Distance".

**M ABHIJEETH SRIRAM** is an Undergraduate Student in SRM Institute of Science and Technology, Ramapuram in the B.Tech Computer Science and Engineering Department. He has previously published 2 papers – "Real time emotion based music player" and "Home appliances control and monitoring using IOT".


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