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# Abstract

In theory, activity recognition has enormous potential for social advantages, particularly in practical, human-centered fields like elder assistance and healthcare. It can be difficult to identify human activity from video or still photos because of issues such backdrop clutter, partially occlusion, variations in scale, viewpoint, lighting, and look. A multiple activity recognition system is essential for numerous applications, such as video monitoring systems, human-computer interface, and robotics for characterizing human behavior. The proposed study focused on the recognition of human activities using the sensory data. For the activity recognition of human objects, we train the different machine learning models. After the training of the all-machine learning models, accuracy, precision, recall and f1-score were calculated for each model. The comparative study was also performed for the evaluation of the models. Best model was selected on the bases of highest accuracy score.

# Introduction

Observing physical activity and recognizing body movements is helpful in a variety of contexts, such as the creation of individualized weight check strategies and the treatment of patients in surroundings involving free-living, especially in an environment where the subject can be moved easily without the constraint of movement by sensors on the body. Hiking, sprinting, racing, and other vibrant movements are examples of physical activity, as are stationary positions like resting, holding, etc. The functioning condition of people can be tracked by low-cost wireless detectors in advanced environments in the real world with different electronic sensors implanted in their daily life routines to analyze various elements of their lives. Several demographics, particularly healthy people and people with different conditions, can benefit from acceleration-based activity monitoring.

Owing to physical inaction, obesity is a disease and condition that is becoming a severe medical issue for a global population [1]. It is growing in importance as a matter of people's health in both developing and growing nations. The WHO (World Health Organization) reports that the prevalence of obesity has nearly doubled since 1980 [2]. According to the WHO, obesity affects an additional 10% of people worldwide. Preventive measures to combat the obesity problem include healthy food and increased daily physical activity. Both nutrition and exercise are said to be significant influencing factors in the research [3-5]. Several dietitians and medical professionals use self-completed questions to track the patient's physical activity levels [6]. To measure various levels of activity among the population, the physical activity rating depends on questionnaires that have also been developed [7]. Observing physical activities can also give information about the user's purpose to advance walking assistance systems and contextual understanding of human-computer interaction technologies [8].

The utilization of self-recorded data to track people's everyday physical activities is laborious and challenging. As a result, there have been a lot of studies over the past 20 years on the use of wearable detectors to track everyday physical activity. In the past ten years, the use of acceleration detectors for human activity monitoring has grown, and even more precise and affordable electronic sensors have become accessible thanks to the development of the Micro Electro-mechanical System (MEMS) innovation [9]. To enable a more thorough, smart in-home surveillance of physical activity, acceleration dependent monitoring methods can be integrated. Gubbi et al. [10] kept track of the exercise routines of stroke patients. Additional health uses for the acceleration electronic sensors include classifying the type of muscular activation [11].

By using a single tri-axial electronic sensor, which is an acceleration-based sensor positioned at the hips, [12] researchers developed the framework of the binary decision tree for the classification of multiple human activities, including rest, walking, and falling. The discrete wavelet transform was used by [13] to categorize various forms of movement, such as walking on a level surface, ascending steps, and descending stairs. By installing multiple sensors on the human body, several systems studied the classification of different physical activities. There are five acceleration electronic sensors that were attached to the subject's shoulder. Various machine learning methods were utilized in order to classify seven distinct kinds of physical activity in order to categorize six distinct sorts of activities, they attached several smart sensors to multiple body placements (wrists, waist, collar, trousers sleeve, jacket pockets, and handbag), reporting accuracy of 80% to 92% for a varied combination of characteristics and locations.

An intriguing summary of accelerometer-related physical activity monitoring was presented by [14]. Using the automated decision tree-based classifier [15] showed an overall average categorization accuracy of 86% while classifying seven different operations (sleeping, rowing, biking, sitting, standing up, running, Nordic walking, and walking). They were utilizing both acceleration detectors, one on the chest as well as the other on the wrist. Multifunctional acceleration detectors of the seven various body regions were utilized to identify thirteen diverse things. The Bayesian classifier was used to achieve a classification accuracy of nearly 90%, employing characteristics from statistical, temporal, and sensitive attributes. They provide an excellent assessment of various wearable sensor-based physical activity wearables.

Employing various time-domain characteristics, twelve multiple activity types (lying down, sit-down, stand-up, bicycling, Nordic walking, climbing and climbing steps, vacuuming, pressing clothing, and jumping the ropes) are categorized in this study. A rotating forest classifier is utilized to categorize physical activities. Correlation-dependent feature selection allows for efficient feature list reduction. In order to show the overall efficiency of the suggested methodology, the outcomes given in this study are finally contrasted with data from other studies.

## Background

The aim of different activity recognition is just to identify the present human physical action being carried out by one or maybe more than one user from the collection of observations that were made while users were engaged in their activities inside the defined area. The idea of Human Activity Recognition (HAR) has recently been adapted to a variety of difficult applications based on the rise of omnipresent, accessible, and compelling technology. Human movement identification has developed into a significant technology that is transforming how individuals go about their everyday lives and influencing a broad range of various applications, including automatic surveillance, assistance technology, healthcare, wellness monitoring, and senior citizen care, to mention a very few. Furthermore, because action recognition technology has developed so quickly and extensively, it is now beginning to support various applications that go beyond human action recognition. Nevertheless, because this field has so many useful and important applications, there are many new difficulties with activity recognition.

The human activity recognition challenge's standard methodology involves collecting some important data from mounted external digital cameras and wearable sensors. The dataset is cleaned up and modified to make it ready for exploitation later. The data is examined to determine the nature of the data and the kind of procedure that can be used in all subsequent steps. Depending on the application or its area, the architecture of further stages may differ greatly. But often, this data is processed to add further useful qualities, which makes it even more applicable. Additionally, the material is divided into segments based on the evaluation that must be done. Eventually, a prediction algorithm is developed to track user behaviors, and its effectiveness is assessed. These identified activities can be used for a variety of purposes, such as identifying changes in user behavior and providing support for the observed action.

## Problem Statement

It seems like the straightforward process of executing HAR is fraught with problems, including difficulties in choosing appropriate techniques and methods for acquiring, organizing, and manipulating data. Choosing the appropriate models to do projections is crucial since it is necessary to account for both intra-class similarities as well as inter-class diversity. Common resource limitations, including processing speed, a limitation of time, or adequate memory, are challenging to manage and present a significant barrier. Additionally, the trade-off regarding processing capability, including accuracy, and overall system latencies is necessary.

The early phases of developing HAR deal with an entirely distinct list of problems. The correct detector, or set of such sensors, has certain qualities and measures to be monitored, and the placement of sensors is indeed important in its own specific ways. Additionally, all of this must be accomplished while keeping consumers' privacy and convenience in mind. Even though the entire procedure might be extremely sensitive to user involvement and engagement, it is not intrusive for users and adapts to their behavior and surroundings.

The following is a succinct statement of the research topic that is addressed by the current studies.

How much do these supervised machine-learning-based algorithms, particularly contrasted with SVM standard models, considerably improve the detection of actual physical human activities with different sensor-based data? The supervised machine learning algorithms are logistic regression, decision tree, random forest, naive Bayes, AdaBoost, and K-Nearest Neighbor.

## Research Objectives

Considering and assessing all previous research, choosing an electronic sensor, as well as a site with tested characteristics, could be one approach to addressing these difficulties. This removes the possibility of an inaccurate dataset and validates the time and effort used to manufacture the overall data that was gathered. Additionally, feature reduction must be done due to the available computational power. Some amount of the activity dataset that was recorded is preferable to reducing some amount of the activity dataset because the high number of users' activity can assist in the model development and training. Our literature survey revealed both of the most well-liked as well as successful methods for features-reduction: principal component analysis (PCA) and correlation analysis (CA). In correlation analysis, different features can be detected that are significantly correlated with one another; properties that represent the same part of the targeted activity values are useless; in addition, they confuse the model and limit how well it can function. Eliminating these unnecessary characteristics could be quite valuable. Following the previous example, principal component analysis likewise reduces the number of different features, but it does so by creating the latest features, which are a linear mixture of previous features. However, PCA collects a substantially large dataset regarding target features when there are fewer characteristics.

In the absence of a technical method that can take advantage of the data processing chores, they are completely pointless. Unfortunately, selecting the best methodology to accomplish this task is challenging. Choosing many techniques, each with a unique procedure of activity to handle this task, could be one strategy. The best method for multiple action detection can be chosen by analyzing and contrasting every one of these approaches.

According to the literature analysis, there are four different ways to execute the supervised ML techniques: informational-based, similarities-based, likelihood-based, and error-based training. All of the previously mentioned sets of computations can be used to produce a solid and important result. The main goal of this project is to complete several activities that need to be finished or successfully completed to achieve this goal. The following is a list of the main tasks. (What did we do?)

* A thorough analysis of the field of research conducted on tests and studies done in the field of human-based activity recognition
* Create the method to accomplish human-based activity identification by recognizing differences between classes and similarities between classes within activities.
* Use a design-enhanced technique to motivate the algorithm to complete human-based activity classification in order to achieve the desired accuracy.
* Assess how well influenced algorithms performed.
* Apply the conclusions to an area of research.

## Limitations and Scope

When numerous datasets are appropriately integrated and then used to train a model, higher predicted performance is observed [16]. However, this research will merely make use of one dataset using the currently used methodology. Some derived parts of an actual dataset collected with the help of sensors are provided by the benchmark experimental usage for the study. The research may have benefited considerably from getting access to the sensor signals obtained, which were still available as extrapolated signals. There are many ways to reduce the dimensionality, but owing to experimental time as well as computational limitations, mostly well-liked approaches from the literature survey were chosen. Many machines learning-based techniques and a variety of used parameters have been identified in the literature survey and can be used to improve knowledge from user data. Moreover, the investigation had to restrict the number of used algorithms and their parameters to a few, so only a single algorithm or model from every family is used with minimal parameter tuning.

Additionally, although different validating approaches were intended to be used in the experimental work, only a single one could be carried out because only that test's findings were substantial enough to allow for the evaluation of the hypothesis.

## Motivation

The motivation of this research is multi-purpose like firstly, discussing the most recent developments in the HAR category and its usage. Secondly, summarizing machine learning-based articles that produce innovative outcomes makes it easier for readers to Modern machine learning-based approaches to HAR. Nevertheless, various machine learning-based applications often concentrate on getting the best accuracy at all costs, as wearable electronic devices have limited restricted-energy storage. On the other hand, energy requirements are a topic that is not frequently discussed. The human activity recognition applications allow for continuous monitoring of human behaviors and their activities, which may also include residential care, sports injury identification, senior citizen care, recuperation, and amusement. The review of the most recent research in human activity recognition applications is done before they are incorporated into the framework. Activity recognition, for example, is the latest trend in human activity recognition examined in this research [17]. Implementing human activity recognition research into passive wearables is the logical next phase. For human activity recognition, the issue of environmental needs is discussed. To the best of the author's understanding, this is an initial review article to talk about energy usage in human activity recognition.

In accordance with the survey, a majority of the people on Earth reside in nations where being overweight or obese causes more deaths than being underweight. However, studies indicate that it can be avoided by following a balanced diet and engaging in some physical activity. 30 minutes every day for the children and 50 minutes for the adults. The National Institutes of Health conducted a study. They found that even modest amounts of leisure-time regular exercise or related activity can add up to 5 years to the human lifespan. Some other research [18] supports this idea and finds that even brief activity bursts can lengthen elderly men's lives. Additionally, engaging in physical activity or exercise has been shown [19] to be quite beneficial for those with depression and anxiety. The human body releases endorphins, which improve the human mood. Additionally, it improves energy levels, assertiveness, and general well-being. It also helps with sleep issues. We are studying from the aforementioned instances how important human physical activity is to people's lifestyles. In order to determine whether they satisfy the guidelines for good fitness or, in some other cases, to accurately identify activity to register in a system, it has now become necessary to keep track of people's physical activity levels. In addition to the health sector, we have applied activity recognition as well as monitoring to numerous additional business sectors. The human physical-activity measurement has a wide range of applications in the entertainment business, including gaming, smartphone applications, athletes' details, and several other professional fields. In Chapter 2, we will have greater details about these applications. This is the main goal of this thesis: to accurately identify people's physical activity. This objective has been made attainable through wearable technology.

## Challenges

Although there are a number of new studies and some applications that address the need for physical activity surveillance, it has certain constraints in terms of dataset collection as well as accuracy. Researchers working on activity recognition encounter a variety of difficulties. Following that, we'll go over a couple of people:

### Data Privacy

The public is understandably concerned about problems related to data security and privacy is given the prevalence of the ubicomp technologies that are proliferating as well as the collection of datasets. Consumers are understandably concerned because cloud-based network malware has become widespread in recent years. Programs that gather information must have the user's permission, be cryptographically secure, and have data protection mechanisms.

### Learning Approach

The majority of research in this activity-recognition domain relies on supervised learning using datasets that have some necessary tags and labels. However, acquiring these kinds of datasets is not simple. Because of this, the datasets that are currently accessible are derived from information gathered by a small number of people and actions. That makes predictions more difficult.

### High-level Activities

A number of low-level actions add up to the high-level activities. The next chapter goes into further information on this. Almost the majority of research work in this activity-recognition field focuses on identifying low-level activities. Investigators are currently facing difficulties describing and modeling the training algorithms for these high-level or lengthy operations.

### Hardware

Although different sensors are fantastic and essential tools for activity recognition, their size and battery time are both drawbacks. They cannot accommodate extremely significant rechargeable battery power because they become compact and much less obtrusive. Therefore, a trade-off must be established between performance and enough precision, or low power, and accuracy and high power.

## Contribution

* For the objective of verification, three alternative approaches are employed. Additionally, we'll examine research gaps that must be addressed and ongoing work that is mandatory to accomplish.
* To assess our used models, we'll employ a variety of measures.
* The many techniques for identifying physical activity are the main topic of our thesis, together with evaluations of which ones are most effective and the conclusions they arrive at.

# Related Work

The emerging area of science called Human Activities Recognition (HAR) is being carefully investigated for applications in a variety of industries, including protection, physical rehabilitation, teaching in sports and well-being, healthcare services for elderly people, geriatric support, and many more. With the aim of activity detection, it is important to recognize when an activity is being conducted as well as its intensity level. It is becoming increasingly viable to do this with continuously increasing precision thanks to advancements in hardware methodology, particularly in wearable device technologies. The subject has many implications, and curiosity about research into it has increased throughout time. When they were first invented, processors could not be "comfortable to handle." The development of wearable sensor devices began in the 1990s. And a completely new universe of opportunities, investigations, and innovations opened up as a result.

## Human activity recognition

Due to its applications in human-centric fields including armed services, defense, and healthcare, activity recognition has grown significantly in relevance during the past ten years [20]. The challenge of activity identification and then recognition has become significantly more serious in recent years as a result of the proliferation of wearable technology devices. The important objective of HAR in the current situation is to recognize users' activities so that computation systems can facilitate people completing their work [21]. Development in digital image processing and computer vision has made significant contributions to this area of study. As opposed to the cognitive, brain functions and burden on it, that are part of the different, larger research-based subject, humans activities and their recognition herein primarily centered on physical and human activity load [22]. Recognizing the gestures and actions from digital images or films in limited locations was a focus of early studies on the HAR. A substantial majority of subject areas have been found to benefit from HAR, such as various activities of everyday-Living (AELs) that were studied by [23], one of the pioneering scientists to use activity recognition. This investigation even further fueled subsequent studies by [24]. By establishing a Human Activity Recognition to assist individuals' everyday activity surveillance, particularly for patients with chronic disabilities or some other psychiatric illness, as well as for rehabilitative purposes, the established medical practices were put to the test [25]. Entertainment, as well as sports segments [26], industrial and operational sectors [27], and other less serious domains, also benefited greatly from Human Activity Recognition. HAR is further investigated to accommodate simple human behaviors such as commuting patterns, toothbrushes, and medicine consumption notes. Note that the Microsoft Kinect is one of the most current and widely used examples of a device that uses human-based activity identification to improve overall gaming performance by recognizing physical motions as well as gestures.

## Data collection with sensors

It is possible to execute activities of recognition for a single individual and may be for a group of users. In order to recognize certain users and follow their behavior, different user identifications might be used. Employing video cameras, it can be done for surveillance and oversight applications. Nevertheless, there may be a variety of techniques to collect datasets for the single-user activity recognition procedure. Due to advancements in sensor technology, it has been determined that employing inertial detectors is the most common HAR technique. The majority of accelerometer devices have evolved to be transportable and small enough to be attached to the human body. They are easier to utilize and better suited because of their adaptable configurations, long-lasting energy charges, computational capabilities, and continuously synchronized engagement [28]. In the context of advanced homes, "Neural Networks-based House" and some other applications that assist in constructing flexible networks to improve the user's experience of their advanced home were the first to integrate detectors for activity recognition [29]. An inertial sensor incorporated with gyroscopes as well as accelerometers has been used for a variety of tasks, including fall identification, human motion tracking, and far-rehabilitation [30]. Multiple sensors combined with different positions have been used in the past to yield a range of outcomes. The accelerometer is one of the most widely utilized detectors in research like this that involves motions repeated over and over. The electromechanical instrument known as the accelerometer is employed to evaluate both static as well as dynamic impact forces. For example, monitoring gravity acceleration can be used to determine the device's degree of tilting and inclination. In numerous investigations, the accelerometer was utilized as a motion detector and produced accurate findings for application [31]. For purposes like picture labeling as well as activity recognition utilizing noise levels, such as if noise is reduced, the user may have been dozing off, sensors that are digital image or audio oriented have also been used [32]. Instruments for global positioning systems (GPS) are also commonly utilized. The GPS detector was utilized to monitor any unusual user behavior as well as to recognize users' activities through position-based data between solitary and numerous individuals [33]. A variety of biosensing methods are used in clinical applications that entail monitoring individuals' vital signs like pulse rate, respiratory rate, and other significant statistics. [34] used polarized pulse rate receiving sensors, forearm chest inertial measurement units, and the human body's temperature detectors to identify hyperthermia in personnel enduring severe weather-related crises. Advanced clothing that recognizes the human body position is also made with biosensors [35]. These use IR detectors to measure body temperature. These devices were then used to distinguish between various degrees of activity that produced lower and higher levels of heat, allowing for differentiation. Additionally, groupings of multiple sensors are used to enhance signal detection. Behavioral sensing and accelerometers were coupled to collect data like human skin heat and energy expended [36]. Aside from the many sensing kinds, the accelerometer and the gyro combo, which is the tool utilized to measure angular velocity, are the most straightforward and effective.

## Wearable sensors' attachment

Look into the value of the sensor, including where it should be placed on the user's body. Their research shows that the electronic sensor is moved from top to bottom, and acceleration data readings slowly rise in amplitude. Therefore, it is clear that location directly affects the overall outcomes of a HAR procedure. [37] illustrates how the sensor can be positioned throughout the body in various places. The detector has been used in numerous investigations with varying degrees of accuracy at multiple locations on the user's body. [38] explored human activity recognition by attaching devices to the wrist and breast as participants engaged in a variety of activities over the course of two hours. The 3 classifiers' optimal output had an accuracy rate of 83%. This research [39], carried out an experiment utilizing triple electronic sensors.

When several additional investigations were examined, a couple attached to the middle of the thighs showed the greatest outcome when several additional investigations were examined. Their experimental success identified four crucial jobs with an overall accuracy of nearly 100%. The sensor at the user's waist and on the lower back, meanwhile, has been producing optimal results in trials that only used one camera sensor at one point on the body. With the single detector situated at the waist, [40], [41], and [42]. Despite recognizing comparable behaviors, Bonomipleted HAR tasks as well as achieved the classification overall accuracy of above 98% and 93%, respectively, despite recognizing comparable behaviors. Consequently, because it has been demonstrated to be effective and because it is nearer to the body's centroid, placing the detector on the waist can be considered optimum [43].

## Applications

In this chapter, we examine many ubiquitous computations as well as activity identification and recognition application domains. The use cases for activity recognition are numerous. It is impossible to describe everything. Following that, we'll list a few

### Health Sector

The applications of various activities detection and recognition in the medical industry are numerous and range from geriatric supported human living to everyday pulse sign surveillance. The healthcare community has focused on identifying and recognizing humans and their physical activities since the 1980s in order to calculate energy and oxygen expenditure [44, 45]. The average human life span remained substantially lower in the 1700s than it is today; hence, supported care wasn't really required. But time passes, average lifespans rise, and reproduction rates fall, resulting in aging people and the requirement for senior supportive health services. Recognizing that movement can facilitate that by:

* Identifying significant effects like fall-down detection.
* Keeping an eye on regular human activities to avoid health issues
* Tracking of someone's sleeping habits, duration of sleep, etcetera.
* Giving medical professionals relevant information that they can utilize to diagnose patients or monitor their condition.

Along with the aforementioned benefits, Human Activity Recognition also aids in medical rehabilitation [46-49], provides assistance to those with impairments [50], and encourages individuals to exercise and burn calories by providing prompts, notifications, and personalized routines. Regular physical activity assessment can also be useful in a number of different healthcare settings, as described in 1.5.

### Fitness and Sports

Human activity recognition in a world of different sports and health has grown significantly, just starting with simple activity trackers and ending with modern, complex Pebble platforms [51] as well as smart wristwatches. There is a vast selection of smart, advanced wearables and technologies in today's market that are specifically focused on measuring and monitoring the actions of the user and giving feedback and incentives. These apps offer specific information related to the activities, such as the route taken, the time and effort put into it, the number of calories burned, etc. Additionally, efforts have been made to recognize sporting events. understanding the patterns of activities, top velocity, and performance evaluation.

### Games

Customers' interest in learning a little more has been stimulated by studies in the video gaming sector on movement-sensing keyboards and virtual reality systems. It became popularized in 2006 with the release of the Nintendo Wii [52] and has since developed into technology just like the full-body VR headsets, Oculus Quest [53]. In contrast to the healthcare industry, where there is a demand to achieve 100% accuracy, many more customers and programmers are participating in it. In addition, a recent study has indeed demonstrated that using gaming machines, such as the Nintendo Wii, to perform participatory physical activities may improve physical therapy and promote healthy senior demographics [54].

### Industry sector

Observing physical activities can be useful in industrial settings for things like worker safety, job analysis, assistance, and learning. The use of wearable electronics by employees facilitates communications, dataset gathering, and colleague monitoring. It is also useful for workshop and assembly tasks in businesses like those that build cars and airplanes. Employers can use it by monitoring employees' performance and obtaining comments, alerts, and announcements related to the task [55]. There is work being done as well to help the hospital sector by automating the tracking of patients' physical health statuses, presenting prioritized sick people to appropriate staff, and distributing clinical charts on mobile portable devices [56].

In addition to the different applications already listed, there are several more disciplines where movement identification and recognition systems are in use, as well as a great number of brand-new ones where the investigation is being conducted. The below areas are where some tasks are completed:

* utilization of activity recognition for contextual or targeted advertising [57].
* Army Surveillance Applications in the Armed Services Sector [58]
* Activities recognition is another technique used in automation to communicate with things and humans.
* Software for monitoring
* In the education sector, [59] investigates using RFID labels to aid in language acquisition.

## Different Activities

In this [60] paper, researchers explain some human activities that are done by individual people in the three groups: body gestures and activity at both low and high levels.

### Body gestures

These are quick motions of the body, such as waving and bending the arm. These extremely brief scheduled actions may be more difficult to identify because they may be performed as a particular gesture or simply random movements, and separating them from the background data may prove difficult.

### Low-level activities

These kinds of activities, such as walking, chatting, running, and eating, are carried out on a minute-by-minute basis. Surveillance and identifying low-level actions are major areas of focus here. A single tri-axial accelerometer is sufficient to detect these kinds of activities [61]. [62] It also emphasizes information gathered from one sensor. The research of activities recognized using merely these sensors in a cell phone has expanded thanks to cell phones. This also presents difficulties. Research has shown that energy usage, location and orientation, learning, and other issues have been raised by research [63–69] by using cell devices for activity recognition.

### High-level activities

Low-level operations are combined with high-level activities, which are completed several times. Trying to get ready, working in an office, buying groceries, guided tours, and so on. are a few examples of such activities. Understanding low-level tasks and the order in which we carry them out is necessary for understanding high-level tasks. For the purpose of detecting high-level activity, we can create a pattern from low-level activity. [70] There were some if limited, efforts done on classifying high-level tasks. High-level as well as lengthy operations still require improvement in their categorization.

### Daily life activities

But, on the other hand, three groups do not adequately classify tasks of everyday life (DLA). DLA was initially defined by [71] with the purpose of identifying activities the person should engage in to maintain their medical. Ever since, the list of DLA activities has been modified and expanded. Basic hygiene (showering, combing, and so on.), using the restroom, clothing, and nourishing themselves are examples of DLAs. Along with ADLs, there are also the Instrumental Activities of Daily Living (IADLs), which are tasks that demonstrate the person's capacity for independence, including food preparation, buying groceries, communication, and socializing. The medical industry places a lot of emphasis on the identification of ADL and IADL.

## Sensors

The complexity and size of activities recognized by recognition detectors can vary from being quite simple to extremely complicated. Transitions and Radio Frequency ID tagging scanners are examples of isolated detectors. Continuous detectors also exist (accelerometers). The more sophisticated detector translates the audio and visual signals. The following section discusses some popular sensors.

### Inertial detector

IMUs, or inertial measurement units, are generally reliable detectors for use in activity recognition. It has been demonstrated that a variety of different activities may be accurately recognized using only IMUs worn on the body. Inertial sensors were used in previous work in activity recognition [72] and [73]. Accelerometers are very common action recognition sensors because they are discreet, precise, affordable, and non-intrusive as compared to a digital camera or microphone.

### Biological sensors

A reliable resource of data for different activity recognition comes from physiological sensors like body temperature as well as pulse beat monitors. However, it has its distinct set of drawbacks, including being extremely complex, sluggish to react (for instance, pulse rate remains raised long following stopping jogging), obtrusive, and, per certain research [74], failing to accurately identify the activity based solely on the physiological dataset. However, once combined using the inertial detectors, they may assess the strength of an effort performed, such as how quickly or forcefully a person runs, how much burden somebody handles, and so on. However, research by [75] found that biological indicators are helpful in identifying and separating particular activities.

### Audio and video-based sensors

Additionally, sound, vision, and digital images are employed to observe how humans behave. Although they are difficult to evaluate and their instruments, for example, digital cameras and microphones, are not always cellphones, and digital images but also audio offer useful datasets for research. They demonstrate that they are the problem only with security concerns as well. The encroachment is not popular with the populace. The problem still exists despite efforts to control time and just collect datasets when necessary. The ability to recognize activities is aided by audio signals. For instance, audio of flipping plates when studying or crunching food can be identified. The noises may also convey details about the surroundings and location, assisting in placing activity in relation to the surroundings.

### Objects Use

[76] investigates the application of active RFID tag scanners to decipher home activities, attaching the RFID tags on household things and scanners on people, so when those individuals communicate with the aforementioned product, it records it as an activity performed, including such things as washing the dishes, brewing coffee, etcetera. Using contacting and binary switching to detect movements, such as the opening and closing of doors and cabinets, or implementing the wireless system to detect high-level actions, is yet another option [77].

### Radio sensing

Using electromagnetic detectors, one can identify things without having to wear the gadget on their person by observing whenever communications are interrupted between the transmitter and the receiver, such as when someone enters or exits the room. By using installation performed in the office entrance, [78] was capable of identifying two actions with setup, "stepping" and "speaking on the mobile phone." However, there hasn't been more research performed utilizing this technique.

### Multiple sensors

The maximum possible outcomes are obtained while logging datasets by utilizing a variety of detectors. When combined with the other detectors, Global Positioning System sensors improve movement detection since they can determine whether an activity is being conducted inside, outside, or in a specific room of the house [79]. The severity of a workout and the amount of energy used throughout that specific activity can be measured with the use of a combination of sensing devices plus inertial sensors [80]. Utilizing both image and audio clip sensors together yields more conclusive results than utilizing just one. In addition to this, there are numerous other types of sensors that are employed in particular industries, such as those that measure the human body's temperature, muscular contractions, and optical properties.

## Techniques

Numerous studies have been conducted on various methods for identifying human physical action. Most of the research is focused on the supervised machine learning techniques listed below:

* Depending on the distance-based technique like (k-NN) K-Nearest Neighbors
* Techniques depend on the decision trees, including CART, ID3, C4.5, and customized-generated branches.
* Statistics-based techniques include LDA, linear discriminant analysis, and Naive Bayes' classifiers.
* Support vector machines, the kernel technique (SVM).
* Concert techniques: additional branches and randomized trees.
* Artificial intelligence-based techniques like artificial neural networks
* Deep learning: Deep neural networks (DNN), artificial neural networks (ANN).

### K-Nearest Neighbor

KNN is a machine-learning method that uses distance to train and is applied to classification and regression issues. This is a fundamental and popular supervised learning method. It is predicated on the idea that related objects cluster collectively and the notion that birds of a feather flock around each other. By voting on neighbors, KNN assigns dataset points to classes depending on training examples that are nearest to them. Several people have utilized this KNN approach to identify activities, including [81]. Iteratively testing different numbers to discover what produces the most reliable data outcome is how we determine the value of k. With k = 3, has an accuracy of 96.65%. [82] observed that K-Nearest Neighbor outperformed C4.5 the decision tree using default scikit-learn specifications (k = 6 nearest neighbors, homogeneous weighted, with p = 3 for Minkowski metrics). To use the Weka framework [83], [84] also received a score of 86.62% accuracy in favor of all this, as compared to the C4.5's 86.03% accuracy.

### Decision Tree

A popular artificial intelligence-based technique, more specifically the machine learning (ML) method, is decision trees. The targeted value is forecasted using different input/training parameters in the predictive technique. It divides the data set depending on the number of factors. There are numerous distinct techniques in the decision tree, and a lot of these are applied to challenges in ML. As demonstrated by [85], CART can be employed independently in combination with different algorithms. [86] applies the CART technique to various datasets containing varied proportions of the learning dataset. With the 50% training dataset on PAMAP2, they increased the accuracy to 95.5 %.  With the support of the Weka toolbox, C4.5 is employed by [87] with an accuracy rate of 86.03%. Although [88] employs an optimized version of these, the outcomes were not superior to those of other approaches. C4.5 has also been employed by [89, 90] in research on activity recognition.

### Random Forest

A random forest is an ensemble approach that arranges various decision trees in a "forest" shape in a random way. The random forest technique selects the greatest characteristic from a randomly selected collection of characteristics when partitioning the node when creating branches. As a result, in a few applications, random forest is a very reliable and effective solution. Utilizing half of the learning data for the random forest, [91] achieved an accuracy of 97.05 percent.

### Linear discriminant analysis (LDA)

Excellent machine learning (ML), a supervised method of LDA, is utilized to characterize and separate categories. It functions by predicting different things about the class wherein the input-set belongs. With a few specific constant prediction issues, it performs excellently. LDA has been applied to speech recognition and visual feature extraction in [92] as well as [93]. Applying LDA, [94] achieved 65.47% accuracy by using the PAMAP2 database and 51% of the training dataset. For instance, LDA's variant known as quadratic discriminant analysis (QDA) is employed for categorization. Both [95] in bioinformatics as well as [96] in biological physics utilize QDA.

### Other approaches

The approaches listed previously used supervised machine learning-based algorithms. Utilizing a labeled dataset to train the project is what is meant by "supervised-based learning." That is, learning under close supervision or labeling, in other words. The vast amount of work on activity recognition is focused on supervised-based methods. There are also several strategies that have been utilized successfully that are unsupervised-based or may be semi-supervised. Unsupervised learning involves the use of data without using labels.

# Related Knowledge

## Logistic Regression

Predictive modeling and classification commonly use of this type of statistical model, also discussed to as a logit model. Based on a particular collection of predictor features, logistic regression computes the probability that an event will happen, such as playing or not playing. Given that the result is a likelihood, the target variable's range is 0 to 1. Logistic regression applied the transformation function (logit function) on the odd. The odd is the percentage of the probability of achievement to the chances of failure. There are three kinds of categorical response-based logistic regression models.

**Binary Logistic Regression:** In this technique, the responder or outcome variable is dichotomous, meaning that there are only two possible outcomes (e.g., 0 or 1). It is recurrently used to determine whether a response is malicious or not, as well as whether a tumor is malignant or not. This method is most frequently used in logistic regression, and it is additionally one of the most widely utilized model for binary classification.

**Multinomial logistic regression:** In this kind of regression model, the outcome feature holds three or more likely values, but there is no prearranged order in which they should be ranked. For instance, in order to more successfully sell their films, movie companies aim to forecast the type of film a viewer will likely watch. The studio may find out how much of an impact a person's age, race, and marital status may have on the genre of movie they enjoy by using a multinomial logistic regression model. The studio can therefore target a particular movie's advertising campaign at an viewers that is most likely to go watch it.

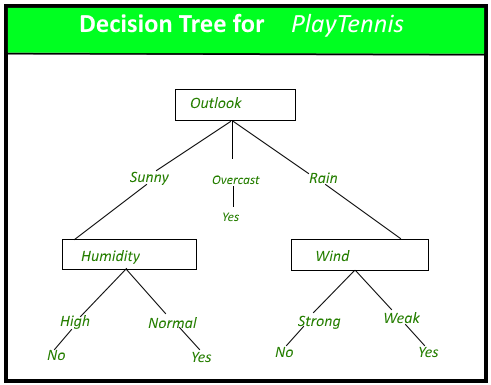
**Ordinal logistic regression:** When the dependent variables have three or more potential scenarios, however in this situation, these values do have a fixed order, the ordinal logistic regression model is used. Grading levels from A to F or rating scales from 1 to 5 are two instances of ordinal replies.

## Decision Tree

The utmost effective and popular technique for classification and forecasting is the decision tree. A decision tree is a subtype of tree based models that resembles a roadmap, in which each internal node denotes an assessment on a feature, each branch a test result, and each leaf node an outcome label.

Building a Decision Tree (DT): By dividing the dataset into subsets depending on an attribute value test, a tree can be "learned". It is known as recursive partitioning to repeat this operation on each generated subset. When the split no longer improves the predictions or when the subset at a node has the same value for the target variable, the recursion is finished. Decision tree classifier building is ideal for experimental knowledge discovery because it doesn't require parameter configuration or domain understanding. High-dimensional data can be handled via decision trees. Decision tree classifiers are often accurate. A popular inductive method for learning classification information is decision tree induction.

The decision tree in the below diagram (Figure 1) categorizes each morning according to whether it is appropriate for playing tennis and then returns the classification associated with each individual leaf. (In this instance, a Yes or No).



**Figure 1:** Working Structure of Decision Tree.

**Gini Index:** The Gini Index is a number that measures how accurately a divide is between the groups that are categorized. A score between 0 and 1, where 1 represents a randomly distributed distribution of the items within classes, is evaluated using the Gini index. In this situation, we wish to have a low Gini index score. The assessment statistic we'll use to assess our decision tree model is the Gini Index.

## Random Forest

Just like names imply, a random forest is combination of different independent trees that work together to made predictions. Each tree in the random forest model predicts a class of target variable and the class that receive the majority votes become the final perdition class and predicted by the random forest model. (See Figure 2).



**Figure 2:** Example of Random Forest Tress.

The knowledge of crowds is the basic idea implemented behind the random forest model, which is a straight forward but effective idea. In the field of data science, the random forest approach is successful because: The best outcomes arise from a lot of very uncorrelated models (trees) cooperating as a team.

## Naive Bayes

Naive Bayes is a fantastic illustration of how the most straightforward approaches are generally the most effective. Machine learning has proven to be not just rapid, precise, and trustworthy, but also simple, despite previous advancements in the field. It has been implemented effectively for numerous applications, but it surpasses at answering natural language processing (NLP) problems. This same Naive Bayes stochastic machine learning approach, that is employed for a wide range of classification issues, is built on the Bayes Rule.

**Bayes Theorem:** The Bayes Theorem is a simple mathematical formula for calculating conditional probability. The possibility of an event happening provided that another event has already occurred (via supposition, presumption, statement, or fact) is known as conditional probability. The formula of Bayes Theorem is calculating the probabilities is below:

The above formula provides information about how frequently A occurs when B occurs, denoted by the symbol P(A|B), also known as the posterior probability. When we know how probable A is on its own, written P(A), how probable B is on its own, written P(B), and how frequently B occurs provided that A occurs, written P(B|A).

## AdaBoost

AdaBoost is a method of ensemble approach that was initially created to improve the efficiency of classification algorithm (usually called to as "meta-learning"). AdaBoost uses an iterative procedure to enhance subpar classifiers by gaining knowledge from their mistakes.

To create a single, improved prediction algorithm, ensemble learning integrates multiple underlying algorithms. For instance, a standard categorization decision tree turns multiple elements into rule questions and, given each element, either produces a decision or takes another factor into account. If there are several choice rules, the decision tree's outcome may become uncertain. for instance, if the threshold to make a prediction is uncertain or we add novel sub-factors for consideration.   Ensemble Methods can be used in this situation. Ensemble Methods combine numerous diverse trees into a single, powerful prediction rather than relying on one Decision Tree to make the appropriate decision.

The Boosting algorithm hunt for to create a powerful classifier (predictive model) from the failures of numerous weaker learners, much like humans try to avoid repeating their errors in the future. You begin by building a model using the training data. After that, you create an additional model from the first one while attempting to minimize its flaws. Models are sequentially added, each one correcting its predecessor till the training data is correctly forecasted or the maximum number of models have been added. Boosting essentially aims to minimize the bias error that develops when models fail to grasp important patterns in the data. it is calculated   by measuring the discrepancy between the anticipated value and the real value.

There are three types of Boosting Algorithms that are following

* AdaBoost (Adaptive Boosting)
* Gradient Tree Boosting
* XGBoost

A highly well-liked boosting technique called AdaBoost (Adaptive Boosting) seeks to combine several weak classifiers into one powerful classifier.

## K Nearest Neighbor

The KNN algorithm takes neighboring objects that are related into account. In other respects, things that are associated to each other are found nearby. Typically, associated data values are close to one another (as shown in below figure). For the KNN method to work, this assumption must be sufficient. KNN encapsulates the concept of similarity by using the basic math we may have learnt as toddlers, such as estimating the distance among points on a map (also called distance, proximity, or closeness). Other methods of estimating distance exist, and depending on the issue at hand, one method may be ideal. However, the common and well-known option is the direct distance (also known as the Euclidean distance).



**Figure 3:** Classification method of KNN

# Methodology

In the methodology section, we will discuss the dataset description, overview of dataset, preprocessing and proposed models for the prediction of human activity.

## Dataset Overview

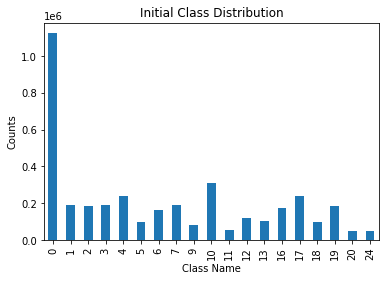
We downloaded the PAMAP2 Physical Monitoring Data Set from UCI repository. The dataset was based on sensory information of human activities. Sensory data was collected from 15 subjects with 3 Sensors (International Measuring Unit IMU). The IMU was adjusted on the wrist of dominant arm, on the chest and over the side ankle of dominant. Each subject need to follow the protocol base on the 12 different activities including the lying, walking, standing, and cycling etc. The activities of subjects that follow the protocol were recorded in Protocol directory. Few of the subject follow the few optional activities and recorded in Optional directory. Collectively, the dataset was based on the two different directories: Protocol and Optional. Protocol directory contain the protocol activities of 14 objects and Optional directory contain the 18 human activities of 14 objects. Both of the directories store the activities of individuals in separate files with .dat extension.

Each file was recorded for one subject per session that includes the time stamp, heart rate (bmp), activity label and attribute of raw sensory data. Each line of the activity file consists of 54 column that contain the timestamp, heart rate and 52 attribute of raw sensory data respectively.

## Preprocessing

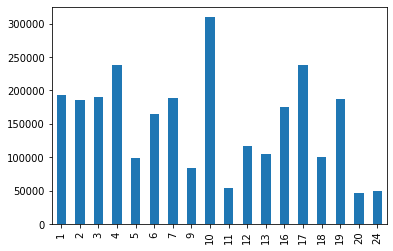
In the preprocessing of the human activity dataset, we perform relative steps for converting, merging, and removing outliers for better performance of the proposed models. Firstly, all the activity dat files were converted into the tab delimited csv files. After the conversion of dat files into CSV files, each CSV contain the 54 features column and 0.3 million samples on average. Total 9 CSV files were generated, nine from the objects followed the protocol activities and five from the objects followed the optional activities.

Further, all the CSV files were merge into the single file for preparing the dataset. The merged CSV file was consisted of 54 column features and 3850505 samples from 14 activity recorded files. The merged CSV file was very large in size due to the large number of sample size. We determine the class labels distribution in the human activity dataset in order to gain a deeper grasp of the collection. The results of a class allocation analysis show how many observations fall into each category for the target attribute. We utilize pandas' designed "value-count" method to evaluate the class distribution. The quantity of activities was calculated for each activity category. In the dataset, we identified 18 categories and roughly 3850505 samples for each category. Additionally, the matplotlib library plotted the classes distribution bar chart using the data from the class distribution. Figure 4 displays the initial class distribution bar chart for the dataset.



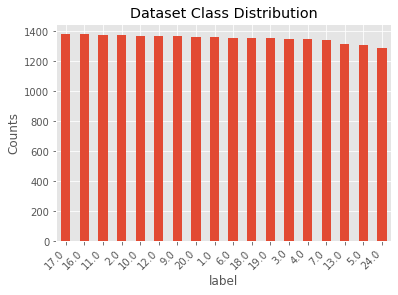
**Figure 4:** Initial Class Distribution of Activity Dataset

In the Figure 4, we can see that the dataset is class unbalance dataset and each class contain the large number of samples. The class label with 0 label with the other activity in the dataset. The other class usually based on the combination two or more categorized that decrease the performance of the model. In the Figure 4, the other activity class is also very imbalance class related to other activity classes. We drop out the other activity class and check the class distribution of remaining dataset (Figure 5).



**Figure 5:** Class Distribution of selected Activities

After this, we convert the dataset into the class balance dataset. For the extraction of class balance dataset, fifteen thousand samples from each class were randomly selected. After the extraction of class balance dataset, the outliers and missing values were removed from the dataset. For handling the missing values and large number, all the samples that have NAN value and large value in sensory features were removed from the dataset. The final class distribution of the dataset in also shown in the Figure 6.



**Figure 6:** Class Distribution in processed Dataset

Lastly, we have the 267329 samples of 18 different activities recorded from 14 different objects. The name of each activity id is also available in Table 1. Each sample was based on the 54 features including the time stamp, activity id, heart rate and sensory data respectively. The overview of dataset statistics is also available in Table 2.

**Table 1:** Mapping of Activity IDs and Names

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Activity ID | Activity Name | Activity ID | Activity Name | Activity ID | Activity Name |
| 1 | lying | 7 | Nordic walking | 16 | vacuum cleaning |
| 2 | sitting | 9 | watching TV | 17 | ironing |
| 3 | standing | 10 | computer work | 18 | folding laundry |
| 4 | walking | 11 | car driving | 19 | house cleaning |
| 5 | running | 12 | ascending stairs | 20 | playing soccer |
| 6 | cycling | 13 | descending stairs | 24 | rope jumping |
| 0 | other (transient activities) |  | | | |

**Table 2:** Statistics of Human Activity Dataset.

|  |  |
| --- | --- |
| Total Objects | 14 (9 follow protocol activities, 5 follow optional activities) |
| Total Samples | 3850505 |
| Processed Samples | 267329 |
| Total Features | 54 |
| Features Name | Timestamp, Activity ID, heart rate, raw sensory data (51) |
| Classification Features | Heart Rate, 51 sensory features |
| Target variable | Activity ID |
| Classes | 18 (mentioned in table 1). |

## Train Test Split

The dataset needs to be divided into multiple subsets for the training, testing, and validation of the model just after preprocessing and feature extraction methods. The scikit-learn library's developed train-test-split method was used to partition the collection into three portions. With some ratio for one group and the remaining samples for the second subset, the built-in train test split function chooses a random sample from each class. The observations in the partitioned subset were not overridden by it. We divided the activity record collections into two separate subsets using the reprocessed data. The processed features dataset was dividing into training and testing set with the ratio of 80% and 20%. After splitting the dataset, the train, and test set contain the 213863 and 53466 samples. The overview of samples in train and test set is revealed in Table 3.

**Table 3:** Samples in train, test and validation set.

|  |  |  |
| --- | --- | --- |
|  | Training Set | Testing Set |
| Number of Samples | 213863 | 53466 |
| Number of Features | 52 | 52 |

## ML Models Training

We employed a variety of machine learning algorithms to classify humans activities using sensory data. For the categorization of activities based on the machine learning models, we employed the Logistic Regression, Decision Tree, Random Forest, Naive Bayes, AdaBoost, and K Nearest Neighbor algorithms. The machine learning algorithm was not created from scratch by us. By using Python scikit-learn module, we initialize machines learning models that have already been constructed. The random state 0 was employed as the initial value for the decision tree and logistic regression model. The bootstrap value of 100 and the parameter value of 5 for maximum depth were used to build the Random Forest model. The SVM model was started with a max-iteration hyper parameter value of 200. The max-depth number for the random forest was set to 5, while the bootstrap value was set to 100. AdaBoost model was loaded with the hyper parameter value n-estimator:100 and 0 random state value. Whereas the KNN classifier initialization value has five n-neighbors. All machine learning models' remaining hyperparameters were set to their default settings. Fundamentally the train set was supplied to the initialized machine learning models for the purpose of training them. Following the conclusion of the model training, each trained model was assessed using 7423 samples from the test set.

## Models Evaluation

Researchers used a variety of evaluation metrics, such as accssuracy, precision, recall, and f1-score, to assess the classification model. The proportion of actual positive instances that accurately foresee good outcomes to all truly positive situations is known as recall or sensitivity. Precision, on the other hand, or confidence, on the other hand, refers to the proportion of expected positive cases that are actually true positives. So, we can mention the recall means “how many samples of particular class you find over the all samples of that class," and the precision will be “how many are correctly classified among that class." The harmonic means of recall and precision is known as the f1-score. The trained classifiers were assessed using the test set, which contained 53466 observations. The formula for that metric was used to construct the evaluation metrics. Eq 1-4 gives the equation used to calculate the measurements.

Eq. 1

Eq. 2

Eq. 3

Eq. 4

# Results

## Environmental Setup

We will talk about the training environment for the proposed frameworks, as well as the libraries and scripting languages that were used. Python was used throughout all of the projects as the scripting language. The trials were carried out using the Python 3.7 release. For the models' training, a Conda environment was created using Python 3.7. The built environment included a complete installation of the libraries needed.

We developed and trained the suggested models using the TensorFlow toolkit, a well-known platform for deep learning models. In our established environment, various libraries were installed. The table that follows lists all essential libraries along with their version numbers (Table 4).

**Table 4:** List of libraries used in environment

|  |  |
| --- | --- |
| **Library Name** | **Version** |
| TensorFlow | 2.3.0 |
| Matplotlib | 3.5.2 |
| scikit-learn | 1.0.1 |
| Pandas | 1.3.5 |
| Numpy | 1.19.0 |
| Seaborn | 0.11.2 |

We perform number of experiments for the Recognition of human activity using sensory data. The detail of all experiments in presented in Table 5.

**Table 5:** List of Proposed Experiments in proposed study

|  |  |  |
| --- | --- | --- |
| **Experiment no.** | **Experiment Name** | **Details** |
| Experiment 1 | Train Test Split | Divide the dataset into a training dataset and a testing set with a proportion of 80% and 20%. Utilize the Scikit Learn library's Train test Split method. |
| Experiment 2 | Logistic Regression | Use the logistic regression for the recognition of human activity. Train the logistic regression model on the 213863 samples of train set. |
| Experiment 3 | Decision Tree | Decision Tree was also train with the samples of train set. After the complete training of the model, test set was used to evaluate the performance of the model. |
| Experiment 4 | Random Forest | Utilize the 213863 observations to learn the Random Forest classifier. Use Random Forest's hyperparameters' default values. After the model has finished being trained, the model should be tested. |
| Experiment 5 | Naïve Bayes | Train the Naïve Bayes model with the 213863 observations. Use the default value for all hyper parameters of Naïve Bayes. After the model has finished being trained, the model should be tested. |
| Experiment 6 | AdaBoost | AdaBoost is the ensemble learning based model that was used to recognize the human activity using sensory data. AdaBoost model was train with the train set and evaluate the performance on test set. |
| Experiment 5 | KNN | Utilize the 213863 examples to train the KNN network. Use the KNN's hyperparameters' default values. After the algorithm has finished being trained, the model should be tested. |
| Experiment 7 | Comparative Study | After all the models have been trained, we execute a comparison study. To assess the optimal model in this study, we draw a comparison chart. |

## Experimental Results

## The experimental results section will use various tables and graphs to illustrate the outcomes of all proposed tests.

## Train Test Split

We obtain the train and test sets by dividing the dataset into two separate sets. These subgroups were produced from the activity dataset by the Train-Test-Split module of Scikit Learn. Figure 7 displays the number of classes in the created train test and validation batch.

|  |  |
| --- | --- |
|  |  |

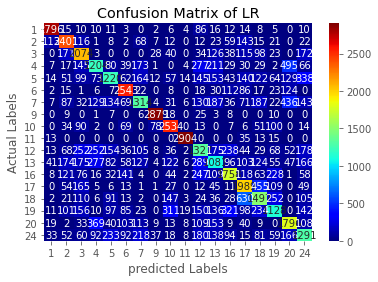
**Figure 7:** Bar Chart of Class Distribution in Train and Test Set.

## Linear Regression

Linear Regression model was trained on the training set for the recognition of human activities. After the complete training of the linear regression model, test set was used for the evacuation of linear regression model. All the selected evaluation measures including the accuracy, precision, recall and f1-score were calculated on the test set. The comprehensive classification report of the trained linear regression model is available in Table 6. For the better consideration of the model performance, confusion matrix was plotted with the 53466 samples of test set and presented in Figure 8.

**Table 6:** Human Activity Recognition - LR Report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report for LR Model** | | | | |
|  | precision | recall | f1-score | support |
| 1 | 0.91 | 0.93 | 0.92 | 3008 |
| 2 | 0.71 | 0.79 | 0.75 | 3023 |
| 3 | 0.58 | 0.71 | 0.64 | 2922 |
| 4 | 0.49 | 0.43 | 0.46 | 2809 |
| 5 | 0.55 | 0.42 | 0.48 | 2900 |
| 6 | 0.76 | 0.84 | 0.8 | 3014 |
| 7 | 0.56 | 0.43 | 0.49 | 3025 |
| 9 | 0.94 | 0.97 | 0.95 | 2966 |
| 10 | 0.74 | 0.85 | 0.79 | 2998 |
| 11 | 0.97 | 0.97 | 0.97 | 2980 |
| 12 | 0.43 | 0.44 | 0.43 | 3037 |
| 13 | 0.41 | 0.36 | 0.38 | 3027 |
| 16 | 0.61 | 0.58 | 0.59 | 3026 |
| 17 | 0.54 | 0.68 | 0.6 | 2942 |
| 18 | 0.49 | 0.5 | 0.5 | 2967 |
| 19 | 0.52 | 0.37 | 0.43 | 3022 |
| 20 | 0.55 | 0.61 | 0.58 | 2933 |
| 24 | 0.45 | 0.45 | 0.45 | 2867 |
|  |  |  |  |  |
| accuracy |  |  | 0.63 | 53466 |
| macro avg | 0.62 | 0.63 | 0.62 | 53466 |
| weighted avg | 0.62 | 0.63 | 0.62 | 53466 |
| Accuracy (Train Set): 0.6480  Accuracy (Test Set): 0. 6309 | | | | |



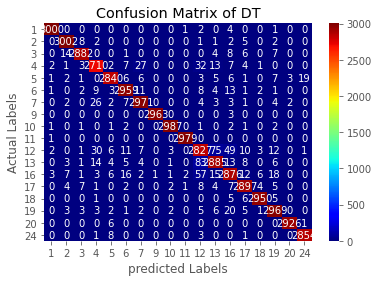
**Figure 8:** Human Activity Recognition - LR Confusion Matrix

### Decision Tree

Decision tree model was trained on the training samples of activity recognition dataset. The model was evaluated using the test set when it had finished being trained. Using instances of test suite, all evaluation metrics were computed using equations 1-4. The complete classification report of the of the decision tree trained model is shown in Table 7. The confusion matrix of decision tree model on test set is presented in Figure 9.

**Table 7:** Human Activity Recognition - DT Report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report for DT Model** | | | | |
|  | precision | recall | f1-score | support |
| 1 | 1.00 | 1.00 | 1.00 | 3008 |
| 2 | 0.99 | 0.99 | 0.99 | 3023 |
| 3 | 0.99 | 0.99 | 0.99 | 2922 |
| 4 | 0.97 | 0.96 | 0.97 | 2809 |
| 5 | 0.99 | 0.98 | 0.98 | 2900 |
| 6 | 0.98 | 0.98 | 0.98 | 3014 |
| 7 | 0.98 | 0.98 | 0.98 | 3025 |
| 9 | 1.00 | 1.00 | 1.00 | 2966 |
| 10 | 1.00 | 1.00 | 1.00 | 2998 |
| 11 | 1.00 | 1.00 | 1.00 | 2980 |
| 12 | 0.93 | 0.93 | 0.93 | 3037 |
| 13 | 0.96 | 0.95 | 0.95 | 3027 |
| 16 | 0.95 | 0.95 | 0.95 | 3026 |
| 17 | 0.98 | 0.98 | 0.98 | 2942 |
| 18 | 0.99 | 0.99 | 0.99 | 2967 |
| 19 | 0.98 | 0.98 | 0.98 | 3022 |
| 20 | 1.00 | 1.00 | 1.00 | 2933 |
| 24 | 0.99 | 1.00 | 0.99 | 2867 |
|  |  |  |  |  |
| accuracy |  |  | 0.98 | 53466 |
| macro avg | 0.98 | 0.98 | 0.98 | 53466 |
| weighted avg | 0.98 | 0.98 | 0.98 | 53466 |
| Accuracy (Train Set): 0.9887  Accuracy (Test Set): 0. 9815 | | | | |



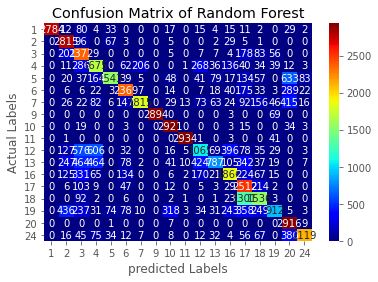
**Figure 9:** Human Activity Recognition - DT Confusion Matrix.

### Random Forest

Random Forest is also a tree-based model that used for the human activity recognition on train set of sensory data. The testing set was used to assess the model's performance following the conclusion of its training. Evaluation measures were calculated on the test set and the comprehensive classification report of the trained model is presented in Table 8. Figure 10 also displays the confusion matrix for the model being tested.

**Table 8:** Human Activity Recognition - RF Report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report for RF Model** | | | | |
|  | precision | recall | f1-score | support |
| 1 | 1.00 | 0.93 | 0.96 | 3008 |
| 2 | 0.70 | 0.93 | 0.80 | 3023 |
| 3 | 0.50 | 0.81 | 0.62 | 2922 |
| 4 | 0.52 | 0.6 | 0.56 | 2809 |
| 5 | 0.88 | 0.53 | 0.66 | 2900 |
| 6 | 0.79 | 0.79 | 0.79 | 3014 |
| 7 | 0.88 | 0.6 | 0.71 | 3025 |
| 9 | 1.00 | 0.98 | 0.99 | 2966 |
| 10 | 0.85 | 0.97 | 0.91 | 2998 |
| 11 | 0.99 | 0.98 | 0.99 | 2980 |
| 12 | 0.5 | 0.35 | 0.41 | 3037 |
| 13 | 0.68 | 0.26 | 0.38 | 3027 |
| 16 | 0.63 | 0.62 | 0.63 | 3026 |
| 17 | 0.45 | 0.85 | 0.59 | 2942 |
| 18 | 0.6 | 0.52 | 0.55 | 2967 |
| 19 | 0.74 | 0.3 | 0.43 | 3022 |
| 20 | 0.62 | 0.99 | 0.76 | 2933 |
| 24 | 0.93 | 0.74 | 0.82 | 2867 |
|  |  |  |  |  |
| accuracy |  |  | 0.71 | 53466 |
| macro avg | 0.74 | 0.71 | 0.7 | 53466 |
| weighted avg | 0.74 | 0.71 | 0.7 | 53466 |
| Accuracy (Train Set): 0.7204  Accuracy (Test Set): 0. 7076 | | | | |



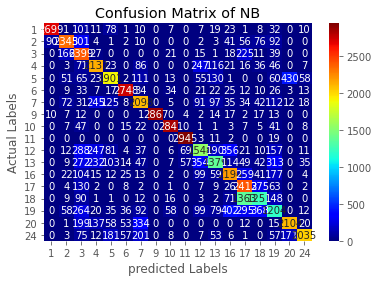
**Figure 10:** Human Activity Recognition - RF Confusion Matrix

### Naïve Bayes

Naïve bayes was trained on the training set of sensory data. After the complete training of the naïve Bayes model, the test set was used to evaluate the model. All the evaluation measures were calculated on the test set. The comprehensive classification report of the Naïve Bayes model is available in Table 9. The confusion matrix of the trained model on test set is also shown in Figure 11.

**Table 9:** Human Activity Recognition - NB Report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report for NB Model** | | | | |
|  | precision | recall | f1-score | support |
| 1 | 0.96 | 0.9 | 0.93 | 3008 |
| 2 | 0.84 | 0.78 | 0.81 | 3023 |
| 3 | 0.54 | 0.82 | 0.65 | 2922 |
| 4 | 0.68 | 0.76 | 0.72 | 2809 |
| 5 | 0.73 | 0.66 | 0.69 | 2900 |
| 6 | 0.92 | 0.91 | 0.92 | 3014 |
| 7 | 0.67 | 0.69 | 0.68 | 3025 |
| 9 | 1.00 | 0.97 | 0.98 | 2966 |
| 10 | 0.94 | 0.95 | 0.94 | 2998 |
| 11 | 0.96 | 0.99 | 0.97 | 2980 |
| 12 | 0.6 | 0.51 | 0.55 | 3037 |
| 13 | 0.63 | 0.46 | 0.53 | 3027 |
| 16 | 0.65 | 0.73 | 0.69 | 3026 |
| 17 | 0.51 | 0.82 | 0.63 | 2942 |
| 18 | 0.57 | 0.42 | 0.48 | 2967 |
| 19 | 0.46 | 0.4 | 0.43 | 3022 |
| 20 | 0.77 | 0.72 | 0.74 | 2933 |
| 24 | 0.91 | 0.71 | 0.8 | 2867 |
|  |  |  |  |  |
| accuracy |  |  | 0.73 | 53466 |
| macro avg | 0.74 | 0.73 | 0.73 | 53466 |
| weighted avg | 0.74 | 0.73 | 0.73 | 53466 |
| Accuracy (Train Set): 0.7426  Accuracy (Test Set): 0. 7314 | | | | |



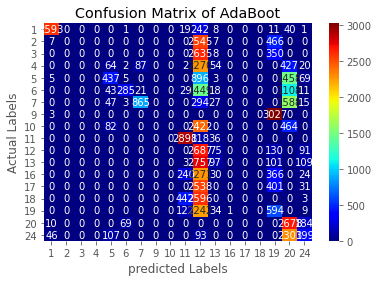
**Figure 11:** Human Activity Recognition - NB Confusion Matrix

### AdaBoost

AdaBoost also trained for the classification of human activities. For this, the train set of the human activity dataset was used for the classification of activities. The model was assessed on the testing sample following the conclusion of the model's training. All the selected evaluation measures were calculated with the 53466 samples of test set. The complete classification report of the trained AdaBoost model is also presented in Table 10. The confusion matrix of the trained model on test set is also shown in Figure 12.

**Table 10:** Human Activity Recognition - AdaBoost Report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report for AdaBoost Model** | | | | |
|  | precision | recall | f1-score | support |
| 1 | 0.97 | 0.89 | 0.93 | 3008 |
| 2 | 0 | 0 | 0 | 3023 |
| 3 | 0 | 0 | 0 | 2922 |
| 4 | 0 | 0 | 0 | 2809 |
| 5 | 0.56 | 0.15 | 0.24 | 2900 |
| 6 | 0.78 | 0.1 | 0.17 | 3014 |
| 7 | 0.89 | 0.3 | 0.45 | 3025 |
| 9 | 0 | 0 | 0 | 2966 |
| 10 | 0 | 0 | 0 | 2998 |
| 11 | 0.77 | 0.95 | 0.85 | 2980 |
| 12 | 0.1 | 0.9 | 0.17 | 3037 |
| 13 | 0.24 | 0.03 | 0.06 | 3027 |
| 16 | 0 | 0 | 0 | 3026 |
| 17 | 0 | 0 | 0 | 2942 |
| 18 | 0 | 0 | 0 | 2967 |
| 19 | 0.11 | 0.2 | 0.14 | 3022 |
| 20 | 0.27 | 0.91 | 0.41 | 2933 |
| 24 | 0.41 | 0.14 | 0.2 | 2867 |
|  |  |  |  |  |
| accuracy |  |  | 0.25 | 53466 |
| macro avg | 0.28 | 0.25 | 0.2 | 53466 |
| weighted avg | 0.28 | 0.25 | 0.2 | 53466 |
| Accuracy (Train Set): 0.2625 Accuracy (Test Set): 0.2531 | | | | |



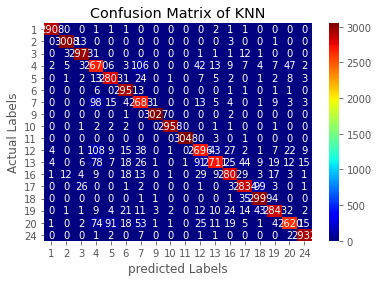
**Figure 12:** Human Activity Recognition - AdaBoost Confusion Matrix

### K Nearest Neighbor

Following completion of training on the train set, the KNN classifier displayed a test accuracy of 0.96% on the testing set. Table 11 displays the full classification report for the KNN classifier. Figure 13 also displays the KNN model's confusion matrix.

**Table 11:** Human Activity Recognition - KNN Report

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report for KNN Model** | | | | |
|  | precision | recall | f1-score | support |
| 1 | 1 | 1 | 1 | 3008 |
| 2 | 0.99 | 0.99 | 0.99 | 3023 |
| 3 | 0.98 | 0.99 | 0.99 | 2922 |
| 4 | 0.87 | 0.91 | 0.89 | 2809 |
| 5 | 0.95 | 0.98 | 0.96 | 2900 |
| 6 | 0.97 | 1 | 0.98 | 3014 |
| 7 | 0.9 | 0.95 | 0.92 | 3025 |
| 9 | 1 | 1 | 1 | 2966 |
| 10 | 1 | 1 | 1 | 2998 |
| 11 | 1 | 1 | 1 | 2980 |
| 12 | 0.92 | 0.9 | 0.91 | 3037 |
| 13 | 0.96 | 0.88 | 0.92 | 3027 |
| 16 | 0.96 | 0.96 | 0.96 | 3026 |
| 17 | 0.96 | 0.95 | 0.96 | 2942 |
| 18 | 0.95 | 0.99 | 0.97 | 2967 |
| 19 | 0.97 | 0.95 | 0.96 | 3022 |
| 20 | 0.96 | 0.89 | 0.93 | 2933 |
| 24 | 0.98 | 1 | 0.99 | 2867 |
|  |  |  |  |  |
| accuracy |  |  | 0.96 | 53466 |
| macro avg | 0.96 | 0.96 | 0.96 | 53466 |
| weighted avg | 0.96 | 0.96 | 0.96 | 53466 |
| Accuracy (Train Set): 0.9788  Accuracy (Test Set): 0.9625 | | | | |



**Figure 13:** Human Activity Recognition - KNN Confusion Matrix

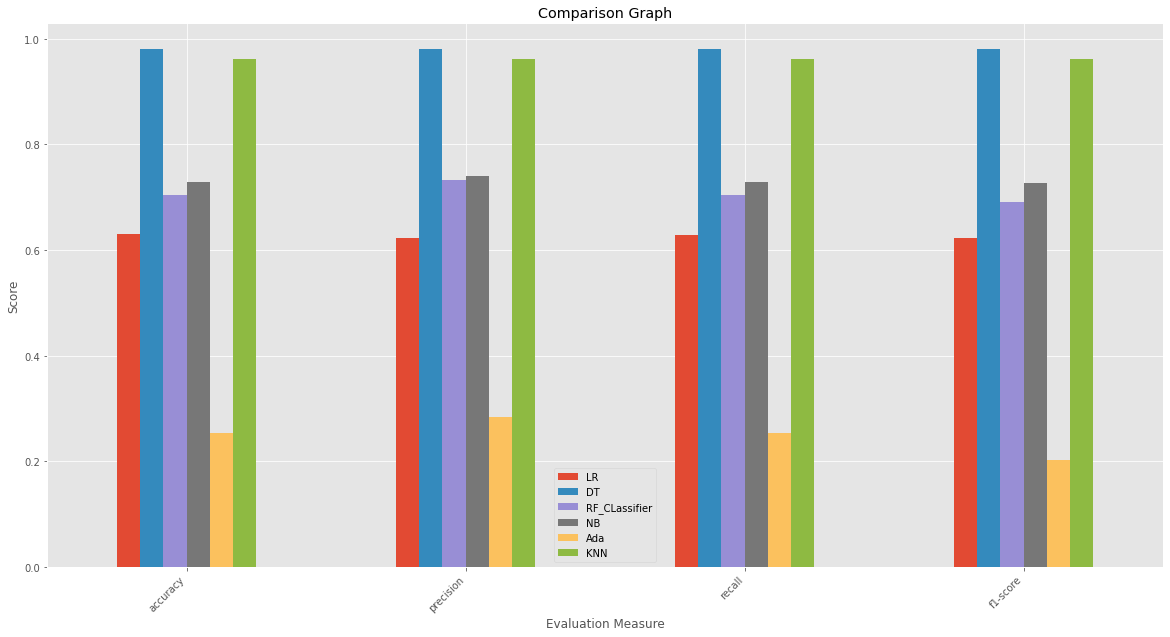
### Comparative Study

Finally, we conduct a comparison analysis of the trained model's performance. The recommended classifiers training results were built on a testing example. Table 12 displays an analysis of all trained models in comparison.

**Table 12:** Human Activity Recognition – Comparative Classification Report

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Metrics** | **LR** | **DT** | **RF** | **NB** | **AdaBoost** | **KNN** |
| **accuracy** | 0.6302 | 0.9805 | 0.7042 | 0.7289 | 0.2531 | 0.9625 |
| **precision** | 0.6231 | 0.9805 | 0.7329 | 0.7401 | 0.2835 | 0.9626 |
| **recall** | 0.6292 | 0.9805 | 0.7040 | 0.7293 | 0.2537 | 0.9625 |
| **f1-score** | 0.6229 | 0.9805 | 0.6901 | 0.7278 | 0.2017 | 0.9623 |

For the purpose of comparing the outcomes, a comparison line graph for each evaluation metric was also drawn. Figure 14 displays the comparison line graph of all classification models.



**Figure 14:** Evaluation Scores of Trained Models.

# Conclusion

In this proposed study, the aim objective was to recognize the human activity using sensory data. The more accurate recognition of human activity will help in development of different robotics applications. For the classification of human activities, we trained numerous machine learning models on the sensory data collected from different objects. We assess each learning algorithm using a separate assessment metric, such as accuracy, precision, recall, and f1-score. We chose accuracy as the primary evaluation metrics because the proposed study's chosen dataset was roughly class balanced. We find that the decision tree and KNN models are more reliable for identifying human activity when compared to other machine learning models based on the accuracy scores of all classifiers. The decision tree and KNN models had accuracy rate of 98% and 96%, respectively, which was the highest result in comparison to other classification model. We made the assumption that Decision Tree is stable enough to be used in real - world environments for the identification of human actions using sensory information by assessing the all-evaluation metrics of the proposed model.

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