Human Activity Recognition Using Smartphones

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***Abstract*—Human Activity Recognition (HAR) is an important activity, which has several potential applications in health monitoring, sports performance analysis, care of the elderly, and automation in a smart home. Precise classification of daily activities using sensor data may provide critical insight into the physical state and behavior of a person, which helps to personalize health interventions and enhance the user experience in a large number of applications. GitHub: https://github.com/27vedika/HAR-using-Smartphones**

I. Introduction

The increasing complexity of SOTA deep learning models (complicated neural networks etc), have significantly boosted accuracy; however, they have also introduced certain computational and memory limitations. These challenges are specifically prevalent for mobile and embedded systems. Thus we need to develop a lightweight model that works efficiently for such systems, using the above dataset while preserving accuracy. Human Activity Recognition, based on the data from these inertial sensors, is a low-cost, scalable solution with the widespread use of smartphones.

II. Literature Review

Human Activity Recognition (HAR) has progressed using traditional machine learning and deep learning techniques over the past few years. Studies show that machine learning algorithms like Decision Trees, Logistic Regression and Multi-Layer Perceptron attain robust performance, with MLP attaining up to 91.7% accuracy on the WISDM dataset. Selecting features optimally and leveraging ensemble methods further boosts accuracy to 97.67%. Ensemble learning and dimensionality reduction techniques (LDA, EPS) can improve HAR accuracy, with some models being as accurate as 99% on UCI-HAR and WISDM datasets. Research Paper: https://paperswithcode.com/paper/leveraging-lda-feature-extraction-to-augment

Smartphones are equipped with built-in sensors, like accelerometers and gyroscopes, that unobtrusively capture users' physical movements. Smartphones have become central to Human Activity Recognition (HAR) due to this quality. Research has shown that smartphone-based Human Activity Recognition (HAR) can attain 96% accuracy in classifying daily activities with a Support Vector Machine (SVM) model. Various ML models, like Decision Trees, k-Nearest Neighbors, and Neural Networks, emphasize how combining inputs from multiple smartphone sensors enhances HAR classification performance. Multiple sensors and optimal feature extraction enable smartphones to become central for HAR classification today.

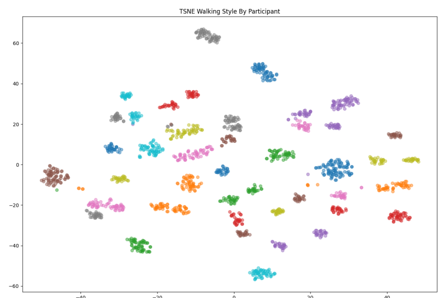

Fig. 1. Comparison of walking styles of different participants using t-SNE

Recent studies in HAR show the efficiency of deep learning models in classifying human activity. CNNs employed for feature extraction on the HARUSP dataset, have achieved a classification accuracy of 96.1%. Novel visualizations of abstract features based on sensors allow a deeper analysis of how sensor data relates to activity classification. This study also introduced a DNN-based fusion model that improves the recognition of activities with low accuracy by leveraging significant features, offering insights into improving deep learning applications in HAR.

III. Dataset Description

The dataset used for the Human Activity Recognition (HAR) project comprises a variety of attributes that capture both the physical movements and characteristics of the subjects involved in the activities. Key attributes include three columns representing triaxial acceleration from accelerometers: tBodyAcc-mean()-X, tBodyAcc-mean()-Y, and tBodyAcc-mean()-Z, which denote the mean acceleration in the X, Y, and Z axes, respectively. Additionally, there are corresponding measurements for triaxial angular velocity from gyroscopes, which provide insights into the rotational movements of the subjects. The dataset contains a total of 561 features, including both time and frequency domain variables, which describe the dynamics of the activities.

The dataset had no missing values, and there were no issues with class imbalances, eliminating the need for any data augmentation techniques.

Also studied the correlation between the features using a correlation heatmap generated.

A. Exploratory Data Analysis:

We analyzed the distribution of activity counts across 20 individuals to gain insights into the dataset. This helped in

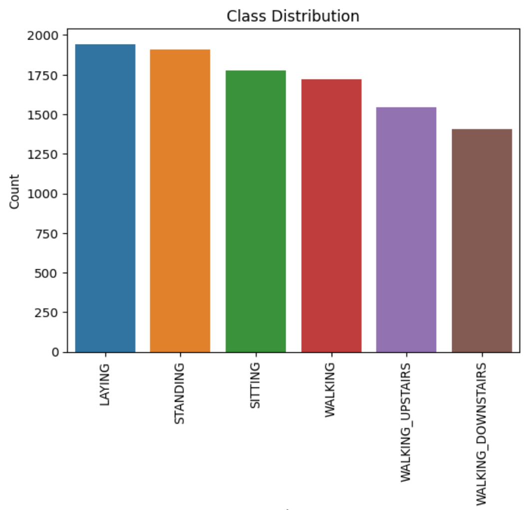

Fig. 2. Classwise Data Distribution

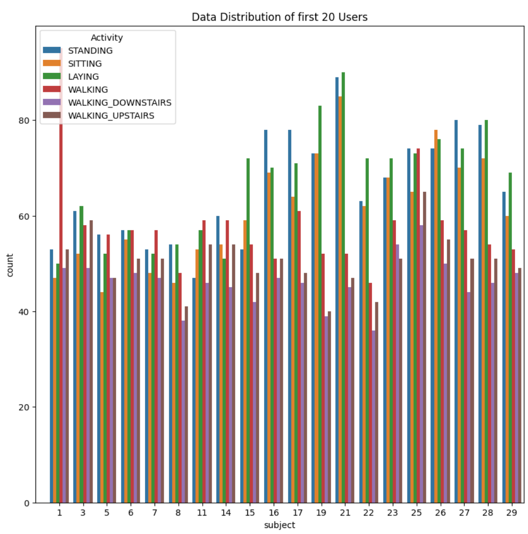

Fig. 3. Data Distribition for Sample 20 Users

understanding the representation of different activities and confirmed that the data was well-balanced across participants, ensuring consistent coverage of activities for each person.

Next, we examined the probability distribution of the tBody-Acc mean across all three axes for both Static and Dynamic activities. This analysis provided deeper insights into how the values vary between these two types of activities, helping to identify potential patterns or differences in movement that could aid in distinguishing between them more effectively.

After pruning some of the unnecessary columns, we implemented dimensionality reduction and visualized the data using t-SNE plots. First, the data is standardized using StandardScaler to ensure uniform scaling. Then, PCA reduces the feature space while retaining 90% of the variance, followed by applying t-SNE for further dimensionality reduction for visualization in two dimensions.

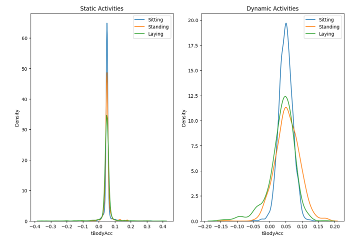

Fig. 4. Probability Distribution of Static and Dynamic Activities

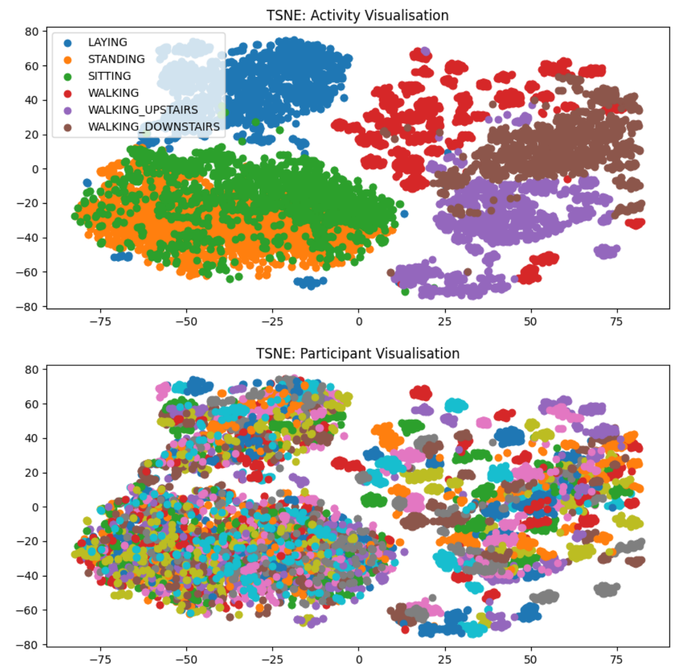

Fig. 5. Visualization of Data on the basis of Activities and Participation

The first subplot visualizes the t-SNE projection of the activities, where each point represents an activity, colored by its label, allowing us to see how well different activities are separated in the reduced space. The second subplot shows the same t-SNE projection but colored by the participants, offering insights into how activities cluster based on individuals. This dual visualization helps us understand both activity differentiation and participant-specific patterns in the dataset.

Visualizing walking trajectories of participants in the Human Activity Recognition dataset provides valuable insights into movement patterns, variations, and outliers in locomotion. These plots help identify consistent trends or irregularities across participants, which are crucial for feature extraction and pre-processing. Understanding spatial and temporal characteristics aids in refining the dataset for model building, ensuring better generalization, improved classification, and reduced noise, ultimately enhancing the accuracy and robustness of predictive models for human activity recognition.

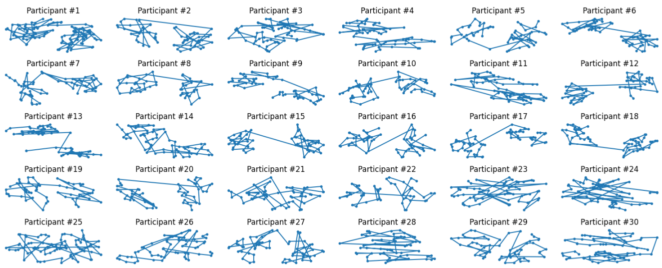

Fig. 6. Walking Pattern Analysis

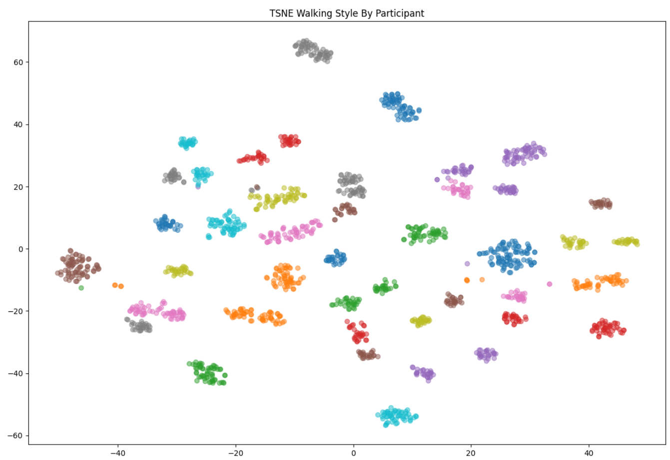

Fig. 7. Enter Caption

The t-SNE clustering visualization reveals distinct walking styles for participants in the dataset, highlighting inherent patterns and groupings based on shared characteristics. These clusters provide an intuitive understanding of variations in walking dynamics, enabling feature analysis and dimensionality reduction. By identifying overlaps, outliers, and compact clusters, this helps refine the dataset, ensuring that relevant features are prioritized during preprocessing. Such insights support better model building, allowing classification or recognition algorithms to effectively learn and generalize across different walking styles, improving prediction accuracy and reducing noise-related issues.

IV. Methodology

Following detailed EDA and review of relevant literature, we spotted 84 features as irrelevant and pruned them to reduce the dimensionality of the model. We used models such as Naive Bayes, Decision Trees, SVM, and Gradient-Boosted Decision Trees (XGBoost) to perform the classification of the data using the pre-processed input to the six different classes possible. To prepare the raw data for classification, we extracted time-domain and frequency-domain features from accelerometer and gyroscope signals, such as mean, standard deviation, energy, and spectral entropy. We experimented with a lot of Classification models, obtaining varying resulting accuracies. But we proceeded with SVM as our final model,

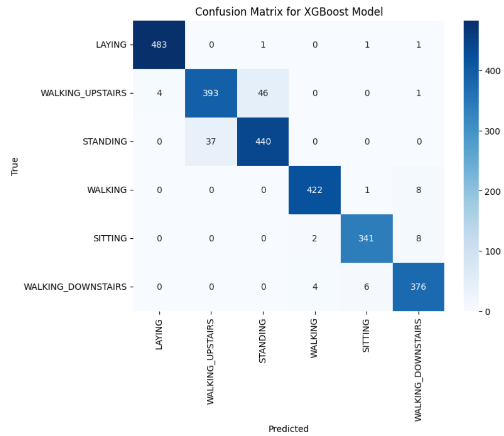

Fig. 8. Confusion Matrix for XGBoost

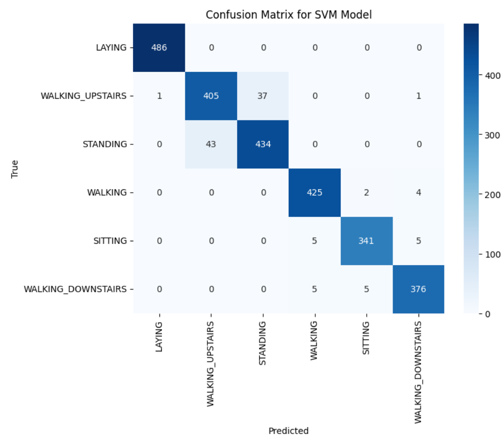

Fig. 9. Confusion Matrix for SVM

which gave great accuracy and was very lightweight and computationally cheap.

We continued with the practical implementation of the system on a mobile device. The data was processed to generate features, preprocessed using PCA for dimensionality reduction and scaling to standardize inputs, and then classified in real time using our SVM model.

V. Analysis

Our XGBoost Model gave a Test Accuracy of **99.3%**, and during the Literature Review, we found the best accuracy found from other researchers' experiments to be upto 99.5%. This model was the upper bound which we could achieve using light-weight models, and on further exploration, we found SVM to give us the closest accuracy with the minimal computation of **95.8%**, with other models at around **85%** accuracy.

VI. Conclusion

This project showcased successful implementation of a lightweight model for real-time human activity recognition using smartphone sensor data. By extracting time-domain and

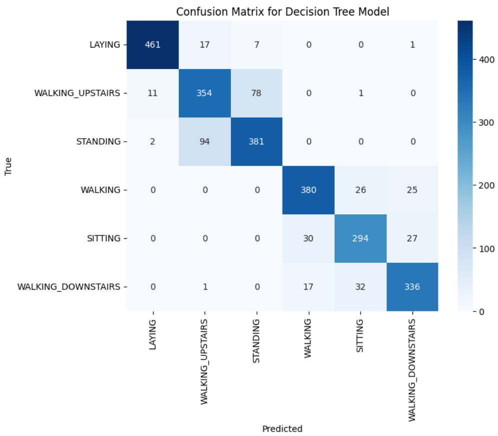

Fig. 10. Confusion Matrix for Decision Tree

frequency-domain features from accelerometer and gyroscope signals, we achieved accurate classification while minimizing computational overhead. This framework enables easy real-time deployment on Android devices without complex models.

VII. References

- Morris, B. *What does your smartphone know about you?* Retrieved from https://www.kaggle.com/code/morrisb/what-does-your-smartphone-know-about-you
- Vazan, M., Sharifi, E., Farahani, H., & Madadi, S. (2024). *Leveraging LDA Feature Extraction to Augment Human Activity Recognition Accuracy*.

A. ***Contributions:***

- Literature Review: Vedika Agarwal and Anand Vimal
- Data Collection and Preprocessing: Vedika Agarwal and Varin Kala
- Feature Extraction: Vedika Agarwal and Varin Kala
- EDA: Soham Ghosh and Varin Kala
- Model Training: Soham Ghosh and Anand Vimal
- Model Evaluation and Validation: Soham Ghosh and Anand Vimal