A Novel Framework for Smart Home Human Activity Identification using Binary Cuckoo Search Metaheuristic

Thesis submitted in partial fulfillment of the requirements for the award of degree of

Master of Engineering
in
Computer Science and Engineering

Submitted By
Gurpreet Kaur
801732014

Under the supervision of:
Dr. Maninder Kaur
Assistant Professor

COMPUTER SCIENCE AND ENGINEERING DEPARTMENT
THAPAR INSTITUTE OF ENGINEERING AND TECHNOLOGY
PATIALA – 147004

June 2019

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "*A Novel Framework for Smart Home Human Activity Identification using Binary Cuckoo Search Metaheuristic* ", in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Computer Science and Engineering* submitted in Computer Science and Engineering Department of Thapar Institute of Engineering and Technology, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Maninder Kaur* and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

Signature.

Gurpreet Kaur

(Gurpreet Kaur)

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

(Dr. Maninder Kaur)

Maninder Kaur

Assistant Professor,

CSED, TIET, Patiala

Acknowledgement

I would like to thank God for blessing me with all the strength and resources required to complete this task. I would like to express my gratitude to **Dr. Maninder Kaur**, Assistant Professor, Computer Science & Engineering Department for guiding me through the whole process and providing me with your knowledge and experience.

I am also heartily thankful to **Dr. Maninder Singh**, Professor and Head, Computer Science & Engineering Department for motivation and providing uncanny guidance and support throughout the preparation of the thesis report.

I am also thankful to the entire faculty and staff members of Computer Science and Engineering Department for their direct-indirect help, cooperation, love and affection.

Gurpreet Kaur

(801732014)

Abstract

Human activity recognition has been a topic of attraction among researchers and developers because of its enormous usage in widespread region of human life. The varied human activities and the way they are executed at individual level are the main challenges to be recognized in human behavior modeling. In this thesis a novel methodology is proposed that recognizes human activities from the behavior of individuals in a smart home environment. The dataset considered in the work is captured using Bluetooth Low Energy (BLE), a popular technology for indoor localization. The proposed framework is a binary cuckoo search based stacking model that collectively exploits multiple base learners for human activities recognition from the gathered accelerometer sensors data mounted on wearable and mobile devices. The work is tested on the newly developed SPHERE dataset to recognize user activities in smart home environment. The experimental results showcase the effectiveness of the proposed approach, outperforming other recent existing techniques on the dataset, giving high predictive accuracy value of 93.77 % via 10-fold cross validation.

Table of Contents

List of Figures

List of Tables

Chapter 1
Introduction

Human behaviour recognition in an automatic manner is vital in several intelligence applications like home services, emergency services, health observation, and help applications, and transportation services [1]. It is predicted that shortly, smart environments that is interacted with the individuals with their specializations will become inseparable part of the standard of living. Since the worldwide increase within the quantitative relation of the old population, the aging in situ gained the utmost importance. It is potential to alleviate the economic effects of worldwide aging by sanctioning the old to remain active and healthy for extended years in their own homes wherever living is a lot of natural and comfy [2].

The survey analysis show that people spend most of their time indoors. Adults in offices, children in schools, oldage people in homes. It is becoming common to have smart home environment with connected devices due to increasing demands. The devices within smart home can both communicate with and gather large loads of data from the surroundings [3].

Throughout the past decade, the advances within the sensor technology [4] and wireless communication networks in terms of capability increase, price potency and power potency created it attainable to use sensors for human activity recognition functions. These small-scale sensors are soon to be deployed in massive scale and produce an immense quantity of information. The demand for techniques to process an enormous quantity of information in an affordable amount of time to extract helpful information will increase because the knowledge or information supply increases. Data-driven methods are needed that are simply applicable to novel settings in order to meet this demand.

To infer the human behavior, data collected is used from the smart environments that require annotated datasets to be trained on. They need time and human effort though recording and annotation of such datasets are pricey. Although the annotated datasets are essential, they are slightly helpful when recorded in laboratory settings due to predefined scenarios since they do not replicate the natural behaviour of human beings. Besides, the analysis of many illation methods so as to seek out the optimum performance in terms of behavior recognition for healthcare purposes requires metrics and methodologies beyond the ones that are available for general use. Moreover, the complex human activities [5] make it troublesome to accurately model them. Whereas hierarchical models will be a remedy for additional accurate illustrations, finding appropriate complexness levels isn't a trivial task. The variety in human activities in terms of period, interactions with the surroundings and therefore the variations within the order of the actions make the matter even additional sophisticated.

There are many examples from daily life activities like making breakfast may encompass many actions like ‘turning on the tea maker’, ‘turning on the toaster’ and ‘getting ingredients out of the fridge’. The order of those actions might modify for various occasions of similar activity or a number of the actions might utterly disappear. Conversely, sleeping activity might not contain such a large amount of actions though it generally lasts for many hours. To properly model the human activities, the right complexness and hierarchy levels ought to be determined. Finally, once automatic human behaviour observance systems are deployed on a world-wide scale for care functions, fine tune the model behaviour for every new house to accurately replicate the residents’ behaviour for that specific house. To accomplish that, annotated knowledge from that home is required. Instead of annotation a dataset consisting of many weeks of information, associate degree algorithmic rule will be accustomed decide that purpose in time it might be most informative to get annotation.

1.1 Wireless Technologies

Locating any wireless technology can be used. Existing wireless indoor positioning infrastructure benefits from many distinct technologies. For configuring hardware and software, network-based, terminal-based, and terminal-assisted, there are three primary system topology options. Positioning accuracy can be enhanced at the expense of wireless infrastructure hardware and equipment.

1.1.1 Wi-Fi-based positioning system (WPS)

Wi-Fi Positioning System (WPS) is used where GPS is inadequate. The place technique used to place wireless access points is based on both the intensity measurement of the received signal and the methodology for "fingerprinting"[6]. The SSID and the MAC address of access are typical parameters for geolocating the Wi-Fi hotspot or mobile access point.

1.1.2 Bluetooth

Bluetooth is all about closeness, not the exact place. Bluetooth was not intended to provide a stapled place such as GPS, but is understood as a geo-fence or micro-fence resolution making it an inner proximity resolution, not an inner positioning resolution. Micro mapping and indoor mapping were combined with Bluetooth and mainly based on Bluetooth autoimmune disorder.

1.1.3 Grid concepts

Instead of measuring long-range, a thick network of low-range receivers can be arranged throughout the space being observed, e.g. in a grid pattern for economy. Because of the small spectrum, only a few near, networked receivers will identify a marked entity. An identified tag must be within the range of the identifying reader so that the location of the tag can be approximated roughly.

1.1.4 Long range sensor concepts

In one mixed signal, most devices use a continuous physical measurement together wi th the identifying information. Reaching through these sensors includes mostly a whol e floor, an aisle, or just a single room. With various sensors and overlapping reach, sh ort reach solutions are implemented.

1.1.5 Time of arrival

Arrival time is that the amount of time it takes for an indication to propagate from transmitter to receiver. As a consequence of the speed of signal propagation, the duration of an indication will be used to calculate the distance directly. In order to realize a place, multiple measurements are coupled with trilateration and multi-alteration. This may be the GPS method used. Systems using ToA generally require an sophisticated system of synchronization to maintain a secure supply of your sensor moment.

The precision of the TOA's mainly based approaches typically suffers from enormous multi-path circumstances in indoor location triggered by the reflection and optical phenomenon of the RF signal from objects such as the surroundings, interior wall, doors,furnishings.However, it is possible to reduce the effect of multipath by impleme nting mainly based methods of temporal or spatial meagreness.

1.1.6 Received signal strength indication

The instrument acquires the indication of signal strength (RSSI). As a consequence of propagating radio waves in accordance with the inverse-square law, the distance may be approximated, backed by the connection between transmitted[7] and received signal power, provided that no alternative mistakes contribute to erroneous outcomes. The interior of the house is not free space, therefore the accuracy of the wall reflection and absorption wedges considerably. Non-stationary objects like doors, furniture, and others will produce an exceptionally bigger downside as they dynamically, unpredictably affect the signal strength.

In order to provide location information, many systems use improved Wi-Fi infrastructure. None of these systems serve any infrastructure as they are designed to function properly. The Wi-Fi signal strength measurement unit is extremely hurling, so the focus in progress assessment is on creating the correct techniques to filter the wrong computer file through maltreatment statistics. Wi-Fi Positioning Systems are typically used on mobile devices as a substitute to GPS, wherever only a few erroneous reflections disturb the results.

1.2 Cuckoo search algorithm

Cuckoo Search (CS) is a Yang and Deb (2009)-inspired developmental optimization algorithm[8]. Cuckoo could be an fascinating bird, not only because of the lovely sounds they are going to build, but also because of their aggressive copy strategy, wherever, in relation to alternative host birds or species, a mature cuckoo lays its eggs. This is known as compulsory parasitism of the brood. The essence of this algorithmic rule is to lay specific eggs and breed their own cuckoos. In this case, if a bunch bird finds out that the eggs are not their own, they either throw away these alien eggs or just leave their nest and build a replacement nest somewhere else. To describe the Cuckoo Search for simplicity, three idealized vital rules are used:

Each cuckoo lays one egg at a time and dumps its egg in a randomly chosen nest. The best nest will be transferred to the next generation with high-quality eggs. The number of available host nests is connected, so the host bird with a probability pa (0, 1) finds a cuckoo's laid egg.

The probability is that, on the grounds of these three laws, the host bird will either throw away the egg or leave the nest and build a totally new nest. By replacing the fraction pa of the nests with new nests (with new random options), this last hypothesis is often approximated for simplicity. The use of Levy flights to produce new options is a major issue, $x^{(t+1)}$

$$x_{(t+1)} = x_t + s\,E_t \, (1) \qquad (1.1)$$

Where Et is derived from a standard normal distribution with zero mean and standard unit deviation for random walks, or derived from Levy flight distribution. Then the random walks can also be combined with the similarity that could be difficult to implement between a cuckoo's egg and the host's egg. Then the quantity of iterations that can be used by a random walker is determined by the step size. Additional inbound condition, which is just too big, will lead in the new reaction being too distant from the old reaction. If s is just too small, the modification is too small to be essential, so such a search is not cost-effective. Therefore, a correct step size is crucial to maintain the efficiency of the search.

1.3 IOT

The Internet of Things (IoT) is a unique concept that is gaining ground in wireless telecommunication's present scenario. The power of the IoT scheme is undoubtedly that it will have a strong effect on many elements of the daily life and behavior of prospective users. The main apparent impacts of the IoT introduction are evident in each operating and domestic areas from the purpose of reading a non-public user. In this context, domestics, power-assisted living, e-health and enhanced learning are just a few samples of possible applications where in the near future the new paradigm can play a leading role. Similarly, the primary apparent consequences are equally noticeable from the point of perspective of corporate clients in fields such as automation and industrial manufacturing, logistics, business, smart transportation of people and merchandise [9].

Different intelligent services, travel navigation, intelligent manufacturing, and other sectors seek to explore the importance of indoor locations. Using wireless sensor networks has facilitated many tasks within the smart home setting, such as observing human behaviour, human operations and environmental monitoring.

Human activity recognition (HAR) has drawn excellent attention in latest years to cate r for continuous observation of human behavior in different fields of sport injury dete ction, ambient aided living, elderly health care, entertainment, smart home surveillanc e[10].

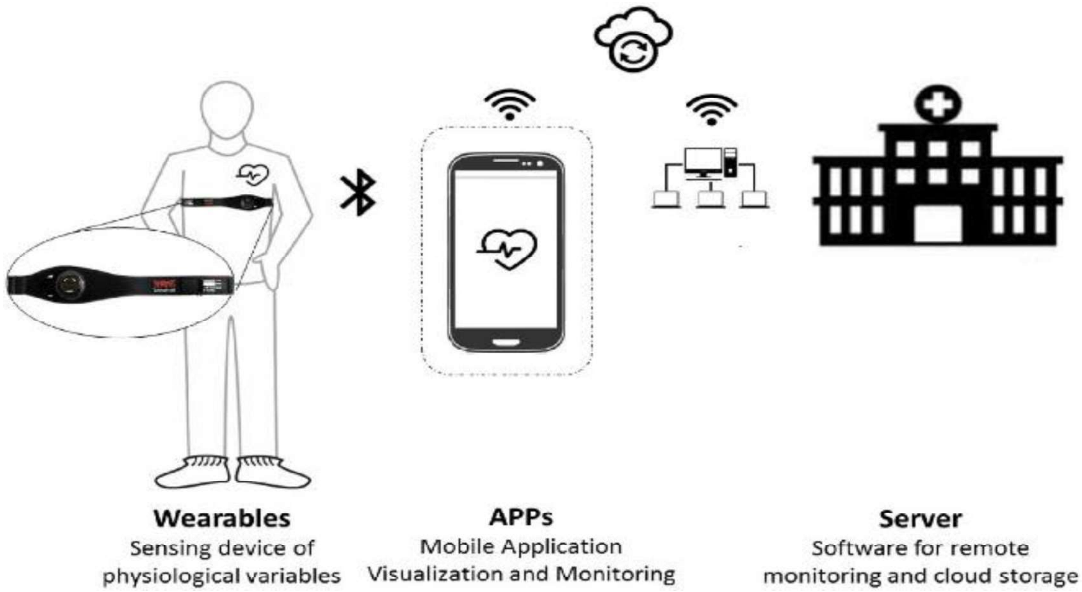


Figure 1.1 IOT

1.4 Classification Algorithms

i. Logistic Regression

By fitting data to a logit function, it predicts the opportunity of an incident occurrence. It is therefore referred to as the regression of the logit. It only operates on binary variables and it adds assumptions like no missing values [33].

ii. Multilayer Perceptron

A perceptron multilayer is classified as a feedforward artificial neural network. A MLP consists of at least three layers of nodes: an input layer, a hidden layer, and a layer of output. Except for internal nodes, each node is a neuron using a nonlinear activation feature [34].

iii. Support Vector Machine (linear kernel)

SVM reflects the training data as points in n-dimensional space, each feature being the value of a particular coordinate and split into categories by a difference. New points are then mapped into the same room, predicting that they fall into a category based on which side of the gap.

It is effective in memory, but it also utilizes costly five-fold cross validation for estimates of probabilities [35].

iv. K-Nearest neighbour

K-nearest neighbors is an algorithm used for classification and regression problems of a simple and lazy kind. It does not build an internal model, but by a majority vote of its k neighbors it stores all available instances to classify the new instance. Among its nearest K neighbors, the instances assigned to the class are most common, measured by a distance function like Euclidean and Manhattan [36].

Even with big training data, it is easy to execute and work effectively and is robust to the noisy training data. It also has some constraints because, owing to the distance calculation of each example from all the training samples, its computation cost is very big.

v. Decision tree

It is a versatile algorithm that can be applied on variables based on both category and constant. It is basically a sort of algorithm of supervised learning. It divides the population into two or more homogeneous sets based on the most important characteristics that make the sets as distinct as possible [37].

vi. Random Forest

It is a meta-estimator working on decision trees principle. It suits the amount of decision trees on different training dataset sub-samples and predicts the model's precision. The over-fitting is controlled.The disadvantages of this algorithm are that it is very complicated and hard to execute. In most instances, it's far better than choice trees [38].

vii. Stochastic Gradient Classifier

Stochastic gradient descent in linear models is an simple and highly economical method. When the sample quantity is exceptionally big, it is not very helpful. It promotes entirely distinct classification loss functions and penalties [39].

It is susceptible to the scaling of features and also needs hyper function parameters.

viii. Naïve Bayes

It is based on theorem of bayes and assumes that it is independent of each other in ever y couple of characteristics. It operates on circumstances in the actual globe such as doc ument classification and spam filtering [40].

It requires no big data set for implementation and is quick compared to other advanced algorithms. Sometimes, though, it's a poor estimator.

1.5 Performance Measurement Parameters:

The performance measurement metrics of machine learning that are choosen to evaluate the performance of machine learning models are very important. Choice of metrics influences how the machine learning algorithms performs. To measure and compare these metrics the following parameters are used:

i. **Accuracy**

Accuracy is the number of correct predictions made by the model in classification problems by all kind of predictions made. it quantifies the precision of learner.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1.2}$$

ii. **Recall**

It is the proportion of rightly categorized activities to the count of true set of categories. TP are the correctly predicted activities. It is computed as in (1)

$$Recall = \frac{TP}{TP+FN} \tag{1.3}$$

iii. **Precision**

It is described in terms of the proportion of accurately recognized human activity to the count of people having that activity. Precision is computed as in (2)

$$Precision = \frac{TP}{TP+FP} \tag{1.4}$$

iv. **F1 score**

It is the harmonic mean of precision and recall value. It is computed as given in (4)

$$F1\ Score = \frac{2*Precision*Recall}{(Precision+Recall)} \tag{1.5}$$

1.6 Introduction to activity recognition

AR is the technique of monitoring and analyzing the conduct and atmosphere of an actor to infer activities. It comprises of modeling operation, behavior and tracking of the surroundings, data processing and recognition of patterns[11]. Walking, sitting, cooking and other day-to-day tasks, for instance. It is made up of three primary parts

1. A sensing module for collecting appropriate activity data such as accelerometer.
2. A module for choice and processing of features that discriminates between operations.
3. A classification module that uses the features to determine the activity of an individual.

There are several approaches for human activity recognition, some of them are explained in brief manner

1.6.1 Vision-Based Activity Recognition

It utilizes visual sensing equipment: camera-based monitoring systems to monitor an individual behavior and thus change the environment. It consists of four steps: human detection, conduct pursuit, recognition of activity, and assessment of high-level activity. Different different methods to assessment, such as a single camera or stereo, used separate strategies to capture the background of the activity. These image-based techniques use single or multiple cameras to reconstruct human 3D creation[12], notice the coordinates of the joints, and remove the limbs of the body. The assessment of the picture is possible through the uninflected structure of the body. This can be accomplished using an algorithmic background subtraction program adapting to the modifications in the environment.

1.6.2 Sensor-Based Activity Recognition

It uses sensor network methods together with its setting to observe an actor's behaviour. In this situation, sensors are linked to humans. Sensor data is collected and analyzed using machine learning algorithms to build activity models and perform activity recognition. They are acknowledged actions in this situation, including physical human movements: walking, running, sitting as in. Most wearable sensors are not suitable for actual apps due to their size or battery life. I will be using wearable sensors or object-attached sensors in a sensor-based strategy. The most widely used machine learning is the Hidden Markoff Model (HMM), a graphically thought-out methodology that characterizes globe observations in terms of state models. Another intelligent range is the Conditional Random Field (CRF) model, which is an undirected grade-related graphical methodology that enables dependencies between observations as well as the use of incomplete information on the allocation of an apparent chance.

1.6.3 Human-Sensing Taxonomy

The process of extracting appropriate data in any setting about an person or group of people.

1) Presence: Presence is probably the most sought-after property in real-world apps when motion sensors (PIR) and proximity sensors are the main prevalent presence sensor. People can be equipped with mobile or wearable appliances, alternatives such as RFID (radio frequency identification) are becoming more frequent.
2) Count: The amount of people in an setting can be inferred either by using a person-counting sensor (or sensors) covering the entire region of concern, or by entering and leaving points in any regard.
3) Location: Using instrumented (such as GPS) or completely uninstrumented alternatives (such as cameras), localization can be accomplished.
4) Track: Tracking is the method of extracting each individual's temporal history in a scene and in a specific region.
5) Identity: There is nothing about a natural tracking extension where each individual is always appointed with the same globally distinct ID instead of relative IDs alone. Identity detection therefore expands surveillance so that even across sensing gaps, it becomes feasible to acquire the spatial temporal history of an individual.

1.7 SENSORS

In recognition of human activity, used multiple sensors to collect raw information. wearable sensor form is used, which is very tiny in size and in daily life operations is convenient for people. Including microphones, accelerometers, GPS, barometers, etc. most of smartphones have mobile sensors.

A. Accelerometer: In phones, the accelerometer is used to find the orientation or to feel the smartphone's acceleration event. An accelerometer measures linear movement acceleration. As in Figure 3, the three axis directions used for reading are predefined. The acceleration is essentially this device's raw data stream. An accelerometer will assess the directional movement of a tool, but during the entire movement it will not be able to properly tackle its lateral orientation or tilt.

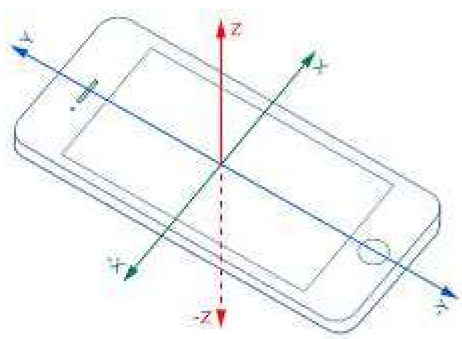


Figure 1.2 Accelerometer

Accelerometer axes on mobile phone

The measurements of the three axes are coupled with a time stamp. Most present accelerometers provide a user interface to sample the frequency so that through testing the user can choose a higher sampling rate. Single and multi-axis accelerometers detect the combined magnitude and direction of linear, rotational and gravity acceleration[13]. They will be used to offer restricted movement sensing characteristics. For instance, a device with an accelerometer will detect rotation from vertical to horizontal in a specific state place. As a result, accelerometers are primarily used for simple motion sensing applications in consumer applications, such as changing the screen of a mobile device from landscape to portrait orientation. Its popularity is due to the very fact that it directly measures the subject's physiological motion status. For instance, if a user changes his / her activity from walking to jogging, an abrupt change in amplitude will occur reflecting on the accelerated reading signal type along the vertical axis [14].

B. Gyroscope:

Gyroscope is a instrument that measures one or more axes around the angular rate of rotational motion. Gyroscopes can properly evaluate complex motion in different ways, trailing the position and rotation of a moving object, not like accelerometers, which can only detect the fact that an object has moved or is moving in a particular direction.

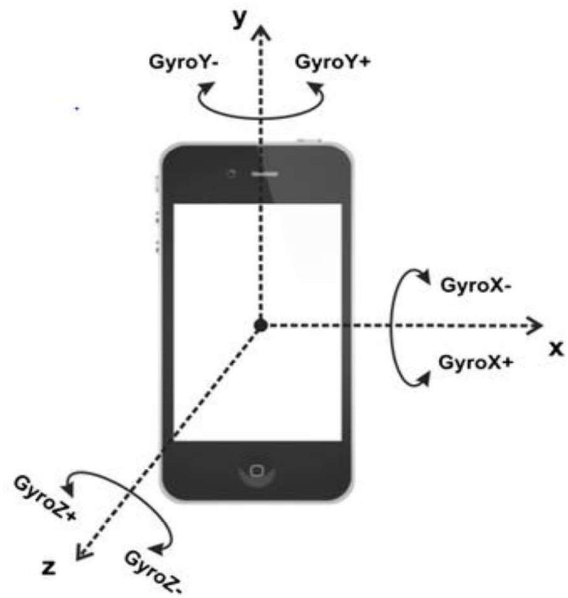


Figure 1.3 Gyroscope

Therefore, gyroscopes considerably enhance the motion sensing capabilities of machines and are used in advanced motion sensing apps in consumer systems such as full gesture detection and video play motion simulation. The axis direction is displayed in Fig. 4. The gyroscope is helpful in navigation applications as well as in some smartphone games using rotation data.

1.8 APPLICATIONS OF HUMAN ACTIVITY RECOGNITION:

There are various applications of human activity recognition. Some are explained as

1. **Daily-life monitoring:**

   Applications in everyday life surveillance are generally aimed at providing a helpful reference for the activity work or helping with exercise and healthy lifestyles. These systems are equipped with built-in sensors such as accelerometer, gyroscope, GPS; and track steps of people, climbing stairs, burning calories, hours of sleep, traveling distance, quality of sleep, etcAn online service is provided to users to review report surveillance and data visualization. Compared to smartphone sensors, these devices are more sophisticated because their sensors are specifically designed to detect and track activity. The limitation is that they are more valuable. These applications normally have similar roles to those on specialized devices. They track user motion logs such as jogging on the route, taking measures and sleeping time. By mining the recorded information and reporting the quality of sleeping, they can give the user an overview of their lifestyle.

2. **Personal Biometric Signature**

   A subject's motion pattern is generally unique and exclusive. For example, when individuals raise their hands, it is nearly impossible for two people's hands to have exactly the same movement patterns. Even if somebody effectively copies others, the differences still occur as a consequence of the bone and muscle movement differences in humans. These variations can be captured by sensors such as accelerometers. Recognition of activity techniques provide an attainable solution for human biometric signature with patterns in motion / gestures. In these applications, pattern recognition methods are used to acquire distinctive patterns of motion that are saved in turn in the database. Because of the omnipresent use of mobile phones, it is simple and possible. On the other side, the signature of the motion can also be used in a malicious way. For example, individuals could use the learned patterns to break user practices, such as typing intelligent phone keyboards or other spying activities.

3. **Elderly and Youth Care**

   In elderly care (both physically and mentally) there is an growing need, partially due to the retirement of the generation of the individual. The primary objective of this assessment in the surveillance of human activity is to create fresh techniques and apps for the care of the elderly. These apps may assist avoid unfortunate occurrences, such as observing the hazardous circumstances of elderly people. A smartphone architecture is created to detect the person's drop. HAR and monitor sensors can encourage elderly individuals in a proactive method, such as life-routine reminders (e.g. taking medication), monitoring remote robotic aid activities. The youth care benefits from the activity identification research. Applications include monitoring babies ' sleeping status and predicting their needs for food or different types of things. HAR methods are also used in the identification of children .

4. **Industry Manufacturing, Assisting**

Recognition of activity techniques can also assist employees in their daily work. This work takes wearable sensors into the workplace −wearable computing is a type of body development that enables an employee to undertake outstanding tasks. Other HAR-based applications include smart cameras capable of perceiving people's gestures in film shooting, automotive robot assistance, etc.

5. **Localisation**

   Recognition of mobile phone activity can foster context awareness and is thus often enforced in localization. One reason to use portable sensors for location rather than GPS is that the GPS signal is typically highly weak in buildings and underground. Portable HAR sensor techniques on the other hand can assist identify the location.

1.9 Chapterization

Organisation of the thesis is stated below

Chapter 2 describes the literature review of the related work done on algorithms implemented on HAR and wireless sensors used in this function.

Chapter3 describes the research gap extracted from the information in literature review and problem statement of this work and also discussed the methodology used.

Chapter4 discussed the proposed methodology for Smart Home Human Activity Identification using metaheuristic approach.

Chapter 5 describes the implementation and results by applying proposed methodology.

Chapter 6 presents the conclusion and future scope of this research.

1.10 Summary

This chapter provides detailed information about the human activity recognition, types of wireless technologies used, sensors, machine learning, machine learning types and different models used

Chapter 2
Literature Survey

In this section, introduction of recognition of human activity is described and discuss a number of technologies that take into account wearable sensors and diverse human operations. Recognition of activity is a essential area of assessment of vision and apps. The aim of the AR is to evaluate (or interpret) in-progress occurrences automatically from information on sensing components and their context. Its applications include police work systems, patient observation systems, and a range of systems that involve interactions between individuals and electronic devices such as people-to-computer interfaces. Most of these applications involve high-level operations recognition, usually comprised of different straight (or atomic) actions by people. There are so many methods in the literature that for indoor and outdoor places dig into recognition of human activity. Entirely distinct works of assessment are discussed and methods for recognizing action. Each of the methodologies is created for simple operations at the individual level and compare distinct solutions to the one suggested.

2.1 HAR Technology

HAR has been self-addressed in two other respects, with internal sensors and wearable sensors being specifically victimized. The systems are placed in predestined points of concern in the event of external sensors that the deduction of operations depends completely on the users ' voluntary interaction with the sensors. The instruments are linked to the user in the event of wearable sensors.

2.1.1 WEARABLE SENSORS

Recognition of gestures based on accelerometer could be a method that is consistent with most physical and computing settings. The area unit of the measuring device detectors is sufficiently small and the area unit is able to fit in small systems and interact wirelessly, which is why it is merely wearable to interact with a nice spectrum of apps. The Nintendo Wii-mote, Lone-Star State Instruments Chronos watch[15], Fitbit and responsive phones are examples of a number of measuring systems based primarily on gesture recognition technologies. The Nintendo Wii-mote involves an integrated 3-axis acceleration detector and connects to the Bluetooth human interface device protocol for transmission information[16].

Moreover, most mobile phones are currently integrated in the GPS scheme, enabling patients to be located in an emergency. In addition, with more cloud-based storage and computing, health-observance devices will become inexpensive, platform-independent, quickly deployable, and commonly accessible[17].

2.1.2 HAR Types

- **Sensor-based, single-user activity recognition:** Sensor-based activity recognition integrates the growing computer network space with fresh information handling techniques and machine learning to model human behavior. Mobile phones provide appropriate device data connected with calculation power to alter the recognition of physical activity to generate a lifetime estimate of energy consumption. Sensor-based activity recognition scientists think that these computers are better adapted to behave on our behalf by empowering current pcs and sensors to observe agent conduct.

  Activity-aware systems[18] galvanized fresh user interfaces and new applications, police work, emergency response, and military missions in great environments. In addition, technologies that acknowledge human behavior from body-worn sensors will open the door to a globe of tender applications such as fitness watching, elder care support, semi-permanent preventive and chronic care, and psychological support. Wearable phones have the advantage of being endless with the client. A fitness application, for instance, may use data about period activity to encourage users to participate in opportunistic activities. In addition, there is no doubt that the general public can accept such activity recognition schemes simply because they are typically simple to demonstrate off or take away.
- **Sensor-based, multi-user activity recognition:** Initial recognition of operations for various users exploiting on-body sensors emerged in the early 1990s during the job of ORL exploiting active badge systems. In an extremely home setting, there is a basic downside of defining device measurement behavior for different users and proposing a unique pattern mining approach to

acknowledge each single-user and multi-user activity in an overly unified resolution.

Jian Lu et al[19] tend to use increasing patterns — a data pattern style that describes important changes between information classifications — to construct our business models, associated recommends a growing pattern based primarily on multi-user activity recognizer to acknowledge each single-user and multi-user activity. In an highly delicate home setting, gathering of real-world activity is conducted by volunteers over a period of time and evaluating the performance of numerous cases of activity in an highly multi-user scenario. The experimental results indicate that our epMAR recognizer's median accuracy is 89%.

- **Sensor-based group activity recognition :** Recognition of cluster activity differs from recognition of single or multi-user activity in this the aim is to acknowledge the behavior of the cluster as an associate in nursing organisation, rather than the interval activities of the individual participants. Cluster conduct arises in nature, which means the features of the conduct of the cluster differ from the features of the conduct of the people at intervals or from any total of that conduct. Modeling the conduct of the individual cluster members is the most challenging, because of the individual's positions in the cluster dynamic at intervals and their connection to the cluster's evolving parallel conduct.

2.1.3 Online Recognition System

Applications using internet activity recognition systems, compared to offline identification, will be extra responsive and interactive. Watching the physical or mental pathologies of patients infinitely in the field of assistance is essential for his or her safety and for rapid recovery. Similarly, in interactive games or simulators, activities and games will improve user knowledge.

2.1.4 Offline Recognition System

Applications using offline system recognition are less responsive and interactive than internet recognition. Application that requires slow response time to use offline HAR schemes, such as application that tracks dietary habits of patients and calculates the calories burned during an exercise routine.

Some of the surveys done are explained below in brief manner:

Zhu and Sheng [20] used Hidden Markov Models (HMM) to detect activities. The accelerometers are used to collect data about the user's corpus and waist. The data is transmitted via Bluetooth protocol to a laptop to process the data. The positioning and setup of this device makes it uneasy as the subject needs to wear wired connections that can interfere with its movements. The information is gathered from one topic, so the evaluation and efficiency are not similar alternative systems.

Thomas Tegou et al [21] suggested a scheme to accumulate understanding about their practices of indoor localization in elderly people's households. Together with their frailty standing, the gathered information was examined demonstrating a correlation between them. The indoor localization scheme is predicated by a chase machine from Bluetooth Beacons using a fingerprint-based operation on the method of the Received Signal Strength Indicator (RSSI). The scheme was tested in realistic environments to achieve an area estimate precision of 93 percent. The assessment of the ten-fold cross-validation of the gathered information exploitation showed an associate degree precision of 83 percent in a supervised person's classification of his / her frailty status.

Panos P. Markopoulos et al [22] provided a distinctive radar-based indoor human gross engine activity classifier using L1-norm Linear Discriminant Analysis (L1-LDA) to detect low-rank subspaces where micro-Doppler signatures are most differentiable from separate movements. Each of the planned classifier's dysfunctional and adaptation implementations is conferred, the latter providing refinement and adaptation to the precise patterns of the human subject of interest. Unlike simple LDA, L1-LDA exhibits resistance to outliers that, thanks to mislabelling, will lie among coaching expertise, e.g. thanks to mislabelling. Using an experiment comparing the performance of the planned strategies with the usual (L2-norm-based) LDA, they used real-data from four motion categories. The findings corroborate that LDA is significantly trounced by the scheduled approaches once the coaching datasets are corrupted with mislabelling, while under nominal coaching understanding they provide comparable efficiency.

The pedestrian's activity will reproduce some linguistic details in the indoor environment. Because of the landmarks for indoor localization, these operations can be used. Baoding Zhou et al[23] suggested a methodology for pedestrian activity recognition supporting a convolutionary neural network. A convolutionary neural replacement network has been intended to mechanically tell the correct alternatives. Experiments demonstrate that the predicted methodology achieves approximately 98% precision in distinguishing nine types of operations, along with still, walk, upstairs, upstairs, upstairs, upstairs, downstairs, downstairs and turning.

Some local area network signal pioneers are scheduled, mostly based on act identification technologies. The main restriction is the absence of a model that will correlate CSI dynamics and human actions in a quantitative manner. Wei Wang et al[24] suggested CARM, an act-recognition and observance scheme based primarily on CSI. CARM has two theoretical backgrounds: a CSI-speed model, which quantifies the correlation between dynamics worth CSI and human movement speeds, and a CSI-activity model, which quantifies the correlation between the movement speeds of different material body elements and a selected act. Through these 2 models, the correlation between dynamics worth CSI and a chosen act is constructed quantitatively. Because of the recognition mechanism, CARM utilizes this correlation and recognizes a specified activity by matching it to the best fit profile. They tend to enforce and evaluate local area network equipment for CARM victimization in many entirely distinct settings and the findings showed that CARM attained a median precision of more than 96%.

Suining He et al[25] provided an overview of latest developments in two main fields of Wi-Fi fingerprint localization: sophisticated localization techniques and ready economic system. The use of spatial or abstraction signal patterns, user cooperation and movement sensors for sophisticated methods to locate users. With regard to the ready-to-use economic system, they address latest developments in decreasing offline labor-intensive surveys, adjusting to modifications in fingerprints, calibrating heterogeneous equipment for signal assortment, and attaining smartphone power.

Teh Ying Wah et al[26] provided a extensive information fusion study and multiple system classification methods for portable and wearable device activity recognition. First, methods and modalities of knowledge fusion were given and, in addition, function fusion was critically evaluated along with deep learning fusion for activity recognition, and their applications, strengths and issues were known. In addition, the study provided a distinct system styles for various classifiers and fusion methods that were lately published in literature. Finally, the issues that need more analysis and enhancements are mentioned.

Ran Zhu et al[27] suggested an individual's activity recognition structure backed by the Convolutional Neural Network (CNN) using a smartphone-based measuring tool, gyroscope and gaussmeter, achieving 62 percent precision, as well as presenting a distinctive CNN ensemble finding confusion between certain operations such as upstairs and walking. The results show that the classification accuracy of the generalized model will reach 96.29%.

Jie Hu et al[28] provided a distinctive methodology based mainly on random forests to generate mid-level alternatives describing information on abstraction and temporal structure for recognition of activity. The model comprises of two distinct components, half-abstraction and half-temporal, which are used to capture the unique features of activity assessment in abstraction and temporal domains. Densely sampled low-level options are tested within the abstraction half and the primary level random forest is true and structurally concatenated to create mid-level abstraction options. Results from the primary level random forest on sparsely sampled points of interest are used within the temporal half to generate mid-level alternatives in pairs. Then the final recognition of these 2 components is based on the weighted total. Themethodology fuses every abstraction and temporal information in a swimming way and creates a lot of descriptive models, which in huge differences could represent more human actions. Experimental findings showed that on offered action and countenance data sets the methodology achieves promising performance.

Using smartphones and sensors, Davide Anguita et al[29] projected a human action recognition (AR) system. Given that these mobile phones are limited in terms of energy and computing power, a distinctive approach to multi-class classification has been estimated. This method adapts the Support Vector machine (SVM) quality and makes use of fixed-point arithmetic to reduce the importance of the operation. It showed a significant increase in computational prices relative to the conventional SVM while retaining comparable precision.

Cagatay Catal et al[30] provided an strategy of classifiers for accelerometer-based activity recognition and a distinctive model of activity forecast backed by classifiers for machine learning. The strategy used J48 decision tree, Multi-Layer Perceptrons (MLP) and logistical methods of regression and combines these classifiers with the common rule of mixture. Throughout the experiments, information from thirty-six users was used in the dataset called WISDM (Wireless Device Knowledge Mining). The model delivers greater efficiency than the MLP-based approach to recognition.

N. Abdul Rahim et al[31] suggested an activity identification strategy using a smartphone-embedded accelerometer sensor using a publicly accessible dataset. Features are selected based on the time and frequency domain. Then, the Principal Component Analysis (PCA) is used to decrease the characteristics ' dimensionality and select the most important ones. In addition, the initial raw information and PCA-based characteristics are contrasted, and various machine learning classifiers also compare time and frequency-domain characteristics. Results showed that PCA-based characteristics achieve greater recognition rates although frequency-domain characteristics have greater precision, 96.11 percent and 92.10 percent precision, respectively.

There are so many methods in the literature that for indoor and outdoor places dig into recognition of human activity. Until now, the use of accelerometer measurements has not been performed in an ensemble strategy based on nature-inspired algorithm. The current research is the first step in defining human activity using the model of machine-learning based on a meta-heuristic strategy that helps in recognizing the human activity in efficient manner.

Table 2.1 Related Work

Author	Methodology	Parameters used for evaluation
Zhu and Sheng et al [20]	Hidden Markov Models (HMM)	Accuracy
Thomas Tegou et al [21]	Naïve Byes, KNN, NN, Decision Tree, Random Forest	Accuracy(93%)

Panos P. Markopoulos et al [22]	L1-norm linear discriminant analysis	Accuracy of proposed methodology is higher than the classification algorithms
Baoding Zhou et al [23]	convolutional neural network	Accuracy
Wei Wang et al [24]	CSI (wifi channel based state information) based	Accuracy, Sensitivity, Specificity
Suining He et al [25]	Advanced Localisation techniques and efficient system deployment	Compare the approaches And discuss the future directions
Teh Ying Wah et al [26]	Linear Discriminant Classifier, Artificial Neural network, Hidden Markov Model, Support Vector Machine, Decision Tree	Comparative analysis of multiple classifier algorithms and fusion methods
Ran Zhu et al [27]	Convolutional Neural Network (CNN)	Precision, Recall, Accuracy
Jie Hu et al [28]	Random forest	Accuracy for improved version of Random Forest
Davide Anguita et al [29]	Support Vector Machine (SVM)	Accuracy
Cagatay Catal et al [30]	J48 decision tree, Multi-Layer Perceptrons (MLP) and logistical Regression	Accuracy
N. Abdul Rahim et al [31]	Convolutional Neural Networks(CNN), Recurrent Neural Networks	Accuracy, Precision, Recall

2.2 Summary

The part of literature survey has clearly defined the methods of recognizing human activities. The use of machine learning algorithms is clearly explained in the next section. Further work done by various authors on recognition of human activities is discussed.

Chapter 3

Research Gap and Problem Statement

3.1 Research Gaps

This section elaborates the research gaps found throughout the analysis by reviewing the already existing literature within the area of Human activity recognition systems.

1. There is a need to develop ensemble models to effectively improve the performance prediction of human activities recognition.
2. There is a lack of sensors that are used to collect the data more effectively.
3. Complex human activities are difficult to recognize. There is a need to develop sensors that can collect related information effectively.
4. Existing approaches did not consider any time frame that leads to efficient recognition of activities.
5. Wearable bands and CCTVs affect the privacy of users, which is why many individuals deny adopting them in their daily lives. In such a situation, a good scheme appears to be the use of some passive strategy such as smart meter information for activity recognition.

3.2 Problem Statement

The increasing wearable sensors require associated strategy to pervasive platforms that help sensors and recognition of activity on countless devices. Reusability and portability are a number of variables inhibiting wearable sensor activity recognition. The omnipresent strategy to activity recognition jointly requires a structure that could reduce the computation on the device. There is a strong desire for adaptive, time-limited platforms for mobile devices that will manage countless stream data produced from different sensing devices to support adjustive activity recognition and mobile apps. Due to the lack of capacities that dynamic activity recognition apps require, such as performance assistance, capacity, real-time, and relevance, the main barriers involved in managing time stream data on a mobile platform.

3.3 OBJECTIVES

The Objectives are as follows:

1. To study, explore and analyze various approaches for recognizing human activities in smart home environment.
2. To design and develop a framework for detection of Human Activity in smart home based on Binary Cuckoo Search Metaheuristic.
3. To verify and validate proposed work in context with existing approaches targeting precision, recall and F-1 measure.

3.4 Summary

In this, firstly the research gaps in the study are discussed and then the problem statement is defined. After that the objectives to achieve are discussed.

Chapter 4

Proposed Framework

This chapter discusses the novel supervised learning framework for smart homes for the activity recognition. The proposed approach for prediction is explained in detail. In this research, "Sphere dataset"[32] has been used as the dataset.

In a Box (SHIB) recovery observance scheme, an annotated dataset of readings acquired during EurValve Smart Home is provided. The SHiB can be a small cost and simply deployable kit intended to obtain information from a wearable wrist-worn home environment. The information provided is intended to judge indoor localization policies at the room level. The wearable unit records readings of tri-axial measuring devices that are sampled and transferred due to a Bluetooth Low Energy (BLE) packet's payload. Four receiving gateways, each located in a typical residential building during a separate room, extract the understanding of the measuring device and verify a Received Signal Strength Indicator (RSSI) for each BLE packet received. RSSI values can represent propagation losses because of distance or shadowing between the wearable transmitter and therefore the entry receiver.

4.1 Data Collection

Using wearable detectors, the information is gathered. BLE (Bluetooth Low Energy) is the wearable sensor used in this study job. The scheme implemented in the room must observe raw information. The wearable sensors gathered the data and then filtered to remove unnecessary fields such as battery wearable level. The device's energy consumption also relies on the sensor's working setup as the operating accelerometer sensor's frequency. A participant registered this information while they stayed in a typical residential house, the SPHERE house in particular. They conducted many daily tasks frequently conducted by a home inhabitant. These actions are also essential to characterize their conduct among the house except to locate a individual. Adding the activities provides an opportunity to explore the connection between the location and activity of wearable BLE RSSI.

The accelerometer readings, denoting the three axis i.e. x, y and z measurements are sampled at 20 Hz from the wrist worn device that contains a tri-axial ADXL362 accelerometer with 74 g range.

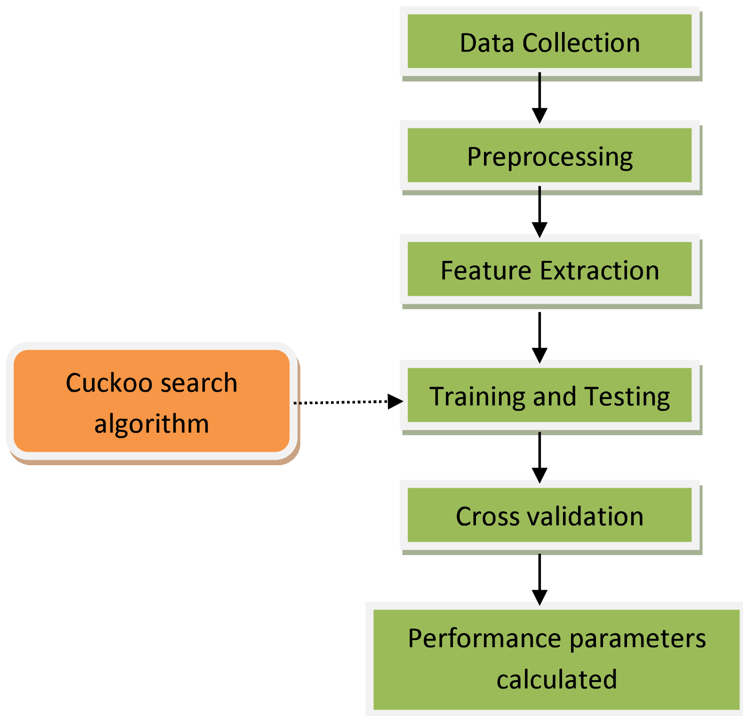


Fig 4.1 Workflow

4.2 Data Preprocessing

Data preprocessing is the technique of converting the raw data into understandable format by eliminating incomplete and inconsistent data contents as well as removal of errors or outliers in the data. The first step of this process is to import the important libraries and the dataset.

1. Check missing values: The missing values are checked and handled properly as it can then end up in inaccurate inferences about the data and can change the results.dropna() function is used to remove all the missing values.
2. Conversion from Categorical to numerical data :The categorical values are converted to numeric encodingfor nominal attributes of the *Gateway*, *Localization* using *OneHotEncoder()* functionality.
3. Timestamp conversion : The timestamp is converted to seconds for faster execution.

4. Splitting the dataset: Splitting the dataset into training data and testing data to make predictions.
5. Standardization: This method is used for normalization of training data. The method is to determine the standard deviation and distribution mean for each feature. Next subtract the mean from each feature and divide each feature by standard deviation using standardscalar() function.

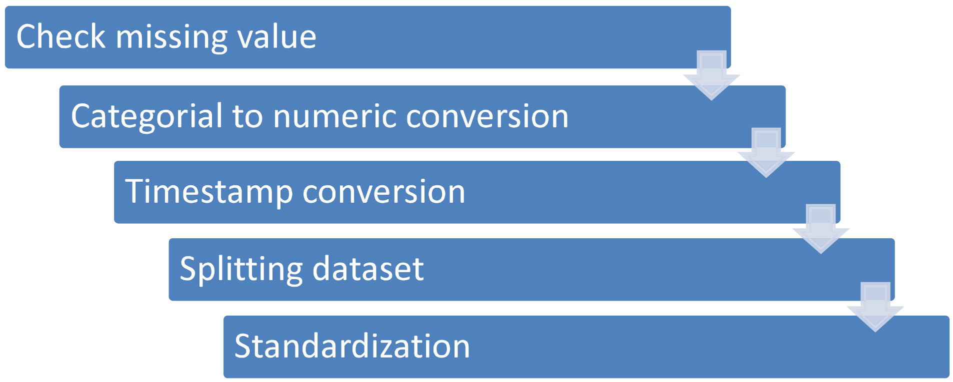


Fig 4.2Preprocessing

Following features are selected for the implementation and observation process.

Table 4.1 No of Features

Timestamp	RSSI	S1x	S2y	S2z	Gateway	Localisation	Activity

4.3 The proposed approach

Step 1: The SPHERE dataset [32] consists of the information recorded at every epoch (the timestamp), the Received Signal Strength Indicator (RSSI) value, the location feature reflecting the true room, receiving gateway node, five accelerometer samples, and accompanying participant activity and utilized for evaluation process.

Step 2 : A number of preprocessing steps like categorical to numeric encoding for nominal attributes of the *Gateway*, *Localization* using *OneHotEncoder()* functionality, *Timestamp* conversion to seconds and normalization of training data are taken for data cleaning.

Step 3: Feature Selection is performed for selecting the best informative features using filter method.

Step 4: Then all machine-learning algorithms (say *n*) are defined for training (machine learning models of level *L1*).

Step 5 : Let $m(m<n)$ be the maximum count of *L1* models that are combined by the level *L2* model.

Step 6 :Randomly generate an initial population of cuckoo eggs defining both Level *L1* and Level *L2* models.

Step 7:Evaluate their respective fitness based on evaluation parameter.

Step 8 : Apply Cuckoo Search algorithm for predefined set of iterations

Step 9: Performance is evaluated using various performance parameters comprising accuracy, precision and recall and F-measure.

Step 10: Finally get results in terms of accuracy.

The method relies on binary cuckoo search based stacking wherein four classifiers and one meta classifier are chosen among the set of 8 base learners using cuckoo search meta-heuristic. The algorithm works by training different combinations of base and meta classifier. The fitness function used for evaluating the performance of a cuckoo is based on accuracy value. The base learners are MLP, Decision Tree, KNN, SGD, Naïve Bayes, Random Forest, Support Vector Machine and logistic regression. Every method is evaluated and is compared with the proposed approach.

4.3.1 Stacking

Stacking is called Stacked Generalization, which could be an approved approach to the ensemble[22]. It's a way for a meta-level (level-1) classifier to mix the classifiers (level-0 or base level) that predicts the proper category that supported the selections of the lower level (level-0) classifiers as shown in Fig. 2. A set of meta-level coaching data is caused by the meta-level classifier. The data on meta-level training is developed by implementing on the coaching data a procedure similar to k-fold cross-validation[23]. For each instance, the outputs of the base classifiers on the side of that instance's actuality class are a meta-instance. On the meta-instances, a meta-classifier is then taught. Once a replacement instance appears to be classified, the output of all the underlying learners is calculated first and then propagated to the meta-classifier that produces the result.

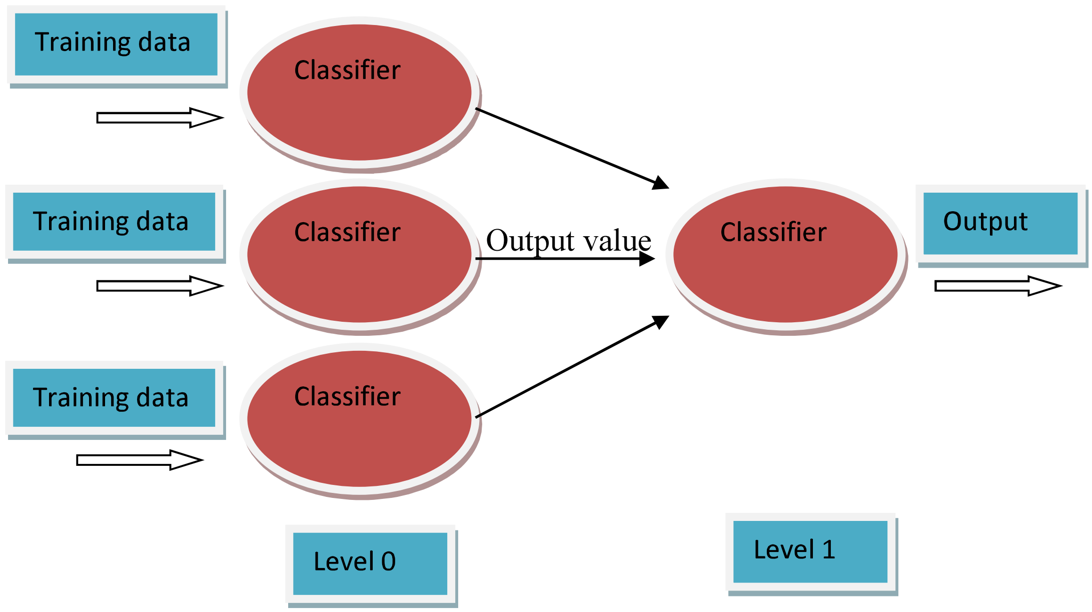


Fig 4.3 BASIC STACKING

4.3.2 Cross Validation

A model is generally provided with data set, known as the coaching information set, and a collection of unknown information against which the model is being tested, known as the check information set, for a prediction issue. The goal is to set the model's own information for testing within the coaching portion, so give perspective on however the precise model adapts to the freelance data set of Associate in Nursing. A cross-validation spherical involves dividing understanding into supplementary sub-sets and then performing analysis on a set. The assessment is subsequently valid on alternative subsets (testing sets). To reduce variability, many different partitions are conducted victimization in several rounds of cross-validation in order to take a total of the outcomes. In estimating model performance methods, cross-validation could be a strong method.

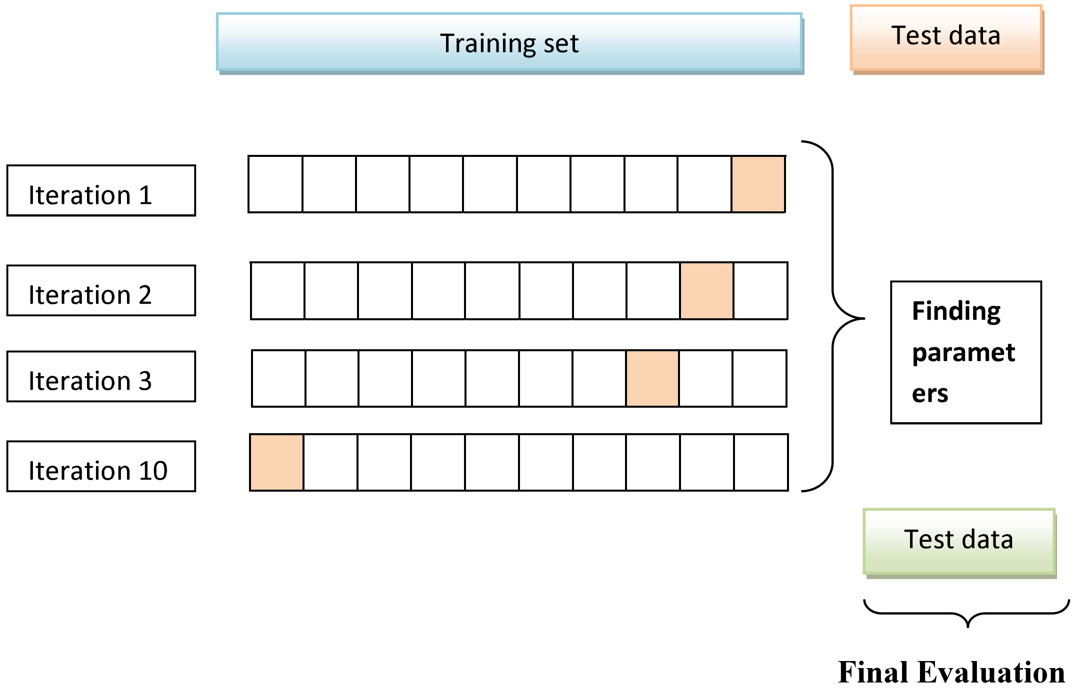


Fig 4.4 10 fold Cross validation

The novel algorithm proposed herein lists of the subsequent phases.

Step 1. The algorithm begins with preprocessing step.

Step 2. Then all machine-learning algorithms (say *n*) are defined for training (machine learning models of level *L1*).

Step 3. Let $m(m<n)$ be the maximum count of *L1* models that are combined by the level *L2* model

Step 4. Randomly generate an initial population of cuckoo eggs defining both Level *L1* and Level *L2* models.

Step 5. Evaluate their respective fitness based on evaluation parameter.

Step 6. Apply Cuckoo Search algorithm for predefined set of iterations

The proposed framework of the algorithm is stated in the figure 1. The following paragraphs gives the description of each machine learning task for activity recognition.

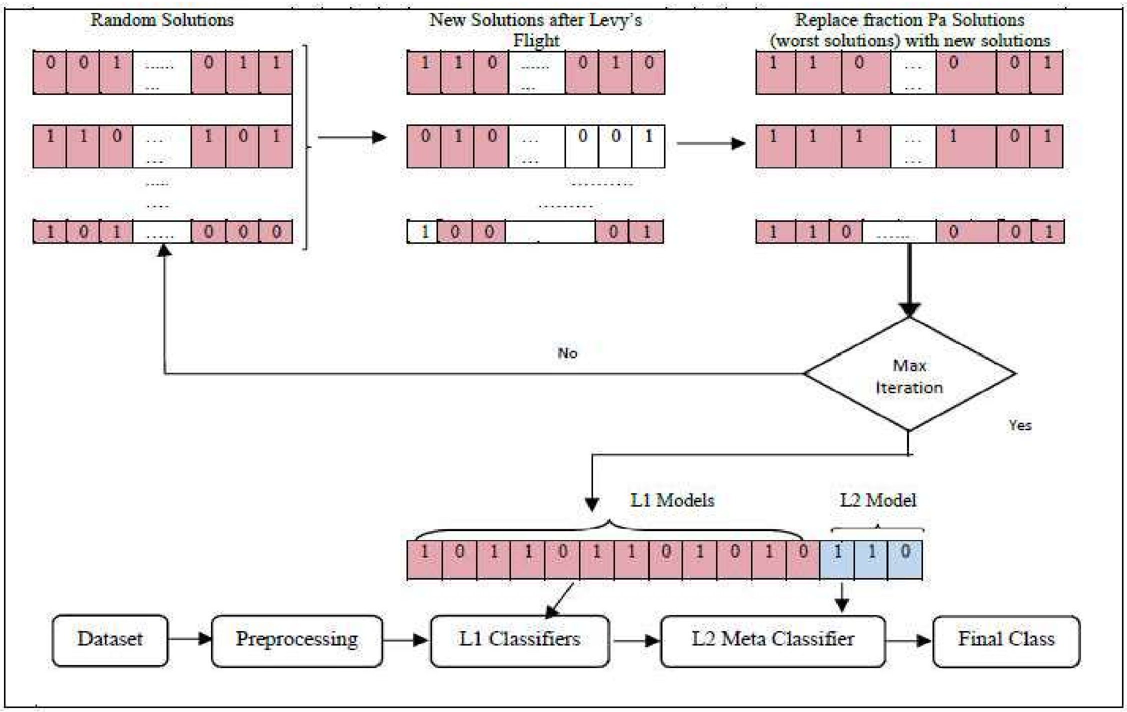


Fig. 4.5 The Proposed Framework

A. Solution Space

Given set *C*of *'n'* base classifiers{ $C_1, C_2, C_3 \ldots C_n$}, the solution space *S* consists of a set of all possible configurations of the *'m'* base classifiers € C where $m<n$ and one meta classifier M_t€ *C*. Let *b*- is number of bits such that $n=2^b$Then the different combinations in solution space are as in (1)

$$S = 2^{b(m+1)} \tag{4.1}$$

Even in the simplest case, the configuration space increases exponentially with the count of base classification techniques and meta classifiers. The job of finding the best model for configuration space is NP-hard problem. Such configuration will require a lot of time even for a small set of classifier. The same problem can be solved easily with meta- heuristic approach by finding the solution in equitable amount of time. Figure 2 represents the flow of the methodology used. The work employs the L1-level (base) classfiers with subsequent application of the L2-level(meta) classiferto predict the output from the earlier first-level predictions via 10 fold cross-validation.

B. Cuckoo Search Metaheuristic

The work utilizes the Cuckoo search meta-heuristic for solving the combinatorial optimization problem. This algorithm is based upon the parasitic behavior of cuckoos that lay their eggs in the other birds nest. The eggs are similar to the host bird eggs. In case the host bird recognize alien eggs, the bird either quits the nest or throw away the eggs. Based on the parasite behavior of cuckoos, the authors [23] proposed a novel meta-heuristic optimization algorithm named Cuckoo search algorithm. In this meta heuristic approach, every nest represents one solution. The algorithm tries to generate new improved cuckoo eggs/solutions by replacing weak eggs/less-fit solutions. The detailed pseudo code of the proposed model for recognizing human activity in indoor environment is given in Figure 4. The main sections of the pseudo code are as follows.

*Population Representation:*The solution is encoded in the format such that it contains information about the base classifier well as meta classifier to be used. Every solution in the population is denoted by a combination of zeros and ones where in different *b* -set of bits represent the each of *'m'* classifiers (acting as a base classifier for level 0) and the last *b* bits classifier (level 2) for stacking purpose. The structure of solution $X_{i,j}^{k}$ is represented as in figure3.

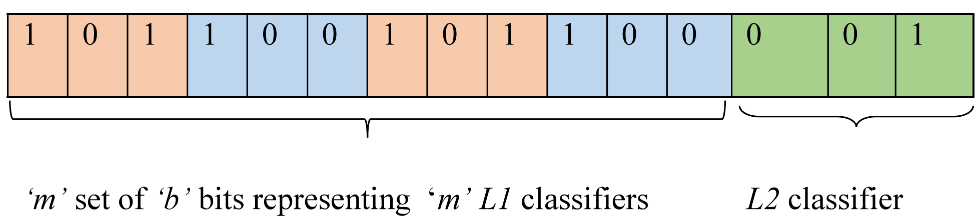


Fig. 4.6 Solution Representation

The eq (4.2) is used to restrict new solutions to binary only.

$$Z(X_{i,j}^{k}) = \frac{1}{1+e^{X_{i,j}^{k}}} \text{ and } X_{i,j}^{k+1} = \begin{cases} 1, & \text{if } Z(X_{i,j}^{k}) < \hat{u} \\ 0, & \text{otherwise,} \end{cases} \quad (4.2)$$

where $\hat{u} \sim U(0,1)$ &$X_{i,j}^{k}$ represents the solution at generation k.

*Generate New Solutions by Lévy Flight:*The levy flight is used to obtain the new solution from the i^{th}randomly chosen solution as in (4.3).

$$X_{i,j}^{k} = X_{i,j}^{k-1} + \alpha \times L \times (X_{i,j}^{k-1} - Optimal\_X_{i,j}) \quad (4.3)$$

where $X_{i,j}^{k}$ the new solution which is generated using Lévy flight; $X_{i,j}^{k-1}$ represents randomly selected solution from the population; α is step size; $\text{Optimal\_X}_{i,j}$ denotes the best solution so far found; and L is the Lévy flight vector or step length. After getting the new solution,the solutions are compared based on the fitness values and the solution with high fitness is kept in the population for further processing.

Discovery of Alien Eggs: Within the population, for every cuckoo egg, foreign eggs are recognized using probability matrix, which is represented as in (4.4)

$$\rho_{i,j} = \begin{cases} 1, & \text{if random}(0,1) < \rho \\ 0, & \text{otherwise,} \end{cases} \quad (4.4)$$

where $\rho_{i,j}$ is probability of discovering alien eggs in the i^{th}solution for the j^{th} variable of cuckoo's dimension.

The comparison of ρ is performed with the outcome of $\text{random}(0,1)$(a uniform random number generator), to check if local random walk is given consideration or not. After determining the discovering probabilities, new solutions are obtained using (4.4).

$$X_{i,j}^{k} = X_{i,j}^{k-1} + LS \times \rho_{i,j} \quad (4.5)$$

where$\rho_{i,j}$signifies the probability matrix and *LS*matrix is local step size, which is obtained by using the formula (4.5).

$$\mathbf{LS} = \mathbf{rand}(\mathbf{0},\mathbf{1}) \times (\mathbf{rand\_perm}(\mathbf{Solution}(\mathbf{i}))\mathbf{rand\_perm}(\mathbf{Solution}(\mathbf{j}))) \quad (4.6)$$

where $\text{rand\_perm}()$ is used to shuffle the solution randomly

If the fitness values(using objective function) of new solution is better than the existing one, the new solution replaces the old one in subsequent iteration The whole steps of solution generation and finding alien eggs is repeated till the maximum number of iterations

Input: Read the dataset(D*S*), Max iterations (G), population size(N), Loss Parameters $(\alpha$ & $\rho)$, Dimensions of Solution (D), **Output*:*** Cuckoo's Solution with best fitness(High Accuracy), Test dataset with Set of Classes C = {Sitting , Walking, Standing, Custom)
Begin:

For each Host Nest in the population, $i = 1: N$

Forevery dimension of egg in Host Nest, $j = 1: D$

Random initialization of cuckoo egg i.e. Solution,$X_{i,j}^{0}$

Fitness $\_i^{th}$ Solution = ∞

End For

End For

While (iterations$< G$)

For every cuckoo egg nest ,$i = 1: N$

New Solution NX_i $Fitness\ FT$ ← Calculate_fitness (DS,X_i^{g-1});

End For

For every cuckoo egg nest, $i = 1: N$

For every dimension of egg in Host Nest, $j = 1: D$

$$X_{i,j}^{g} \leftarrow X_{i,j}^{g-1} + L\acute{e}vy\ Flight\ (as\ in\ (2));$$

End For

New_X_i ← Cuckoo_Fit (DS,X_i^g, FT$_i$);

End For

For each Host Nest, $i = 1: N$

For each dimension of egg in Host Nest, $j = 1: D$

Generate local step size, LS using (5) and $\rho_{i,j}$ using (3)

$$X_{i,j}^{g} = X_{i,j}^{g-1} + LS * \rho_{i,j}, (as\ in\ (4));$$

End For

New_X_i ← Cuckoo_Fit (DS, X_i^g, FT$_i$);

End For

End While

End

Algo 4.1The proposed approach

4.4 Methodology of Cuckoo search Algorithm

Step 1: Generate the initial population Si of n host nests.

Step 2: Get a cuckoo randomly by using levy flight. Evaluate the fitness of the cuckoo's eggs with the host eggs.

Step 3: If the fitness of the cuckoo's egg is better than the host's egg then replace the egg in nest k with cuckoo's eggs.

Step 4: If host bird notice it, the nest is abandoned and buit the new one. The worst solutions are abandoned.

Step 5: Find the best solutions and rank them

Step 6: If rank is less than maximum generated value then post- process the results.

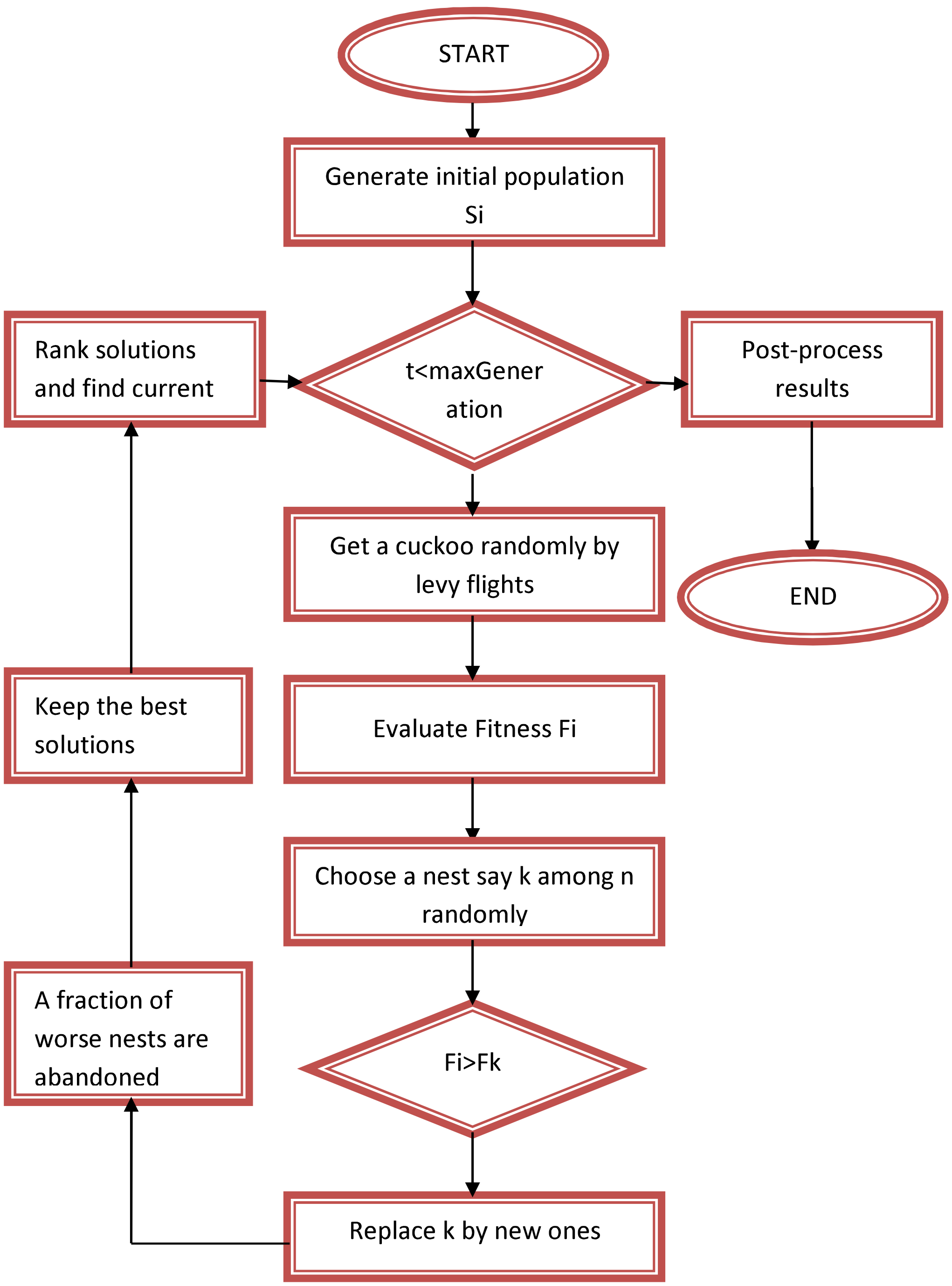


Figure 4.7 Basic Cuckoo search methodology

4.5 Performance parameters

- **Accuracy**

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4.7}$$

- **Recall**

$$Recall = \frac{TP}{TP+FN} \tag{4.8}$$

- **Precision**

$$Precision = \frac{TP}{TP+FP} \tag{4.9}$$

- **F1 score**

$$F1\ Score = \frac{2*Precision*Recall}{(Precision+Recall)} \tag{4.10}$$

Here TP stands for True Positive, FP for False Positive, TN for True Negative and FN for False Negative which can be obtained by drawing a confusion matrix. It is used to define the performance of model by taking actual values and predicted values and is displayed in the form of matrix as shown below in table 4.2:

Table 4.2. Confusion Matrix

		Predicted	
		Negative	Positive
Actual	Negative	TN	FP
	Positive	FN	TP

4.6 Summary

In this chapter, proposed framework binary cuckoo search based stacking using several machine learning models Logistic Regression, MLP, SVM (linear kernel),KNN, Random Forest, Decision Tree, SGC and Naïve Bayes is explained in detail. The performance parameters required are also discussed.

Chapter 5

Implementation and Experimental Results

This chapter discuss about the experimental setup for the proposed framework as well as implementation and results.

5.1Experimental Results

5.1.1 Minimum Software and Hardware requirement

Table 5.1 H/W and S/W requirements

1	PROCESSOR	i7
2	RAM	8 GB
3	HARD DISK	80 GB
4	OPERATING SYSTEM	WINDOWS 10
5	PROG. LANG	PYTHON

5.1.2 Implementation of Classification algorithms

The implementation of the classification algorihms is done in python language using the methods and adding libraries like sklearn.tree, sklearn.svm and many more. Table 5.1 presents the detailed information about the methods, libraries and tuning parameters.

TABLE 5.1 THE MODELS WITH TUNING PARAMETERS

Model	Method	Libraries	Tuning parameters
MLP	MLPClassifier()	sklearn.neural_netw ork	neighbours=30, Committees=10
Decision Tree	decisionTreeClassifier( )	sklearn.tree	minsplit = 20, minbucket =7, maxdepth=30
KNN	kNeighborsClassifier()	sklearn.neighbors	n_neighbors=0.05
SGD	SGDClassifier	sklearn.linear_model	None
Naïve Bayes	nnet()	sklearn.naive_bayes	maxit=100, hlayers=10, MaxNWts=1000
Random Forest	RandomForestClassifie	sklearn.ensemble	mtry=3, importance=TRUE

	r()		
Support Vector Machine	LinearSVC()	sklearn.svm	nu=10, epsilon=0.5
Logistic Regression	LogisticRegression()	sklearn.linear_model	Penality='l2',C=0.31, random_state=0

5.2 Results

The proposed ensemble recognition model reveals its dominance in comparison to classic base models, and the predictive strength of the developed ensemble model highlights its superiority in human activity recognition in contrast to the classical models.

- The proposed ensemble predictive analytic model combines the qualities of individual prediction models for better prediction and consistent results.
- The ensemble approach is appreciably performing better than the best performing model (Random forest) of base models.
- The superiority of the novel ensemble recognition model is validated well on the SPHERE dataset containing the feature set gathered through the accelerometer sensor.

Table IV presents average values of precision, recall and F-measure for executing various models for 10 runs using 10 fold cross-validation. The results are shown for each activity. The main evaluation parameter used in this work is predictive accuracy. The proposed cuckoo search based stacking model gives best performance, giving high recognition rate for all the considered activities. It gives a 0.962 precision value and a 0.975 recall value for the sitting activity.

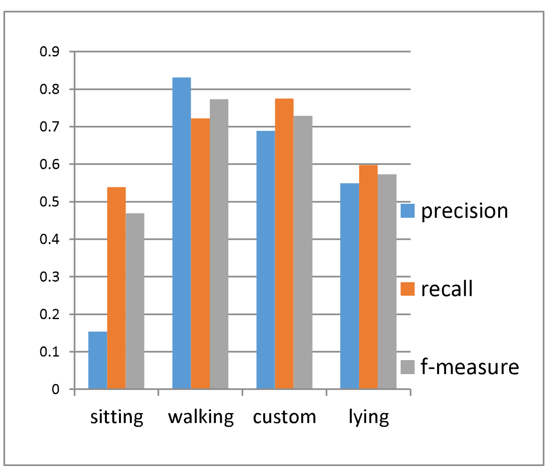
Table 5.2 Comparative results of performance metrics for indoor activity recognition

Model	Activity	Precision	Recall	F-measure	Accuracy (%)
Logistic Regression	Sitting	0.539	0.469	0.502	
	Walking	0.831	0.722	0.773	63.1609
	Custom	0.689	0.775	0.729	
	Lying	0.549	0.598	0.573	

	Weighted average	0.633	0.632	0.630	
Multilayer Perceptron	Sitting Walking Custom Lying	0.753 0.918 0.861 0.744	0.734 0.876 0.838 0.803	0.744 0.896 0.849 0.772	80.6036
	Weighted average	0.808	0.806	0.807	
Support Vector Machine (linear kernel)	Sitting Walking Custom Lying	0.528 0.831 0.672 0.558	0.497 0.719 0.759 0.568	0.512 0.771 0.713 0.563	62.594
	Weighted average	0.628	0.626	0.625	
K Nearest Neighbor	Sitting Walking Custom Lying	0.867 0.937 0.847 0.844	0.852 0.866 0.893 0.856	0.859 0.900 0.869 0.850	86.6198
	Weighted average	0.867	0.866	0.819	
Random forest	Sitting Walking Custom Lying	0.918 0.925 0.901 0.916	0.934 0.927 0.895 0.905	0.926 0.926 0.898 0.911	91.4364
	Weighted average	0.915	0.91525	0.91525	
Decision tree	Sitting Walking Custom Lying	0.922 0.927 0.897 0.904	0.928 0.922 0.889 0.910	0.925 0.924 0.893 0.907	91.1245
	Weighted average	0.9125	0.91225	0.91225	
Stochastic Gradient Classifier	Sitting Walking Custom Lying	0.895 0.924 0.908 0.889	0.913 0.925 0.876 0.900	0.904 0.924 0.892 0.895	90.1672
	Weighted average	0.904	0.9035	0.90375	
Naïve Bayes	Sitting Walking Custom	0.702 0.781 0.815	0.754 0.799 0.697	0.727 0.790 0.751	75.6515

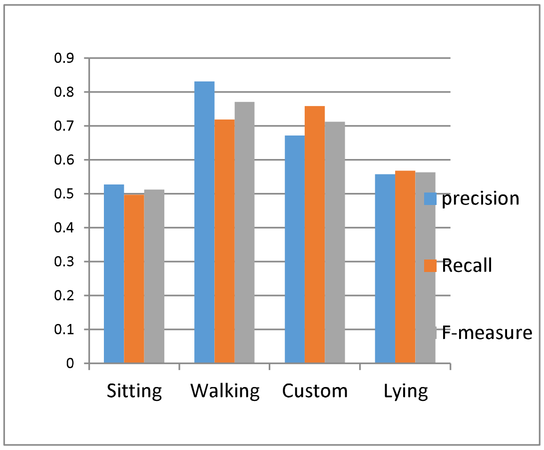
	Lying	0.751	0.790	0.770	
	Weighted average	0.751	0.790	0.770	

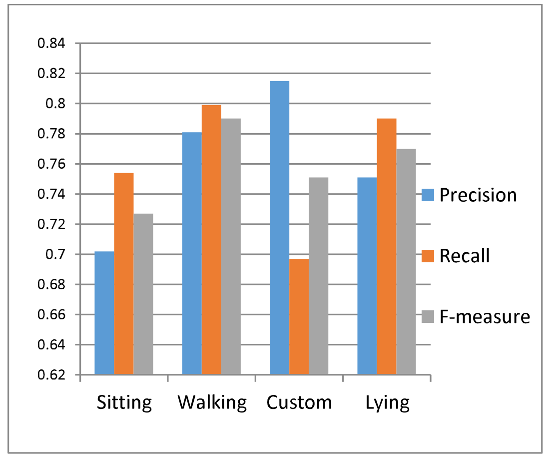
Furthermore, in the lying activity, the recognition reaches good precision (0.932) and recall (0.924) values. Marginally inferior performances are obtained with regard to custom activity i.e. 0.912 of precision and 0.907 of recall. In comparison to the base learners, the proposed approach gives best performances with an accuracy of 93.77%.Figure 5 (i-viii) shows the performance of classification models in recognizing each activity. Four classifiers (Random Forest Tree, SGD, Decision tree Classifier(DT) and KNN) among eight have good precision and recall values in each user activity. In case of precision, again, RF and DT are having good values of precision in comparison to KNN and SGD. KNN is the worst performer for all activities except sitting, where KNN shows better performance in terms of precision (0.937) than RF and DT. The models RF and DT have comparable results with better recall values in comparison to KNN and SD for all activities. Among all these, Logistic regression model is the worst performer in terms of all evaluation parameters. Figure 5(viii) depicts that the proposed method i.e. cuckoo search based stacking model shows excellent performance in recognizing all the activities, giving highest precision and recall values.



(i) Logistic Regression

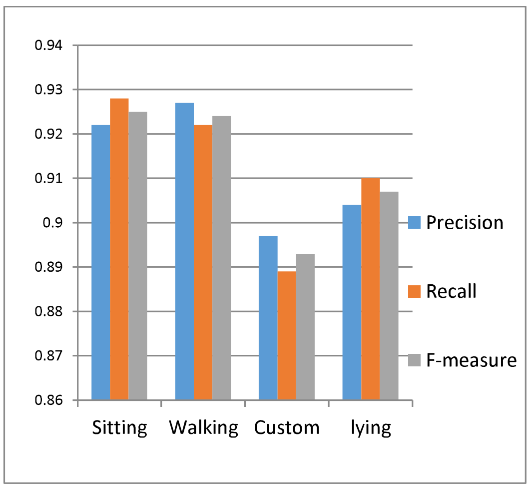
(ii) Multi Layer Perceptron



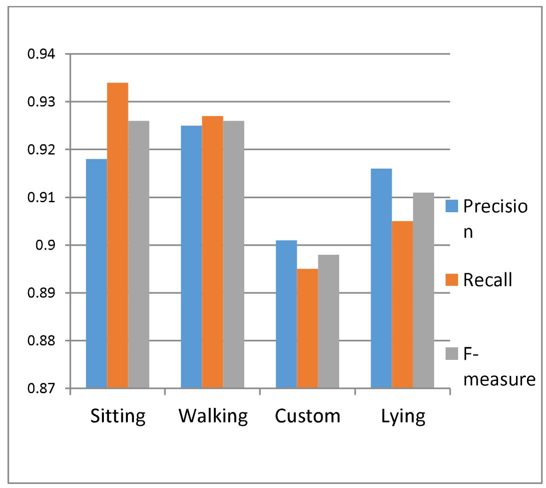


(iii) Support Vector Machine

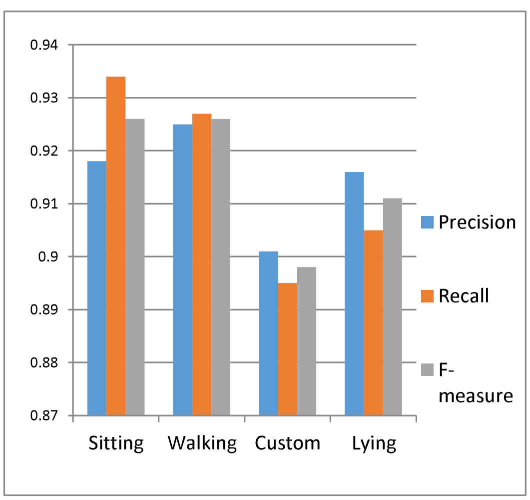
(iv) Naïve Bayes



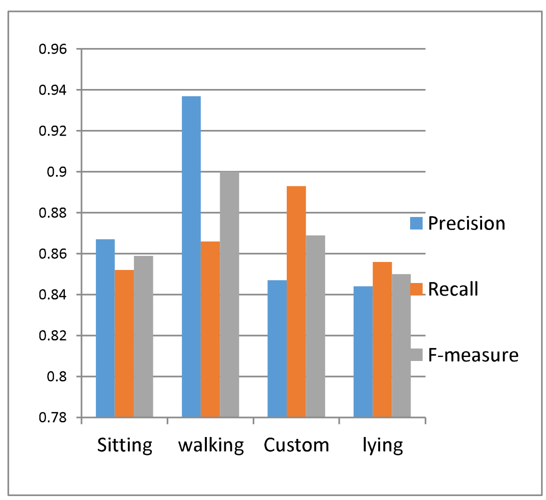
(v) Decision Tree



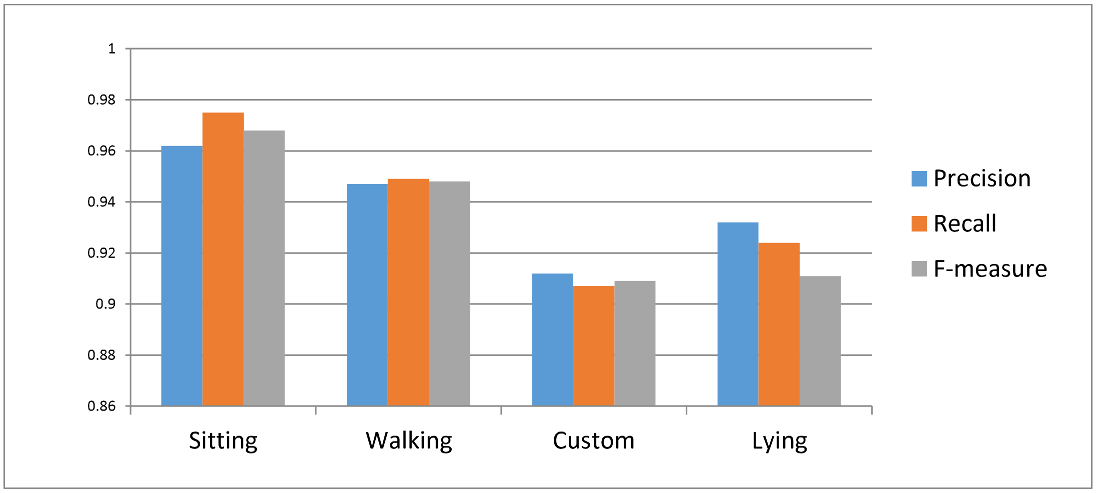
(vi) SGD



(vii) Random Forest



(viii)K Nearest Neighbour



(viiii)The proposed approach

Fig. 5.1. (i-viiii) The average precision, recall and F measure values for 8 base classifiers and proposed approach

The performance comparison of all the considered models and proposed model is graphically visualized by drawing boxplot [33]. It depicts the empirical distribution of the data. Fig. 5.2 (i, ii, iii) represents the boxplot for existing and proposed models. In this plot, the name of the models is represented by the x-axis and y-axis labels the corresponding parameter under consideration. It is observed from the boxplots that the proposed model gives better and consistent results in comparison to other models. for the considered performance metrics. The reason is that the proposed model explores optimal combinations of learning scheme. The stability of the models is also achieved due to the absence of outliers. The boxplot reveals that even the minimum precision value achieved by the proposed model is higher than the maximum precision values of other models. It is also depicted that the proposed model performed better than base models in terms of recall and f-measure.

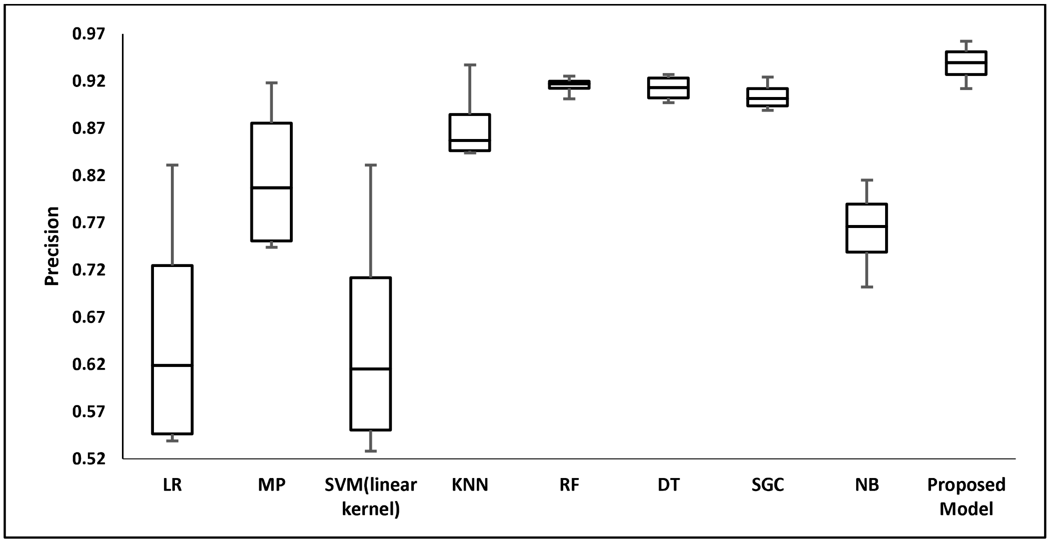


Fig. 5.2. (i) Precision value of base classifiers and proposed approach

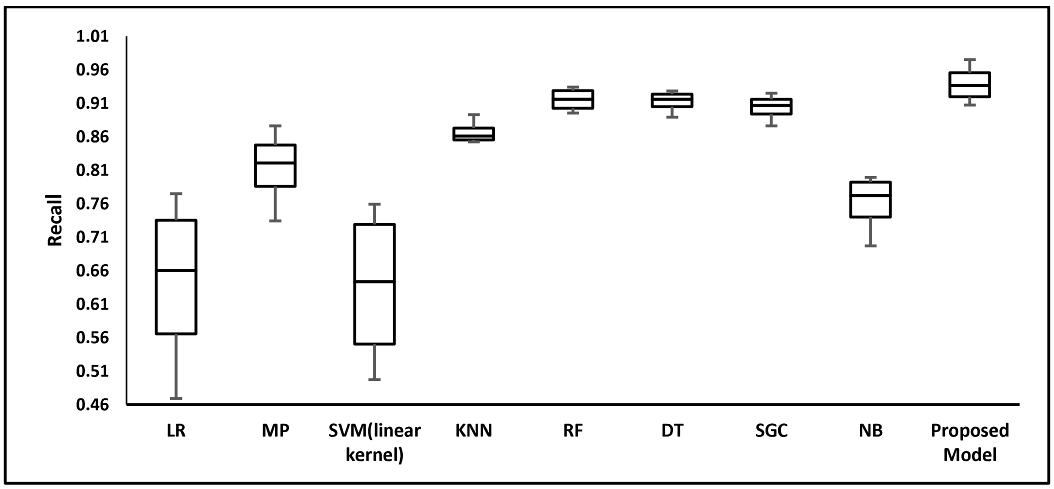


Fig. 5.3 Recall value of base classifiers and proposed approach

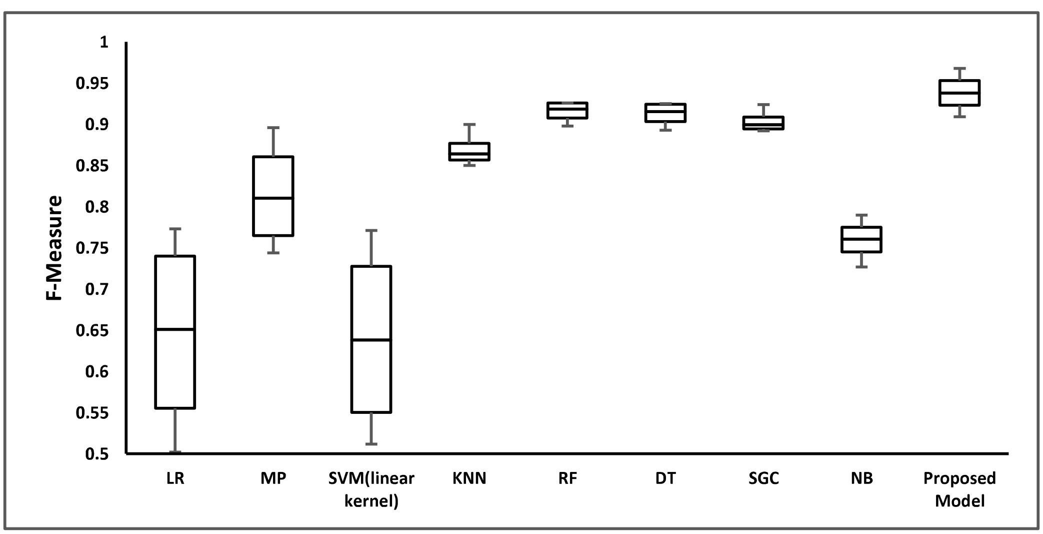


Fig. 5.4 F -measure of base classifiers and proposed approach

Figure 5.4 depicts the accuracy rate of the experimented classification models. The models RF, DT and SGD showcase almost same accuracy value of about 0.90 whereas SVM and logistic regression are worst performer with accuracy value (approx. 0.60). It is clear from the figure that the proposed model achieved highest average accuracy rate of approximately 93.7% for classifying human activities via 10-fold cross validation. The results showcase the effectiveness of the metaheuristic based stacking ensemble approach in exploring all possible configurations in contrast to the base learners.

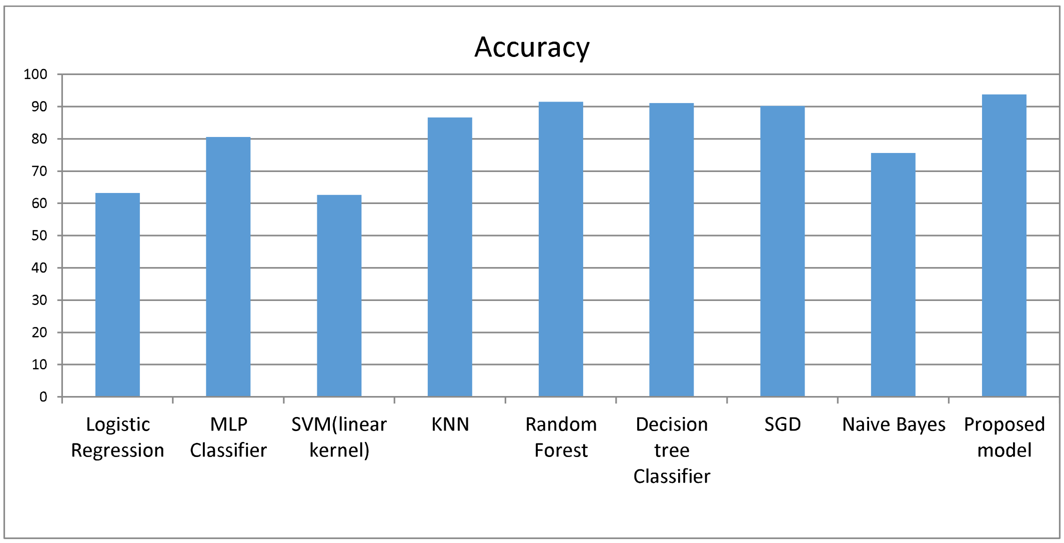


Figure 5.5 Comparative analysis of accuracy values of proposed model with base classifiers

5.3 Summary

This chapter provides implementation of machine learning algorithms and also discussed about various parameters like accuracy, precision, recall and f-measure of the algorithms and compare them to the proposed approach.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

In this thesis, a novel model is proposed based on selection of right choice of classification models to recognize the human activities from the data collected from the accelerometer sensor. For the purpose of human activity recognition experiments are conducted with eight different classifiers. These classifiers are Logistic Regression, MLP, SVM (linear kernel),KNN, Random Forest, Decision Tree, SGC and Naïve Bayes. Among eight classifiers Random forest proven to give best results with accuracy of 91.4 %. In comparison to the base learners, the proposed approach gives best performances with an accuracy of 93.77%. The resultant model utilizes the power of base learners by trying different configuration of base-classifiers and meta-classifier using cuckoo search metaheuristic .

6.2 Future Scope

The resultant efficient configuration is further exploited to recognize the activity on test bed. The proposed model outperformed the base leaners in terms of accuracy. The work can be further extended by tuning the parameters of the classifiers using metaheuristic approaches .The work may be further enhanced by augmenting the feature set from the fetched instances of gyroscope sensor and fine recordings from the GPS sensor to recognize activity within a locality

References

[1] Alemdar, H. and C. Ersoy, “Wireless Sensor Networks for Healthcare: A Survey”, Computer Networks, Vol. 54, No. 15, pp. 2688–2710, 2010.

[2] Why Population Aging Matters: A Global Perspective, Tech. rep., National Institute on Aging, U.S. Department of Health and Human Services, 2007.

[3] Montori, Federico, Luca Bedogni, and Luciano Bononi. "A collaborative internet of things architecture for smart cities and environmental monitoring." IEEE Internet of Things Journal5.2 (2018): 592-605

[4] Wannenburg, Johan, and Reza Malekian. "Physical activity recognition from smartphone accelerometer data for user context awareness sensing." *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 47.12 (2016): 3142-3149.

[5] Liu, Ye, et al. "From action to activity: sensor-based activity recognition." *Neurocomputing* 181 (2016): 108-115.

[6] He, Suining, and S-H. Gary Chan. "Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons." IEEE Communications Surveys & Tutorials 18.1 (2016): 466-490.

[7] Chang, Ning, Rashid Rashidzadeh, and Majid Ahmadi. "Robust indoor positioning using differential Wi-Fi access points." *IEEE Transactions on Consumer Electronics* 56.3 (2010): 1860-1867.

[8] Yang, Xin-She, and Suash Deb. "Cuckoo search via Lévy flights." *2009 World Congress on Nature & Biologically Inspired Computing (NaBIC)*. IEEE, 2009.

[9] L. Atzori, A. Iera, and G. Morabito, “The internet of things: A survey,” Comput. Netw., vol. 54, no. 15, pp. 2787–2805, 2010.

[10] Cedillo, Priscila, et al. "A systematic literature review on devices and systems for ambient assisted living: Solutions and trends from different user perspectives." 2018 International Conference on eDemocracy& eGovernment (ICEDEG). IEEE, 2018.

[11] J. W. Lockhart, T. Pulickal, and G. M.Weiss, Applications of mobile activity recognition, in Proc. 14th Int. Ubiquitous Computing Conf., Seattle, USA, 2012, pp. 1054-1058.

[12] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin- Perianu, and P. Havinga, Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey, in Proc. 23rd Int. Architectureof Computing Systems Conf., Hannover, Germany, 2010, pp. 1-10.

[13] O. D. Lara and M. A. Labrador, A survey on human activity recognition using wearable sensors,Communications Surveys & Tutorials, IEEE, vol. 15, no. p. 1192-1209

[14] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell, A survey of mobile phone sensing, Communications Magazine, IEEE, vol. 48, no. 9, pp. 140-150, 2010.

[15] Gavrila, D. M. The visual analysis of human movement: A survey. Computer Vision and Image Understanding. Vol.73.1, p. 82-98, 1999.

[16] Ehreumann, M., Lutticke, T., and Dillmann, R. Dynamic gestures as an input device for directing a mobile platform. In Robotics and Automation, 2001. Proceedings 2001 ICRA. IEEE International Conference. IEEE, Vol.3, p. 2596-2601, 2001

[17] Botts N, Thoms B, Noamani A, Horan TA: Cloud computing architectures for the underserved: public health cyberinfrastructures through a network of health ATMs**.** *System Sciences (HICSS), 2010 43rd Hawaii International Conference on;5–8Jan. 2010* 2010, 1-10.

[18] Choudhury, Tanzeem, et al. "The mobile sensing platform: An embedded activity recognition system." *IEEE Pervasive Computing* 7.2 (2008): 32-41.

[19] Gu, Tao, et al. "Mining emerging patterns for recognizing activities of multiple users in pervasive computing." *2009 6th Annual International Mobile and Ubiquitous Systems: Networking & Services, MobiQuitous*. IEEE, 2009.

[20] Khan, A. M., Lee, Y. K., and Lee, S. Y. Accelerometer's position free human activity recognition using a hierarchical recognition model. In e-Health Networking Applications and Services (Healthcom). 12th IEEE International Conference, p. 296-301, 2010.

[21] Tegou, Thomas, et al. "A Low-Cost Indoor Activity Monitoring System for Detecting Frailty in Older Adults." Sensors 19.3 (2019): 452.

[22] Markopoulos, Panos, Sivan Zlotnikov, and Fauzia Ahmad. "Adaptive Radar-Based Human Activity Recognition with L1-Norm Linear Discriminant Analysis." IEEE Journal of Electromagnetics, RF and Microwaves in Medicine and Biology (2019).

[23] Zhou, Baoding, Jun Yang, and Qingquan Li. "Smartphone-Based Activity Recognition for Indoor Localization Using a Convolutional Neural Network." Sensors 19.3 (2019): 621.

[24] Wang, Wei, et al. "Understanding and modeling of wifi signal based human activity recognition." Proceedings of the 21st annual international conference on mobile computing and networking. ACM, 2015.

[25] He, Suining, and S-H. Gary Chan. "Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons." IEEE Communications Surveys & Tutorials 18.1 (2016): 466-490.

[26] Nweke, Henry Friday, et al. "Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions." Information Fusion 46 (2019): 147-170.

[27] Zhu, Ran, et al. "Deep Ensemble Learning for Human Activity Recognition Using Smartphone." 2018 IEEE 23rd International Conference on Digital Signal Processing (DSP). IEEE, 2018.

[28] Hu, Jie, Yu Kong, and Yun Fu. "Activity recognition by learning structural and pairwise mid-level features using random forest." *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*. IEEE, 2013.

[29] Anguita, Davide, et al. "Human activity recognition on smartphones using a multiclass hardware-friendly support vector machine." *International workshop on ambient assisted living*. Springer, Berlin, Heidelberg, 2012.

[30] Catal, Cagatay, et al. "On the use of ensemble of classifiers for accelerometer-based activity recognition." *Applied Soft Computing* 37 (2015): 1018-1022.

[31] Nweke, Henry Friday, et al. "Deep learning algorithms for human activity recognition using mobile and wearable sensor networks: State of the art and research challenges." *Expert Systems with Applications* 105 (2018): 233-261.

[32] https://github.com/rymc/a-dataset-for-indoor-localization-using-a-smart-home-in-a-box.

[33] Castilla, Elena, Nirian Martín, and Leandro Pardo. "A logistic regression analysis approach for sample survey data based on phi-divergence measures." *The Mathematics of the Uncertain*. Springer, Cham, 2018. 465-474.

[34] Zhang, Yudong, et al. "A multilayer perceptron based smart pathological brain detection system by fractional Fourier entropy." *Journal of medical systems* 40.7 (2016): 173.

[35] Guenther, Nick, and Matthias Schonlau. "Support vector machines." *The Stata Journal* 16.4 (2016): 917-937.

[36] Brindha, S., K. Prabha, and S. Sukumaran. "A survey on classification techniques for text mining." *2016 3rd International Conference on Advanced Computing and Communication Systems (ICACCS)*. Vol. 1. IEEE, 2016.

[37] Jadhav, Sayali D., and H. P. Channe. "Comparative study of K-NN, naive Bayes and decision tree classification techniques." *International Journal of Science and Research (IJSR)* 5.1 (2016): 1842-1845.

[38] Sagi, Omer, and Lior Rokach. "Ensemble learning: A survey." *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery* 8.4 (2018): e1249.

[39] Zhang, Le, and Ponnuthurai N. Suganthan. "A survey of randomized algorithms for training neural networks." *Information Sciences* 364 (2016): 146-155.

[40] Kharde, Vishal, and Prof Sonawane. "Sentiment analysis of twitter data: a survey of techniques." *arXiv preprint arXiv:1601.06971* (2016).

List of Publications

[1] **Gurpreet Kaur, Dr. Maninder Kaur, "**Binary Cuckoo Search Metaheuristic-based Supercomputing Framework for Human Behavior Analysis in Smart Home", Journal of SuperComputing.