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# HUMAN ACTIVITY RECOGNITION USING SMARTPHONES

Project Submitted to the
SRM University AP, Andhra Pradesh
for the partial fulfillment of the requirements to award the degree of

**Bachelor of Technology**
**in**
**Computer Science & Engineering**
**School of Engineering & Sciences**

submitted by

**Padala Saket Sai(AP20110010690)**

**Penubothu Gautham Sai Swaroop(AP20110010687)**

**Singamaneni Sriram(AP20110010630)**
**Kondavaradala Deepak Manidra(AP20110010698)**

Under the Guidance of

**Dr. Pandu Sowkuntla**

**Department of Computer Science & Engineering**
SRM University-AP
Neerukonda, Mangalgiri, Guntur
Andhra Pradesh - 522 240
May 2024

# DECLARATION

I undersigned hereby declare that the project report **HUMAN ACTIVITY RECOGNITION USING SMARTPHONES** submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology in the Computer Science & Engineering, SRM University-AP, is a bonafide work done by me under supervision of Dr. Pandu Sowkuntla. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree of any other University.

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| Name of student | : | Padala Saket Sai | Signature | : | ................................ |
| Name of student | : | Penubothu Gautham Sai Swaroop | Signature | : | ................................ |
| Name of student | : | Singamaneni Sriram | Signature | : | ................................ |
| Name of student | : | Kondavaradala Deepak Manidra | Signature | : | ................................ |

**DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING**

**SRM University-AP**

**Neerukonda, Mangalgiri, Guntur**

**Andhra Pradesh - 522 240**

# CERTIFICATE

This is to certify that the report entitled **HUMAN ACTIVITY RECOGNITION USING SMARTPHONES** submitted by **Padala Saket Sai, Penubothu Gautham Sai Swaroop, Singamaneni Sriram, Kondavaradala Deepak Manidra** to the SRM University-AP in partial fulfillment of the requirements for the award of the Degree of Master of Technology in in is a bonafide record of the project work carried out under my/our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

| | |
|---|---|
| Project Guide | Head of Department |
| Name : Dr. Pandu Sowkuntla | Name : Prof. Niraj Upadhayaya |
| Signature: ....................... | Signature: ....................... |

# ACKNOWLEDGMENT

I wish to record my indebtedness and thankfulness to all who helped me prepare this Project Report titled **HUMAN ACTIVITY RECOGNITION USING SMARTPHONES** and present it satisfactorily.

I am especially thankful for my guide and supervisor Dr. Pandu Sowkuntla in the Department of Computer Science & Engineering for giving me valuable suggestions and critical inputs in the preparation of this report. I am also thankful to Prof. Niraj Upadhayaya, Head of Department of Computer Science & Engineering for encouragement.

My friends in my class have always been helpful and I am grateful to them for patiently listening to my presentations on my work related to the Project.



Padala Saket Sai, Penubothu Gautham Sai Swaroop, Singamaneni Sriram,
Kondavaradala Deepak Manidra
(Reg. No. AP20110010690, AP20110010687, AP20110010630,
AP20110010698)
B. Tech.
Department of Computer Science & Engineering
SRM University-AP

# ABSTRACT

This research examines the use of machine learning in identifying human activities through smartphone sensor data. We are attempting to determine if an individual is on foot, ascending stairs, descending stairs, seated, upright, or reclined. We achieve this by analyzing the data collected by sensors that track the speed and direction of movement of the phone. We experimented with various machine learning techniques such as Logistic Regression, Linear and Kernel SVM, Decision Trees, and Random Forest to determine the most effective method for predicting an individual's activity. This study contributes to enhancing systems that are capable of identifying individual's activities, which proves beneficial for tasks such as managing one's well-being, tracking physical fitness, and enabling smartphones to understand your actions better.

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# LIST OF FIGURES

# Chapter 1

# INTRODUCTION

Human Activity Recognition (HAR) derives from the confluence of technologies and human behavior analysis, and it bears great potential across a spectrum of domains, including but not limited to healthcare, fitness, and interactive computing. Automated recognition and classification of human activities based on sensor data provide scope for personalized health monitoring and rehabilitation support, besides context-aware applications.

With smartphones equipped with so many sensors, HAR is more possible. With the availability of smartphones loaded with a rich set of sensors, HAR is now possible because of them. This has made way for intelligent and innovative solutions to real-world problems.

This study capitalizes on the wealth of data captured by smartphone sensors, mainly accelerometer and gyroscope, as it plunges into the realm of HAR. This is the direction in which the current project went a step further with the use of the dataset, which was collected from 30 subjects performing six different tasks with different movements and postures. The dataset in which Machine learning models are trained and evaluated, as a result, sifts out diverse scenarios and individuals carefully.

Beyond its immediate applications, HAR holds promise in fostering a deeper understanding of human behavior and activity patterns. From such subtle movements and postures, HAR can deduce insights into the health, well-being, and daily activity of a person. In these cases, HAR goes up to the enhancement of user experiences in interactive environments. This enables the user to interact naturalistic with devices and applications that adapt to preferences and contexts.

Despite its potential, smartphone-based HAR presents certain challenges. Sensor data can be susceptible to variations due to factors like phone placement on the body, individual movement patterns, and even environmental conditions. Additionally, battery consumption associated with continuous sensor monitoring needs to be optimized for real-world applications.

However, these challenges are coupled with exciting opportunities. Advancements in machine learning, particularly deep learning techniques, are leading to more robust and accurate HAR models. Furthermore, the integration of additional sensors like magnetometers and barometers can provide richer data, enabling the recognition of a wider range of activities. As research progresses, smartphone-based HAR has the potential to become a cornerstone of personalized health management, fitness monitoring, and the development of intuitive and context-aware mobile applications.

The widespread adoption of HAR applications necessitates careful consideration of privacy and security concerns. Sensor data collected from smartphones can be sensitive, potentially revealing information about an individual's location, routines, and even health conditions. Implementing robust anonymization techniques and transparent data collection practices are crucial to ensure user trust. Additionally, securing this data from unauthorized access or breaches is paramount. By addressing these concerns proactively, researchers and developers can foster the responsible development and deployment of smartphone-based HAR for the greater good.

# Chapter 2

# MOTIVATION

With smartphones becoming an integral part of our daily life, the use of Human Activity Recognition has increased. In the world, where there is an incline in the death of people due to cardiac arrests, monitoring the movements, health of the people is very important. This situation made us think abut this topic out of various topics and we chose this topic. With the help of theses devices like accelerometer and gyroscopes, Human Activity Recognition was possible. With the help of these sensors, this project aims to create very advanced solutions for domains in the healthcare.

In this growing field of HAR, by working on this project, it helped us to gain experience and also helped us to improve our knowledge in Data Preprocessing, EDA (Exploratory Data Analysis), Machine Learning techniques for improving accuracy. This project also helped us in building our communication skills, team coordination skills and also presentation skills. We also hope that this could be useful in the healthcare sector and could contribute for a good change in the world and make it a better place.

The ubiquitous nature of smartphones coupled with the power of machine learning algorithms like Logistic Regression, Random Forest, Decision Trees, Kernel SVM, and Linear SVC presents a transformative opportunity for personalized healthcare solutions. The alarming rise in deaths due to cardiac arrest underscores the critical need for early intervention. HAR has the potential to play a vital role in this area by monitoring activity patterns that might signal health risks. Our project utilizes these machine learning models to analyze smartphone sensor data. By building a system that can detect anomalies or changes in movement patterns, we aim to provide crucial insights that could prompt further medical evaluation. Early detection facilitated by this technology can significantly improve patient outcomes and potentially save lives.

Compared to traditional methods of activity monitoring, smartphone-based HAR offers several compelling advantages. Firstly, smartphones are ubiquitous, making them a readily available tool for data collection. Users already carry them throughout the day, eliminating the need for additional wearables. Secondly, smartphones are equipped with a rich set of sensors like accelerometers and gyroscopes, which can capture detailed information about movement patterns without intruding on daily activities. Finally, the processing power of smartphones allows for real-time analysis of sensor data, enabling immediate feedback and potential intervention if necessary.

Undertaking this project on Human Activity Recognition using machine learning models wasn't just about the technical aspects. It provided us with a valuable opportunity to develop a growth mindset. We faced challenges in data analysis, model selection, and fine-tuning algorithms. Overcoming these hurdles fostered our perseverance and problem-solving skills. Furthermore, working collaboratively on this project honed our communication and teamwork abilities. These transferable skills will undoubtedly benefit us in future endeavors, both academic and professional. By equipping ourselves with a strong foundation in machine learning and a collaborative spirit, we aim to contribute meaningfully to the advancement of technology in the healthcare domain.

# Chapter 3

# LITERATURE SURVEY

In this paper, Moola and Hossain investigate the Human Activity Recognition (HAR) system in detail with a focus on deep learning techniques. The study clearly outlines four basic steps under a comprehensive architectural definition of the HAR system: data acquisition, pre- processing, feature extraction, and classification [1]. Most of the review and study papers have compared in-depth the performance of classical machine learning techniques, such as K- nearest neighbours (KNN), Naive Bayes, and Support Vector Machines (SVM), with modern deep learning state-of-the-art models, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Gated Recurrent Units (GRU).

The paper sheds light on performance in these methods based on an analyzed 48 systematic studies for some few factors, such as the type of activity recognized, the algorithm used, and the equipment used for data acquisition [1]. In addition, this study thus reviewed difficulty recognition in using accelerometer sensors to recognize human activities in deep learning with traditional machine learning paradigms and between online and offline systems. Subasi, Fllatah, Alzobidi, Brahimi, and Sarirete conducted in-depth research on smartphone sensors in human activity recognition. The research employed the use of ensemble learning techniques such as bagging and boosting for improved classification accuracy [2]. The approach the study takes is centered on smartphones, since an approach with Json mainly aims at gaining an intervention using the capabilities of its built-in Json capabilities. This work was trying to overcome this limitation by providing ensemble learning methodologies with the help of human activity recognition systems, and thereby enhancing the robustness and reliability of the recognition systems. [2].

They are diverse in motion because the activities targeted for recognition include walking, running, ascending and descending stairs, sitting, and standing [2]. Specifically, this work describes the effectiveness of ensemble learning to enhance classification performance for human activity recognition from smartphone devices by rigorously evaluating and comparing all these standalone classifiers vis-à-vis ensemble ones [2]. Dhanraj, De, and Dash propose an ingenious idea for the recognition of human activities using CNNs-powered smartphones [3]. A robust and effective human activity recognition system using smartphones is the subject of this paper, in which raw sensor data from the accelerometer and gyroscope of the device are used as inputs to the CNN model. The CNN architecture is carefully designed to effectively capture spatial dependencies within the sensor data that help in proper recognition of activities like walking, running, sitting, standing, climbing upstairs, and climbing downstairs [3].

The authors also present a complete experimental setup to draw a comparison in performance with conventional machine learning algorithms, such as the decision trees, random forest, and support vector machine, of the CNN-based approach [3]. The results highlighted the effectiveness obtained in the state-of-the-art classification accuracy and robustness when they need to be obtained for smartphone-based human activity recognition tasks [3].

# Chapter 4

# ANALYSIS OF DATASET

The dataset includes distinct characteristics about human behaviour, like BodyAccmeanX, BodyAccmeanY, BodyAccmeanZ, BodyAccstdX, and others. Every row signifies a distinct observation, and each column correlates to a unique characteristic. This dataset contains 564 columns in total, which consist of characteristics connected to body acceleration, gravity, and gyroscopic readings. Moreover, the dataset contains columns for subject identification and activity labels [4].

To examine this data set, we can use a variety of statistical and machine learning methods. These methods include activities like preparing data, analyzing data, selecting features, training models, and assessing performance.

Our goal is to uncover information about human behavior and activity patterns by examining this dataset. Moreover, our goal is to create accurate predictive models that can classify various activities using sensor data [4]. These models can improve healthcare, fitness tracking, and interactive computing applications by offering real-time activity recognition and personalized insights for users.

# Chapter 5

# IMPLEMENTATION

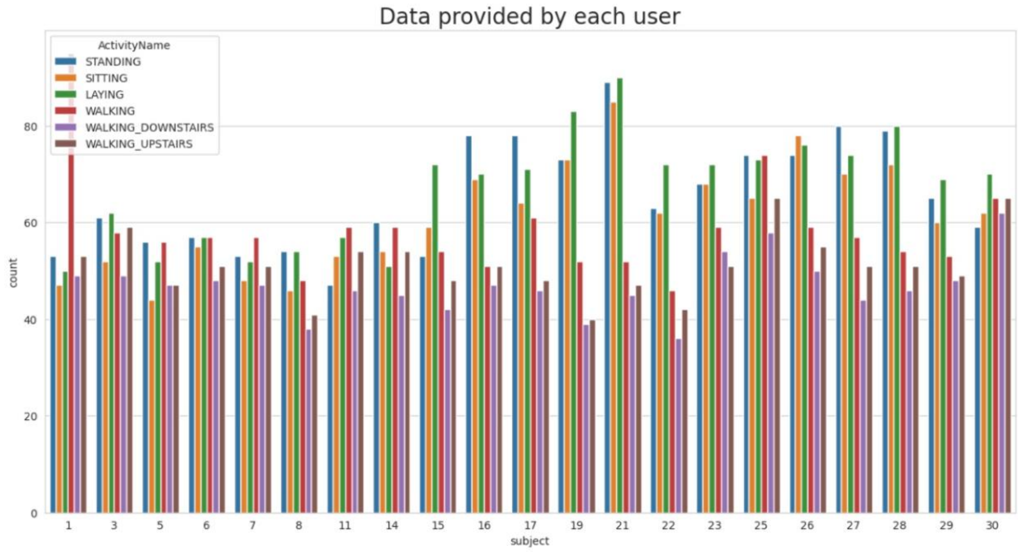


Figure 5.1: **We have got almost same number of readings from all the subjects**

This phase outlines the implementation of multifaceted activities, starting from preprocessing the sensor data so that it becomes clean and relevant for this study. Thus, after raw sensor readings, noise filtering techniques are applied to them, followed by segmentation into fixed windows. Each window encodes a snapshot of human activity, with 128 readings in the window following one another at 50% overlap, giving the best possibility to pick up temporal dependencies.

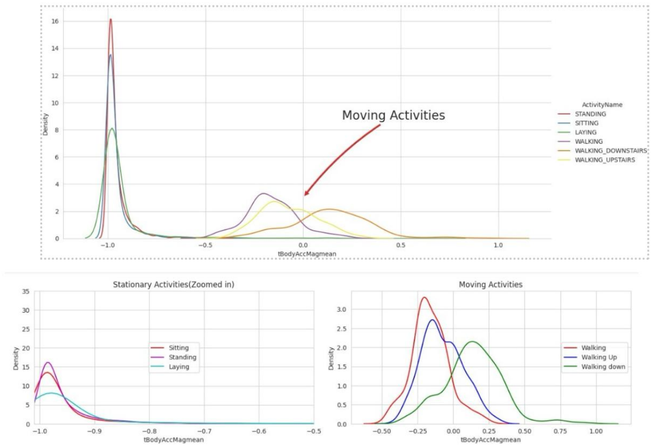


Figure 5.2: **Stationary and Moving activities are completely different**

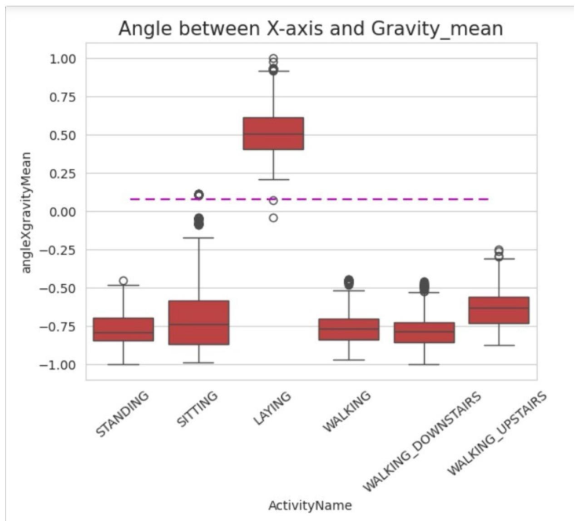


Figure 5.3: **Magnitude of an acceleration can separate it well**

- If the average total acceleration (tAccMean) is less than -0.8, the activities are likely to be Standing, Sitting, or Lying down.
- If the average total acceleration is greater than -0.6, the activities are likely to be Walking, Walking downstairs, or Walking upstairs.
- If the average total acceleration is greater than 0.0, the activity is likely to be Walking downstairs.
- We can correctly classify about 75% of the activity labels, but there

might be some errors.

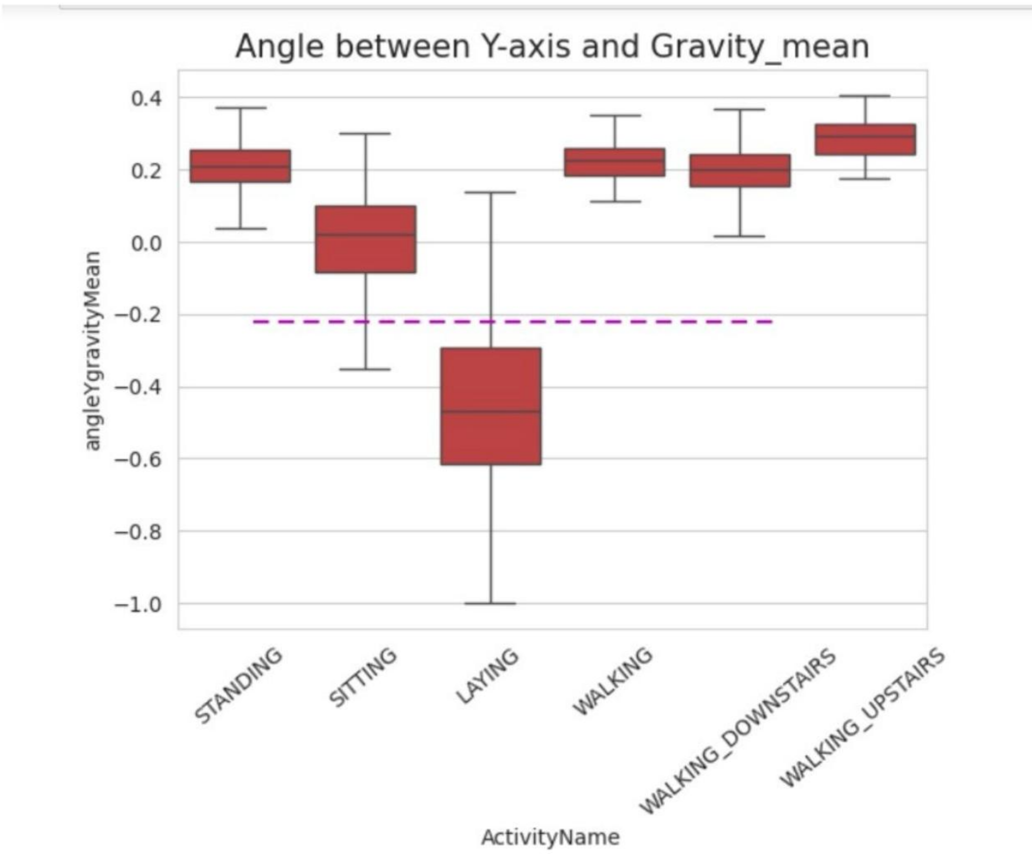


Figure 5.4: **Position of Gravity Acceleration Components also matters**

- If the average angle between the X-axis and gravity is greater than 0, then the activity is Lying down. With just one if-else statement, we can correctly classify all data points related to the Lying down activity.

  Algorithms can greatly enhance prediction accuracy.

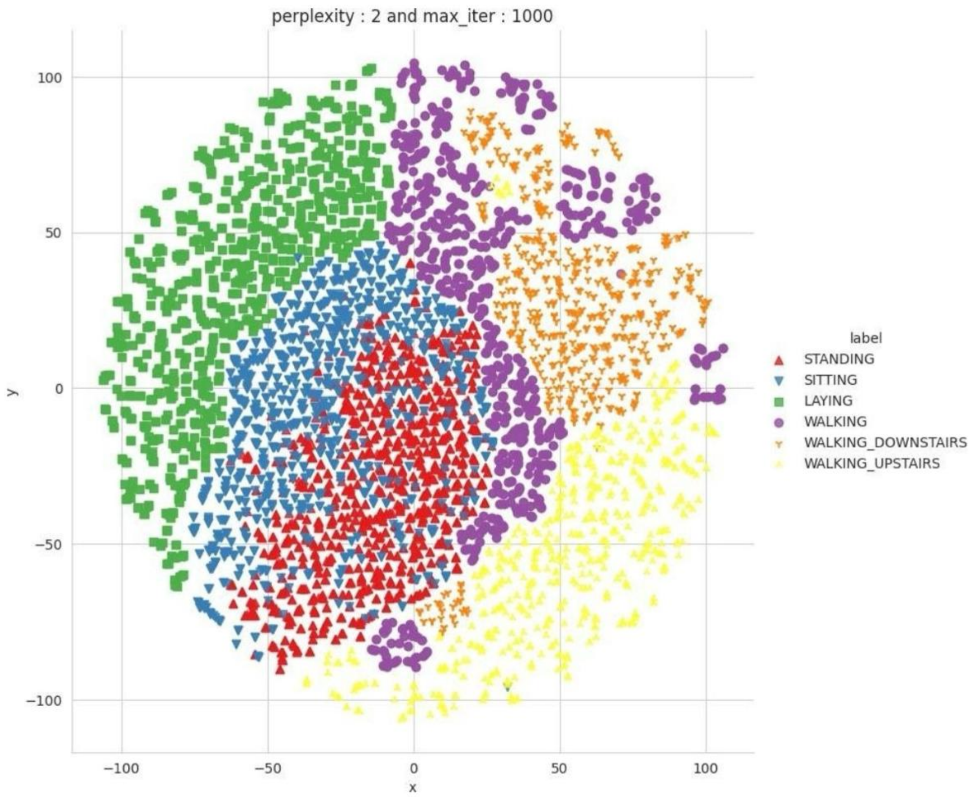


Figure 5.5: **Perplexity 2, 1000 iterations:**

- Nearest Neighbours computation: 0.426s.
- Conditional probabilities computation: 0.071s.
- Iteration 50 to 1000: Gradual reduction in error over iterations, with decreasing gradient norm.
- Final error: 1.627915, indicating convergence.
- Total time: Approximately 3 minutes.

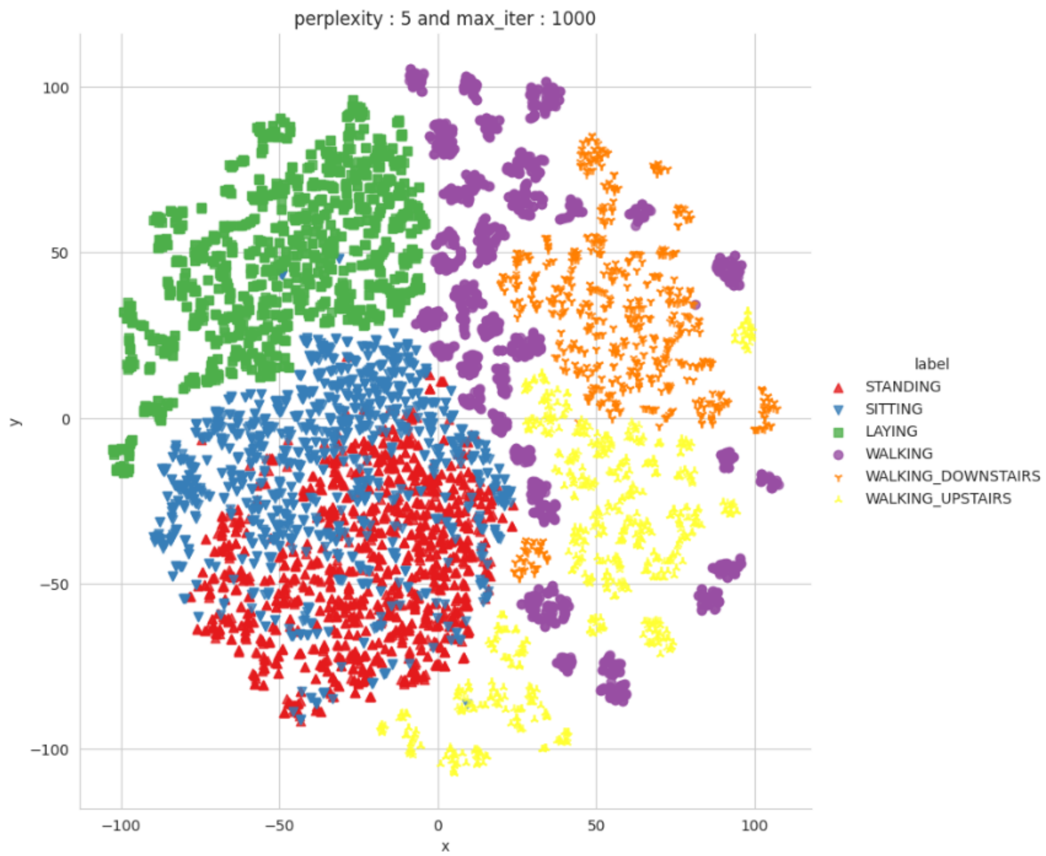


Figure 5.6: **Perplexity 5, 1000 iterations:**

- Nearest Neighbours computation: 0.263s.
- Conditional probabilities computation: 0.122s.
- Iteration 50 to 1000: Similar trend as perplexity 2, but faster convergence.
- Final error: 1.566424, indicating convergence.
- Total time: Approximately 3 minutes.

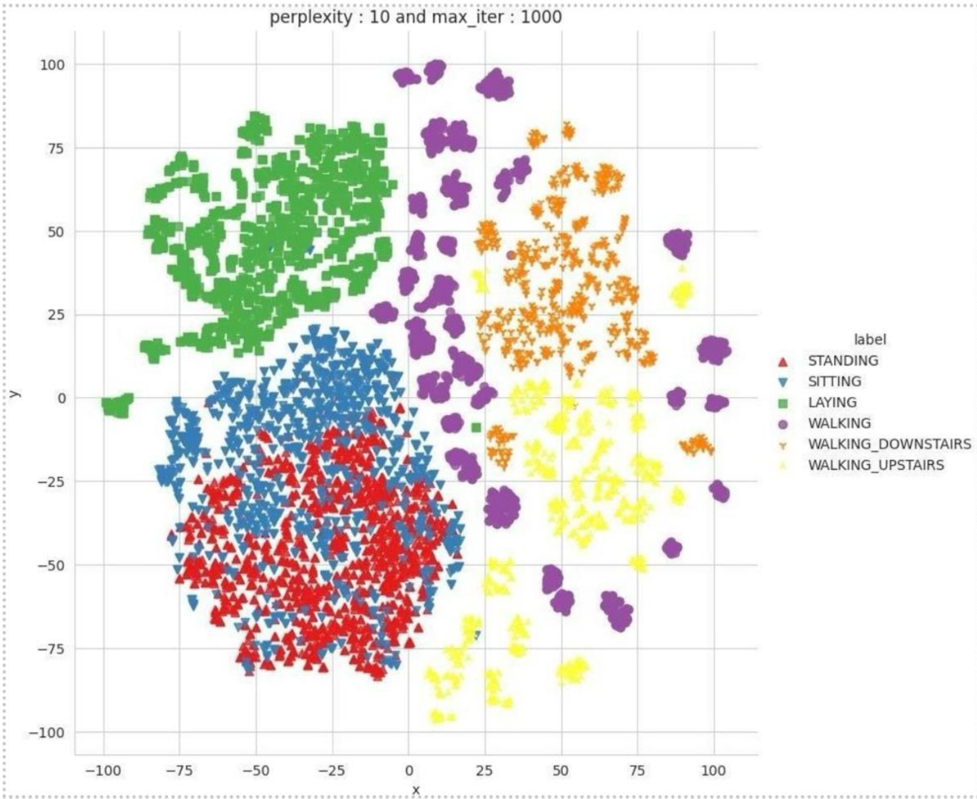


Figure 5.7: **Perplexity 10, 1000 iterations:**

- Nearest neighbours computation: 0.410s.
- Conditional probabilities computation: 0.214s.
- Iteration 50 to 1000: Similar trend, further improvement in convergence speed.
- Final error: 1.499968, indicating convergence.
- Total time: Approximately 3 minutes.

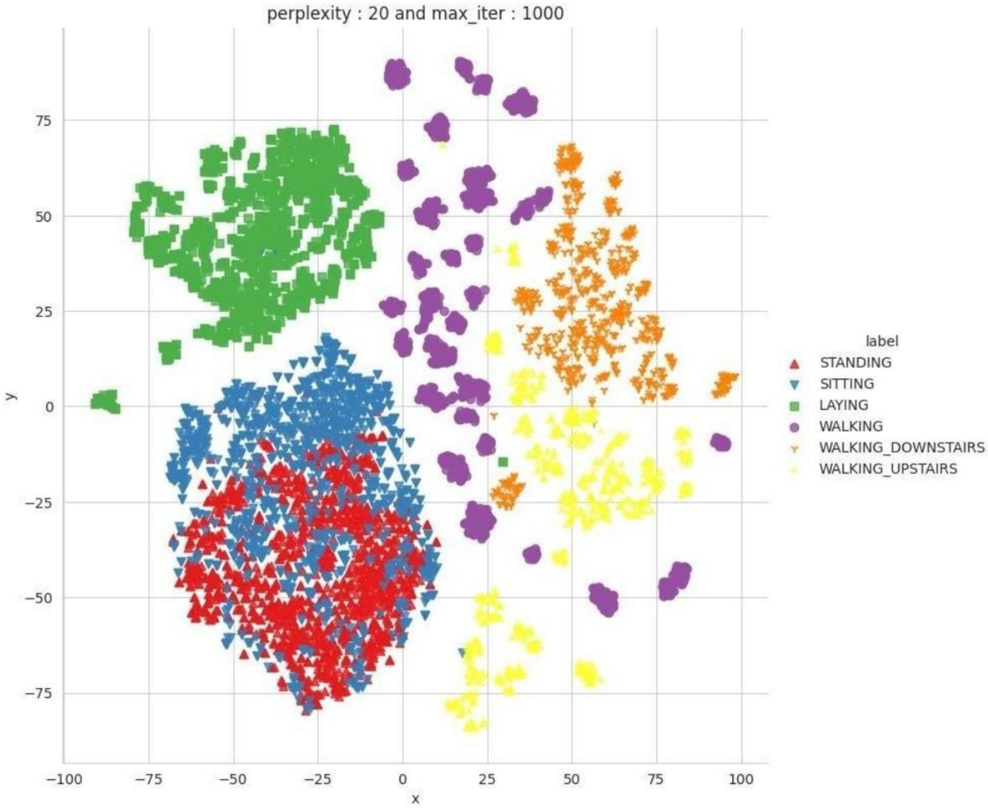


Figure 5.8: **Perplexity 20, 1000 iterations:**

- Nearest neighbours computation: 0.425s.
- Conditional probabilities computation: 0.355s.
- Iteration 50 to 1000: Consistent reduction in error, faster convergence.
- Final error: 1.418997, indicating convergence.
- Total time: Approximately 3 minutes.


Figure 5.9: **Perplexity 50, 1000 iterations:**

- Nearest neighbours computation: 0.376s.
- Conditional probabilities computation: 0.844s.
- Iteration 50 to 1000: Steady reduction in error, slower convergence than lower perplexities.
- Final error: 1.287424, indicating convergence.
- Total time: Approximately 3 minutes.

Feature engineering presents an important step in the pipeline, where one seeks to extract informative features from segmented windows. 561 attributes are designed upon the knowledge of the domain and signal processing techniques. The features encapsulate statistical measures in time and frequency domains, which contain essential characteristics of the motion and posture of humans. After the extraction and selection of features, a suite of machine learning models was used in this work to carry out the HAR task. Added Grid Search: hyperparameter tuning, which is well known for its simplicity and interpretability.

Whereas Linear Support Vector Machines (SVMs) and Kernel SVMs provide strong powers for classification, totally exploited hyperplanes and tricks of the kernel separate activity boundaries. These implemented algorithms are Decision Trees, Random Forest and others, which ensure that a proper deal of complex patterns and data hierarchies is taken care of. These accuracies, precisions, recalls, and F1-scores derived by the model after the following strict cross-validation do inform the model performance. Model evaluation follows strict cross-validation. It includes the hyperparameters tuned by GridSearchCV and ensures the better performance of the model, but no overfitting. The output models are studied to show effectiveness in reaching accurate classification of human activity, with a great potential for casting light on subtle interplay among feature representation, algorithmic complexity, and predictive performance.

# Chapter 6

# HARDWARE/ SOFTWARE TOOLS USED

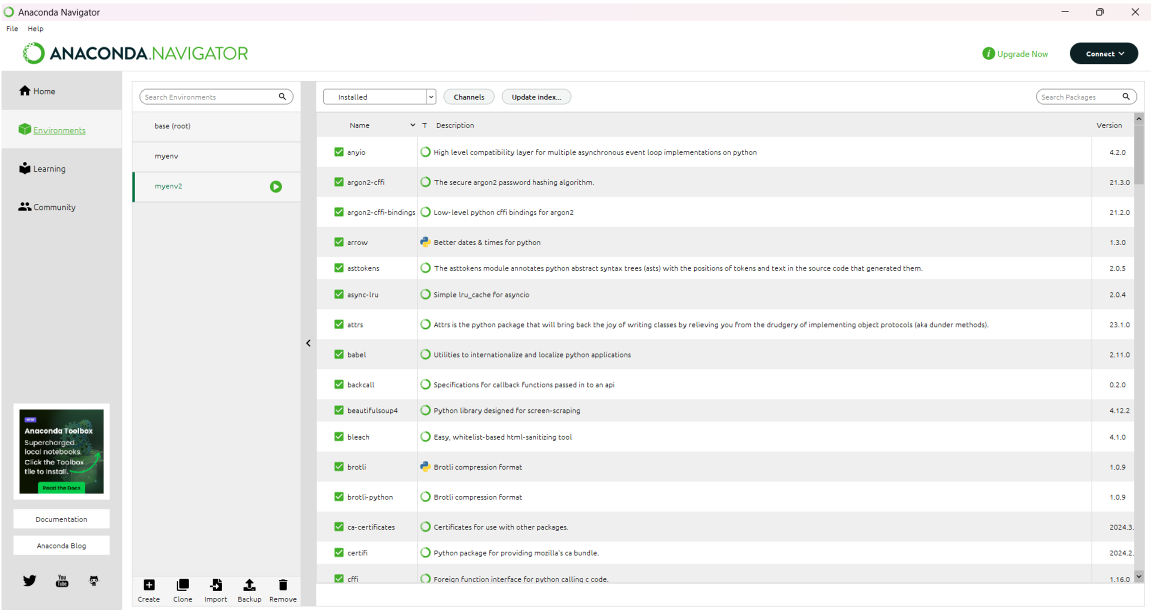


Figure 6.1: Anaconda Navigator

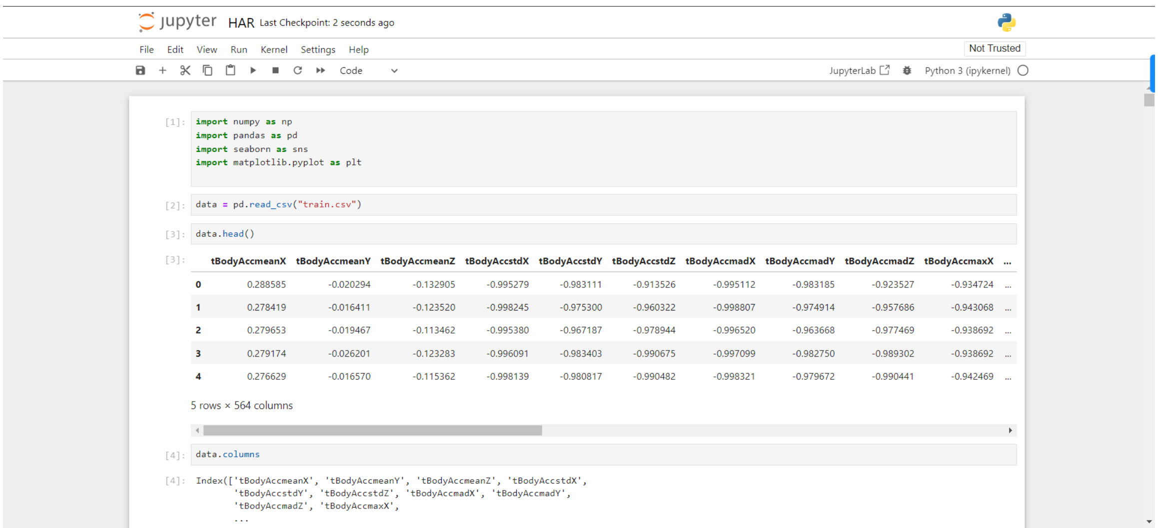


Figure 6.2: Jupyter Notebook

# Chapter 7

# RESULTS & ANALYSIS

Different levels of accuracy were observed when evaluating models, with Logistic Regression, Linear SVC, and rbf SVM classifier showing the best performance, all achieving accuracy scores close to 96%. And all the algorithms classification report and confusion matrix are shown below.

## 7.1 LOGISTIC REGRESSION


Figure 7.1: LOGISTIC REGRESSION

```
------------------------
| Classifiction Report |
------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.96      0.88      0.92       491
          STANDING       0.90      0.97      0.93       532
           WALKING       0.94      0.99      0.97       496
WALKING_DOWNSTAIRS       0.99      0.96      0.98       420
  WALKING_UPSTAIRS       0.97      0.94      0.96       471

          accuracy                           0.96      2947
         macro avg       0.96      0.96      0.96      2947
      weighted avg       0.96      0.96      0.96      2947
```

Figure 7.2: LOGISTIC REGRESSION REPORT

## 7.2 LINEAR SVC WITH GRIDSEARCH

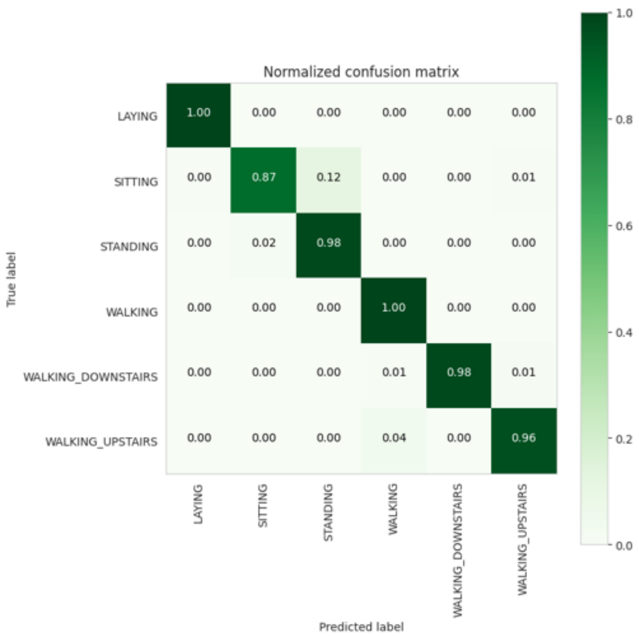


Figure 7.3: LINEAR SVC WITH GRIDSEARCH

-------------------------
| Classifiction Report |
-------------------------

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| LAYING | 1.00 | 1.00 | 1.00 | 537 |
| SITTING | 0.98 | 0.87 | 0.92 | 491 |
| STANDING | 0.90 | 0.98 | 0.94 | 532 |
| WALKING | 0.96 | 1.00 | 0.98 | 496 |
| WALKING_DOWNSTAIRS | 1.00 | 0.98 | 0.99 | 420 |
| WALKING_UPSTAIRS | 0.98 | 0.96 | 0.97 | 471 |
| accuracy | | | 0.97 | 2947 |
| macro avg | 0.97 | 0.97 | 0.97 | 2947 |
| weighted avg | 0.97 | 0.97 | 0.97 | 2947 |

Figure 7.4: LINEAR SVC WITH GRIDSEARCH REPORT

## 7.3 KERNEL SVM WITH GRIDSEARCH


Figure 7.5: KERNEL SVM WITH GRIDSEARCH

```
-------------------------
| Classifiction Report |
-------------------------
```

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| LAYING | 1.00 | 1.00 | 1.00 | 537 |
| SITTING | 0.97 | 0.90 | 0.93 | 491 |
| STANDING | 0.92 | 0.98 | 0.95 | 532 |
| WALKING | 0.96 | 0.99 | 0.97 | 496 |
| WALKING_DOWNSTAIRS | 0.99 | 0.95 | 0.97 | 420 |
| WALKING_UPSTAIRS | 0.95 | 0.96 | 0.95 | 471 |
| accuracy | | | 0.96 | 2947 |
| macro avg | 0.96 | 0.96 | 0.96 | 2947 |
| weighted avg | 0.96 | 0.96 | 0.96 | 2947 |

Figure 7.6: KERNEL SVM WITH GRIDSEARCH REPORT

## 7.4 DECISION TREES WITH GRIDSEARCHCV

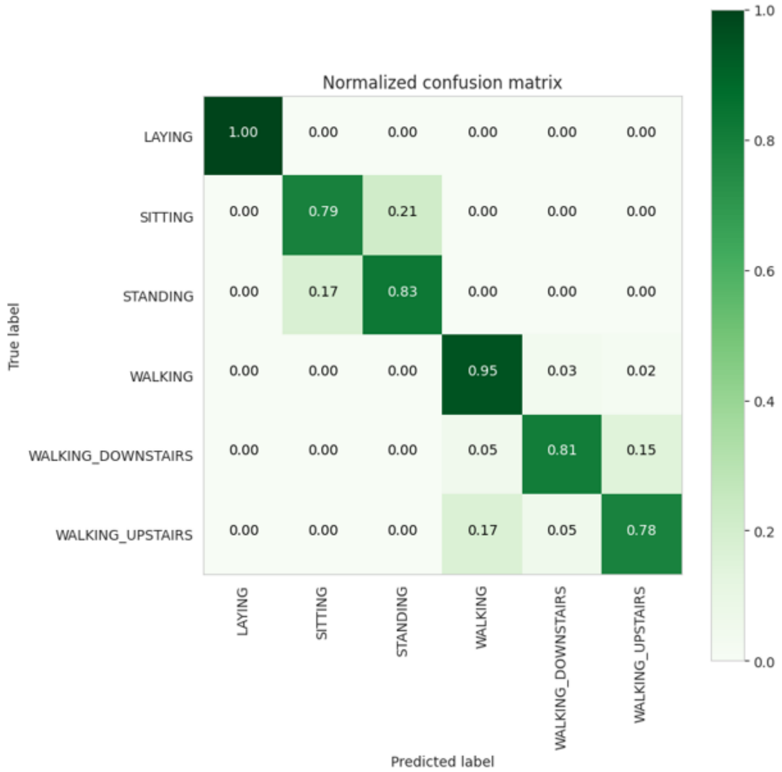


Figure 7.7: DECISION TREE WITH GRIDSEARCHCV

| Classifiction Report |

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| LAYING | 1.00 | 1.00 | 1.00 | 537 |
| SITTING | 0.81 | 0.79 | 0.80 | 491 |
| STANDING | 0.81 | 0.83 | 0.82 | 532 |
| WALKING | 0.83 | 0.95 | 0.88 | 496 |
| WALKING_DOWNSTAIRS | 0.89 | 0.81 | 0.85 | 420 |
| WALKING_UPSTAIRS | 0.84 | 0.78 | 0.81 | 471 |
| accuracy | | | 0.86 | 2947 |
| macro avg | 0.86 | 0.86 | 0.86 | 2947 |
| weighted avg | 0.86 | 0.86 | 0.86 | 2947 |

Figure 7.8: DECISION TREE WITH GRIDSEARCHCV REPORT

## 7.5 RANDOM FOREST CLASSIFIER WITH GRIDSEARCH

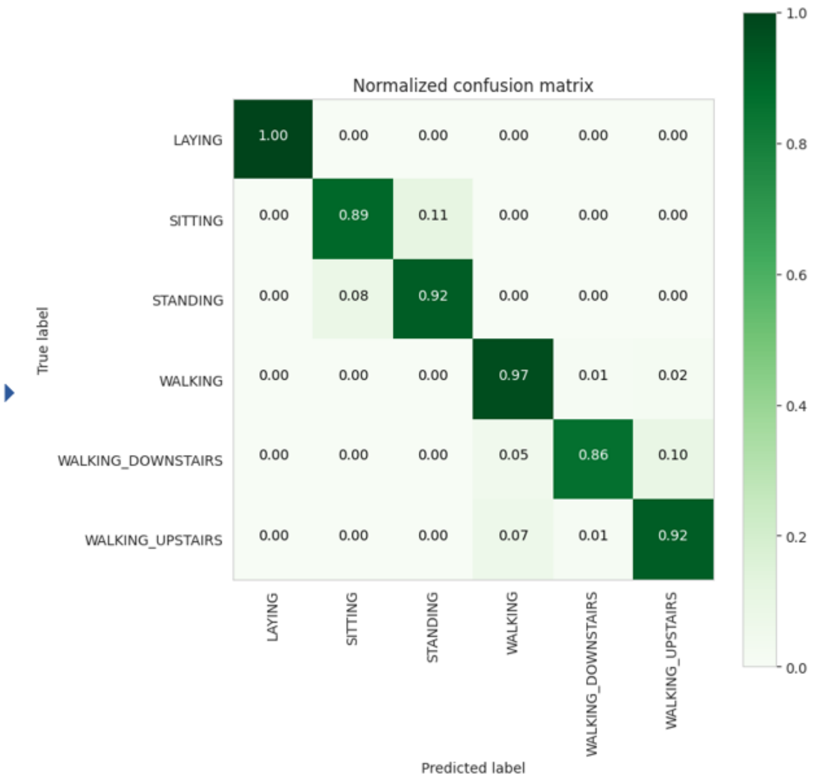


Figure 7.9: RANDOM FOREST CLASSIFIER WITH GRIDSEARCHCV

```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.91      0.89      0.90       491
          STANDING       0.90      0.92      0.91       532
           WALKING       0.90      0.97      0.94       496
WALKING_DOWNSTAIRS       0.97      0.86      0.91       420
  WALKING_UPSTAIRS       0.90      0.92      0.91       471

          accuracy                           0.93      2947
         macro avg       0.93      0.93      0.93      2947
      weighted avg       0.93      0.93      0.93      2947
```

Figure 7.10: RANDOM FOREST CLASSIFIER WITH GRIDSEARCHCV REPORT

## 7.6 FINAL RESULT

```
                          Accuracy     Error
                          ----------   --------
Logistic Regression   :   95.93%        4.072%
Linear SVC            :   96.67%        3.325%
rbf SVM classifier    :   96.27%       3.733%
DecisionTree          :   86.22%       13.78%
Random Forest         :   92.87%       7.126%
```

Figure 7.11: **Models Comparision**

# Chapter 8

# CONCLUSION

The research shows that it is possible to use data from smartphone sensors for successful Human Activity Recognition. Comparing different machine learning models gives important information on how suitable they are for HAR tasks, showing that Logistic Regression, Linear SVC, and rbf SVM classifier are the most effective options. This study adds to the continued investigation of machine learning uses in identifying human activities, providing a basis for further research on advanced models and feature engineering methods for better precision.

Ultimately, merging machine learning algorithms with data from smartphone sensors offers a powerful way to enhance HAR capabilities. In addition to its technical advantages, HAR has broader implications for improving healthcare services, enabling tailored interventions, and gaining a better understanding of human behavior. With technology advancing, there is endless potential for HAR to transform different areas, emphasizing the importance of ongoing research and innovation in this growing field.

As smartphone-based HAR continues to evolve, it's crucial to acknowledge and address the ethical concerns surrounding user privacy. Sensor data collected from smartphones can be sensitive, potentially revealing information about an individual's location, routines, and even health conditions. Therefore, future research and development efforts should prioritize the implementation of robust anonymization techniques and transparent data collection practices. By fostering trust and prioritizing user privacy, we can ensure that the advancements in HAR contribute to a positive and responsible future.

## 8.1 SCOPE OF FURTHER WORK

The integration of this project in the healthcare sector would be the future work. When it happens, there would be more accuracy and could bring in a positive difference to the world. In the future we will also try to build better deep learning models for human activity recognition using smart phones using different deep learning techniques which may outperform machine learning models and maximize the prediction accuracy and minimizes the error.

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