# Students Activity Recognition through Machine Learning Approaches

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***Abstract*— Movement recognition is currently one of the most well-known applications of AI calculations. Researchers created many student activity recognition (HAR) systems that turn smartphone readings into various forms of physical activity. It is used in a multitude of industries, including biomedical engineering, game development, and developing more precise metrics for athletic training. Supervised machine learning models can be taught to foresee a person's activities by collecting data from their linked sensors. This project will make use of data from the UCI Machine Learning Repository. This document includes data collected from the phone's multiple sensors, such as the accelerometer, gyrator, and others, and is used to create regulated expectation models using AI techniques like SVM and Arbitrary**

**It records data from the phone's sensors, such as the accelerometer and spinner, and uses AI techniques such as assist vector machines and random backwoods to create controlled expectation models. This data can be used to predict six types of development: walking, walking higher up, walking on the bottom floor, sitting, standing, and lying. We will use a confusion matrix to compare the precision of several models.**

***Keywords*— Confusion Matrix, Decision Tree, Random Forest, Student Activity Recognition, SVM.**

***ICTIEE* Track*: Technology Enhanced Learning***
**ICTIEE Sub-Track: Next Gen learning Environment: Integrating AI for enhanced education.**

## I. INTRODUCTION

Thanks to its groundbreaking work in ubiquitous computing, Student Activity Recognition (HAR) has blossomed into a sophisticated area of study. In the past ten years, the number of smartphones sold has increased at a dizzying rate. A report by Deloitte predicts that by 2026, one billion people in India will own smartphones, with sales of internet-enabled phones being particularly high in rural regions. How much information that can be produced by a PDA's sensor is straightforwardly relative to the quantity of PDAs available for use. Several inertial sensors, including a gyroscope and accelerometer, are built inside the smartphone. The life tracking and fitness industries are two that are seeing a proliferation of real-time sensor applications. The goal of these apps is to gain a better knowledge of student behavior by recognizing student activities using mobile sensors embedded in smartphones (Aggarwal, 20, 2011; Bahzad et al.,2021).

Depending on the motion of the smartphone, the data from these sensors could change. These smartphones have become an integral part of everyone's routines. Using a mobile device takes up most of one's day (Bisboy et al., 2016). We can track the user's movements using information gathered from the phone's sensors. The objective of movement acknowledgment is to utilize this information to prepare models that can think about the thing the client is doing at present. Inertial measurement unit (IMU) sensors in smartphones have been used to categorize common user actions such as sitting, walking, jogging, running, and stair climbing during the past ten years (Chen et al, 2017; Davide et al. 2012; Davide et al, 2013; Hassan et al. 2018; RoNao et al. 2016, Voicu et al 2019). Data used in this publication is modified data from the UCI machine learning repository. An individual's actual work can be ordered into six unmistakable states: sitting, standing, resting, strolling, strolling higher up, and strolling first floor. This categorization will be achieved through the use of prediction classification models generated by supervised machine learning algorithms. This sort of concentrate for the most part starts with get-together crude sensor information, then, at that point, utilizes that information to extricate qualities in the time area or recurrence space. At long last, it prepares an AI model to order the client's ways of behaving in view of those elements. Machine learning models that apply these techniques have achieved activity classification accuracies of above 95% (Berchtold et al. 17; Voicu et al. 2019). A confusion matrix, the Random Forest Classifier, and Support Vector Machines (SVMs) will be used to evaluate the created models' accuracy (Parkka 2006). The design of this report is as per the following: In Segment 2A, we go over the review's informational collection and the methodology accustomed to it before its use in the trial. The methodology that was used is detailed in Section 3. There is a discussion of observations in Section 4.

### *A. Dataset description*

Thirty individuals partook in the review and recorded themselves completing ADLs while wearing a cell phone with inertial sensors connected to its midriff. This data is used to create the Student Activity Recognition database. Assigning each action to one of the six categories is the goal. With every dataset entry comes the following details:

1) Both the expected body speed increase and the complete speed increase estimated by the accelerometer (triaxial speed increase).

2) The triaxial rakish speed of the whirligig.

3). A 561-highlight vector with time-and recurrence space factors.

4) Its action assignment.

5) A method for distinguishing the person who completed the examination.

## II. Literature Review

In the field of artificial intelligence (AI), student activity recognition (HAR) alludes to the act of perceiving and marking student exercises from crude information gathered from various sources (purported gadgets).The following are some examples of such devices: wearable sensors (Pham C. et al, 2020), inertial sensors for electronic devices (such as smartphones)(Qi et al. 2018), camera devices (such as Kinect) (Wang et al, 2019a, Morsheda et al., 2023), closed-circuit television (CCTV) (Du et al. 2019), and some pieces of commercially available hardware (COTS) (Ding et al. 2015; Li et al 2016).

First, signal activity collection; second, data pre-processing; third, activity detection based on artificial intelligence; and fourth, the user interface for managing HAR are the four typical steps of HAR (Figure 1). Multiple strategies can be used to implement each level, giving the HAR system multiple possibilities. The choices are already difficult enough without having to consider the application domain, data gathering device type, and processing of artificial intelligence (AI) algorithms for activity detection (Gupta et al. 2022).

Sensors equipped with accelerometers can convert the mechanical acceleration due to gravity or motion into a voltage signal. Accelerometers are commonly employed for the measurement of static acceleration as a result of gravity, dynamic acceleration as a result of an animal's motion, and the

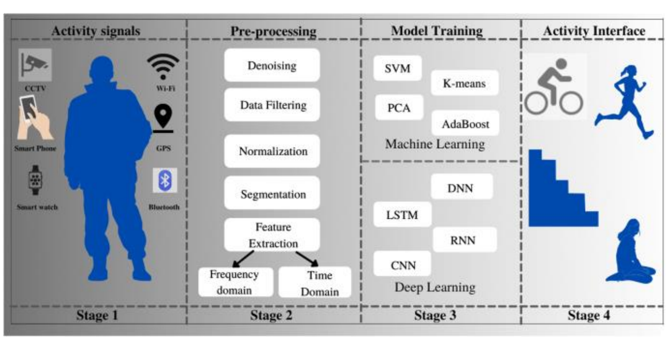



Fig. 1. Student Activity Recognition: A Four-Step Process.
(Image source: Hx P. et al. 2017)

low-frequency component of acceleration (Devi et al 2022).

Each of the approaches we've covered relies heavily on data processing. There is a strong correlation between the input quality attributes and performance. Finding the most significant data in the Student Movement Acknowledgment dataset utilizing cell phones has been the subject of earlier examinations (Davide et al. 2012; Davide et al. 2013). A common practice is to examine the signal in both the frequency and time domains. We used a machine learning system to forecast, based on the activity column, how well the 30 participants had done on each of the six tasks. Researching device orientation is one part of data preparation (StrAczkiewicz 2021). The orientation of the device can affect smartphone measurements, which can be influenced by factors including clothes, body shape, and movement during dynamic activities (Chen et al. 2017).

## III. Methodological Aspects

Thirty people, ranging in age from nineteen to forty-eight, took part in the studies. Wearing a smartphone, each participant engaged in six tasks. Utilizing the implicit accelerometer and gyrator, we consistently recorded 3-pivotal rakish speed and 3-hub straight speed increase at a pace of 50Hz. With the goal that the information could be physically named, the tests were recorded. Over two thirds of the members provided preparing information and 30% delivered test information, which were then arbitrarily parted into two sets to make the last dataset.

Prior to being caught in 2.56 second fixed-width sliding windows with half cross-over (128 readings/window), the spinner and accelerometer information were pre-handled with commotion channels. To decouple the speed increase information from the sensor from the impacts of gravity and

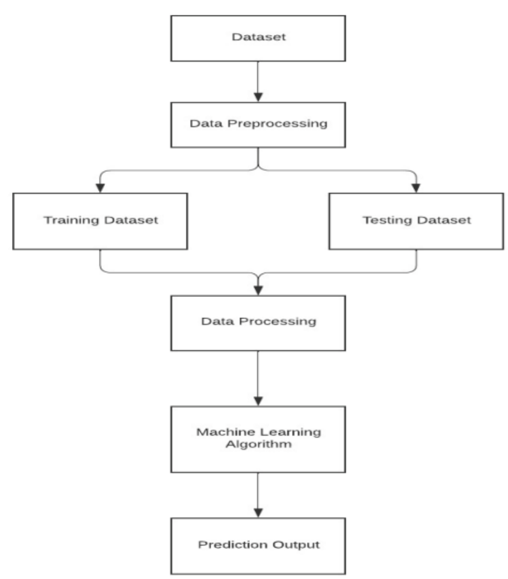



Fig. 2. Execution of framework model

body movement, a Butterworth low-pass channel was utilized. A channel with an end recurrence of 0.3 Hz was utilized since it is guessed that the parts of the gravitational power are of low recurrence. Each casing's properties were extricated as a vector by computing factors from the time and recurrence spaces.

*A. Data Importing*

Kaggle received the data in a.csv format. To guarantee a random distribution of observations, the data was shuffled. Confusion matrices, Random Forest Classifiers, and Support Vector Machines (SVMs) all employ different models nowadays.

*B. Pre-processing Data*

When you want to use raw data in a machine learning model, you have to do data preprocessing. It is the essential and starting move toward fostering a model for AI. While doing an AI project, we don't be guaranteed to experience spotless and arranged information. Information should be cleaned and designed before any move can be made on it. Thusly, we utilize the information arrangement task.

*C. Support Vector Machine*

One machine learning method for data analysis and pattern recognition is the support vector machine, or SVM. A regression or classification model might be born from it. When supporting vector machines (SVMs) are employed for classification purposes, they represent classification categories as spatial points. In the event that the focuses can be isolated utilizing straight lines, then a simple linear support vector machine (SVM) is built. When hyperplanes fail to distinguish between points in one dimension, Kernel Tricks are employed to transfer them to a higher dimension. When the focuses have been meant higher aspects, hyperplanes are utilized to highlight the boundaries between different categories.

*D. Random Forest*

By using a bootstrap test of the preparation information and a haphazardly chosen subset of factors, irregular woods (RF)

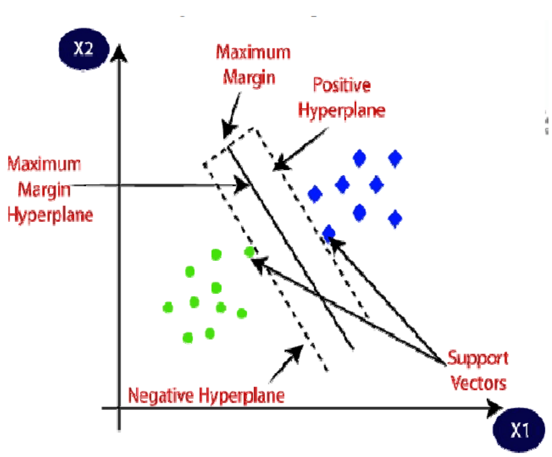



Fig. 3. Simple linear SVM

fabricates a gathering of unpruned choice trees for characterization purposes. In the Irregular Backwoods strategy for AI, an enormous number of trees — frequently more than 500 — are made fully intent on characterizing perceptions utilizing each tree separately. Our expression for how each tree sorts a given class is "casting a ballot" for that class. Timberland pick the characterization with the most votes. We constructed a Random Forest model using the Kaggle random Forest module for our research. One thousand trees were seeded.

*E. Decision Tree*

Although Decision Tree is most often used to tackle classification difficulties, it is capable of handling regression

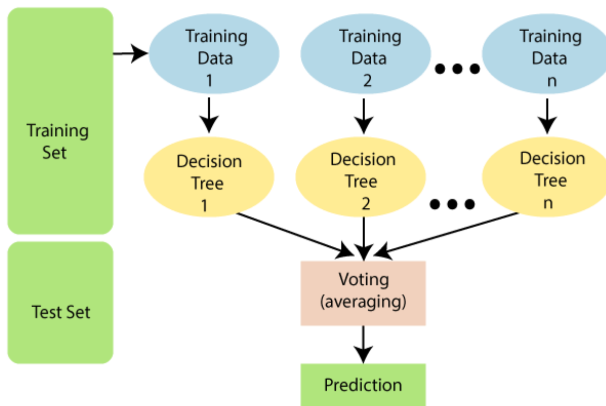



Fig. 4. Machine Learning Random Forest Algorithm.

concerns as well. It is a supervised learning strategy. Inside this tree-organized classifier, properties of the dataset are put away in inner hubs, choice principles are addressed by branches, and the end is given by each leaf hub.

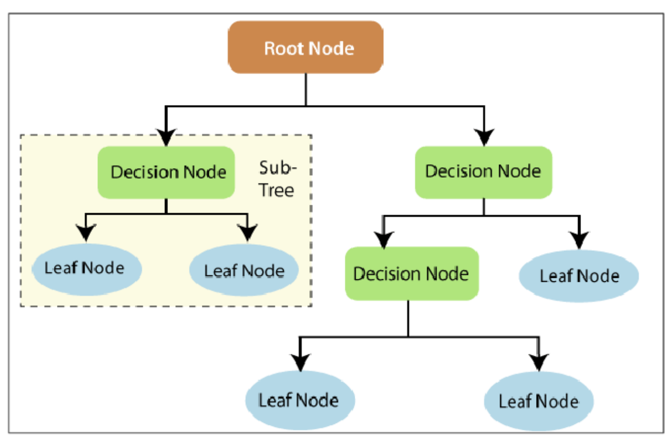
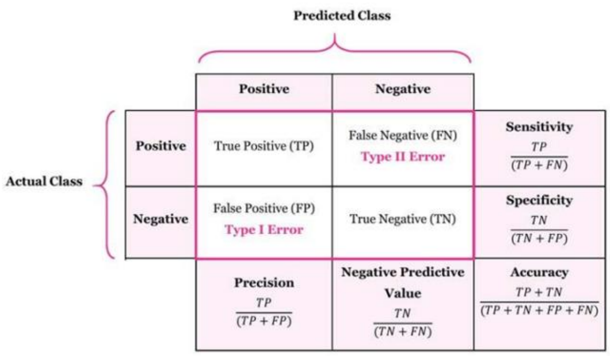



Fig. 5. Decision Tree Algorithm based Machine Learning Classification ([2])

### *F. Confusion Matrix*

Typically utilized in supervised learning, confusion matrices are utilised to evaluate the efficacy of algorithms in Machine Learning. Each line of the grid addresses the genuine worth of the class that should be anticipated, while every segment addresses the expected worth. In our investigation, we used the Confusion Matrix to quantify the rate of misclassification of the different models.



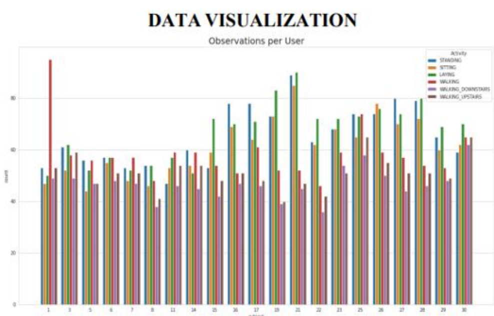




Fig. 6. Observation per user

The method is adopted following conventional Machine Learning approaches with appropriate dataset and training test mechanism. The SVM classifier is used. The Confusion Matrix and comparative studies provided above.

The use activities has been presented in the following

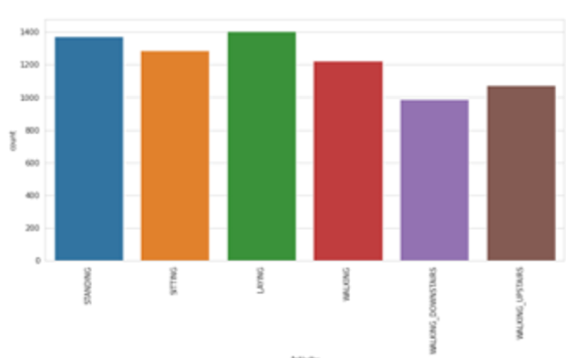


Fig. 7. Activity per user

The experimental results have been presented in the following table.

TABLE I
EXPERIMENTAL RESULTS

| Sl No | Algorithm used | |
|---|---|---|
| 1 | Default SVC score | 0.9748 |
| 2 | Some hyperparameter where Kernel used rbf and C=100.0 | 0.984 |
| 3 | Random Forest classifier | 0.9816 |
| 4 | Confusion Matrix | 0.9748 |
| 5 | Decision Tree | 0.94 |

The above result in the Table I signifies that there is not much variations in adopting different classifiers whereas the 2nd in the above table seems to be comparatively promising.

The concluding remarks are presented in the next section.

## CONCLUSION

Using data collected by smartphones' sensors, this work aims to build a strong system for student activity detection. Given the widespread use of smartphones for communication, e-commerce, social networking, healthcare, and a plethora of other daily tasks, it stands to reason that these devices could be ideal for activity recognition.

Numerous fields, including healthcare and surveying people, can benefit from activity recognition technologies. In this research, we developed an identification system that can be accessed by smartphones. It can identify six different student behaviours: walking, standing, lying, sitting, and even going upstairs and downstairs. The system improved performance by reducing feature dimensionality after collecting time series data from an integrated accelerometer, which permitted it to produce 561 elements in the time and recurrence areas. The activity data was trained and evaluated using four passive learning approaches: confusion matrix, decision tree, support vector machine, and random forest classifier. The most effective SVC configuration with rbf and c=100.0 resulted in a classification rate of 98.8 percent in our testing. Similarly, Random Forest, Decision Tree, Confusion Matrix, and SVM with default hyperparameters all perform similarly to the processed data. In an effort to reduce the expense of data tagging, algorithms were explored. We find that SVM gains the most headway and produces the most dependable expectations subsequent to applying the administered learning technique to every one of the four classifiers. Potentially new features and a real-time smartphone system integration are in the works for future development.

The observations made through found fact can be extended further by using Semi supervised Learning approaches because in some real world classroom situation, partially unlabeled data may also occur in order to identify some more human gesture. This may be taken into consideration in further study.

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