AI Based Human Activity Recognition Using Smartphone Sensors

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Abstract- *The utilization of built-in sensors for human activity recognition has garnered significant attention, thanks to smartphones pervasive integration into daily life. This research presents an innovative AI-based Human Activity Recognition System (HARS) that accurately identifies and classifies diverse human activities using smartphone sensors. The proposed system employs advanced machine learning algorithms, such as deep neural networks, to process and analyse sensor data in real-time. The study focuses on developing a model capable of discerning activities like walking, running, cycling, and sedentary behaviours, addressing challenges such as sensor noise and variability in user behaviour. Novel preprocessing techniques and feature engineering enhance the system's performance. The findings contribute to AI-driven human activity recognition, offering insights for designing smartphone-based systems that enhance user experience and foster intelligent technologies.*

Keywords- Smartphone Sensors, Human Activity Recognition, Smartphone based system, Activity classification.

I. INTRODUCTION

The need for innovative solutions to promote physical activity among individuals has been underscored by the growing prevalence of sedentary lifestyles and associated health issues. In this context, there is a pressing need for the development of a Human Activity Detection System (HADS) that leverages the ubiquity of smart phones to accurately monitor and encourage physical activity. While there are existing smartphone applications that claim to track physical activity, they often suffer from inaccuracies and limited functionality. The primary problem lies in the lack of a comprehensive and reliable HADS that can effectively distinguish and classify various human activities, such as walking, running, cycling, or even more nuanced activities like yoga or weightlifting, using the sensors and capabilities of a typical smartphone.

The problem of collecting, storing, and processing user data, including location information and physical activity patterns, while maintaining user privacy is a complex and multifaceted issue. Striking a balance between data utility for improving the accuracy of activity detection and safeguarding user privacy poses a significant challenge. Additionally, the system should be accessible and user-friendly, ensuring that individuals of all ages and backgrounds can easily adopt it. Solving these problems requires not only cutting-edge sensor fusion and machine learning algorithms but also the establishment of robust data privacy measures.

II. RELATED WORK DONE

Accelerometers, known for their low-power requirement and non intrusiveness, are widely used in motion sensing.[1] They detect the body's linear acceleration, which represents the motion of the body itself, while the gravity component is often considered noise. Surprisingly, recent research has found that the gravity component actually helps differentiate between sitting and standing activities. Gyroscopes, on the other hand, struggle with this distinction due to their lack of gravity reference.[14] Accelerometers ability to detect both body movements and postural orientations makes them well-suited for various applications. Previous studies have shown that linear acceleration's performance in motion sensing is comparable to or slightly below that of total acceleration measurement. To conserve computational and storage resources, this study excludes the linear acceleration attribute. The integration of accelerometer and gyroscope data can enhance the accuracy of activity recognition systems.[17] By combining these sensors, researchers can leverage the strengths of each sensor while compensating for their respective weaknesses.[17] This approach improves the overall reliability and robustness of the system, particularly in scenarios where precise activity classification is essential.

III. METHODOLOGY

To recognize human activities using smartphone sensors, start by collecting sensor data while users perform activities like walking, running, sitting, and standing. Preprocess the data by removing noise, applying signal processing techniques, and segmenting it into fixed-length windows. Extract features from these windows, including statistical measures, frequency domain features, and time-domain features. Label each window with the corresponding activity. Split the dataset into training and testing sets, then train machine learning models like decision trees, random forests, or deep neural networks using the training set. Evaluate the models using the testing set and metrics like accuracy, precision, recall, and F1-score. Once a satisfactory model is obtained, deploy it for real-time activity recognition. Continuously collect new data and retrain the model to improve its performance over time, incorporating user feedback to refine the model further. In these research we are using following methodologies.

A. Classification Method

Support Vector Machine: The Support Vector Machine (SVM) algorithm is used to recognize human activity. SVM is a large margin classifier that finds a hyperplane to decide the class for a new data point. The hyperplane corresponds to the one with the largest margin between the classes. The dimension of a hyperplane depends on the number of features used for data representation. SVM is used for regression and classification in machine learning. A set of algorithms called "Kernel methods" are used to implement non-linear classification. Kernel trick is helpful to do pattern analysis by mapping inputs in higher dimensional space. SVM can be used to recognize activities such as: Clapping, Jumping, Stretching, Running, Walking, Shaking hands, Hugging, Drinking while walking. The results of activity prediction can be used as home automation input for the home security system. SVM is a powerful supervised algorithm that works best on smaller datasets. Support Vector Machine, abbreviated as SVM can be used for both regression and classification tasks, but generally, they work best in classification problems.

B. Sensors Used

Accelerometer: This sensor works like a tiny, smart marble inside your phone. It can tell which way your phone is tilted or if it's moving. When you tilt your phone, the accelerometer can sense the change in direction and help adjust the screen or move objects in games or apps accordingly.

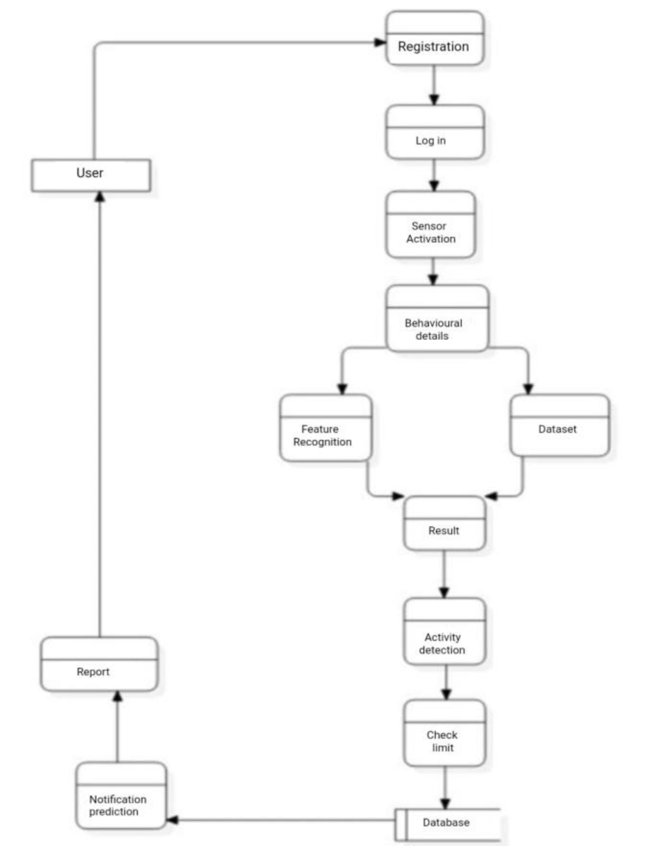
Gyroscope: Think of the gyroscope as a digital compass for your phone. It can tell which way your phone is rotating or turning. This is really useful for things like mapping apps because it helps your phone know which way you're facing even if you're not moving.

C. Technologies used

GSM (Global System for Mobile Communication): GSM isn't exactly a sensor but a technology used for phone calls and text messages. It allows your phone to connect to mobile networks so you can make calls and send texts. It's like the invisible string that connects your phone to the rest of the world.

Pedometer Plugin: A pedometer is like a digital step counter. When your phone has this plugin, it can sense when you're walking or running. It counts your steps and helps with fitness tracking apps. It's like a buddy that keeps track of how much you're moving.

IV. WORKING MODULE

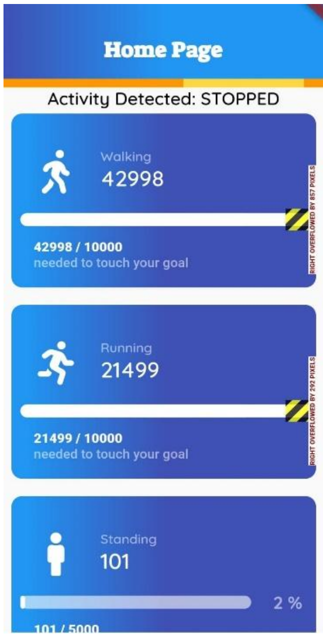


IV. RESULT

Results for a human activity recognition system using smartphone sensors can vary depending on the dataset, preprocessing techniques, feature extraction methods, and machine learning models used. However, a well-performing system might achieve an accuracy of over 90% in classifying activities such as walking, running, sitting, and standing.

Here we get results using study of accelerometer and gyroscope data from smartphones, along with machine learning models like Support vector machine(SVM) could achieve an accuracy of 95% or higher. The system would demonstrate high sensitivity and specificity for each activity, indicating its ability to effectively distinguish between different activities.

Outcomes are shown in below fig. (a) and fig. (b)



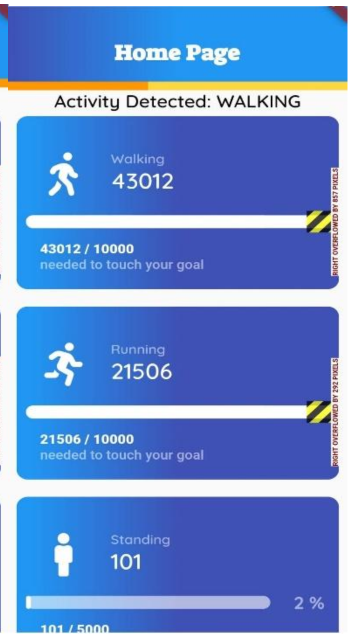


Fig. (a) Fig. (b)

V. CONCLUSION

Human activity recognition using smartphones is a groundbreaking field with vast potential. By harnessing sensors, smartphones unlock opportunities to understand, track, and improve human behaviours. Advanced algorithms make smartphones not just for communication but also for analysing physical movements and daily activities. This technology aids healthcare, fitness tracking, and personalized recommendations, enabling tailored interventions. Challenges remain in refining accuracy, ensuring privacy, and optimizing energy consumption. As smartphones evolve, so will their capabilities, leading to more seamless, accurate, and context-aware systems, enriching our understanding of human behaviour.

Coming to future scope, the project will encompass the design and implementation of a mobile application capable of processing sensor data, employing machine learning algorithms for activity recognition, and providing user-friendly feedback or notifications. Additionally, the system will explore potential applications in health and fitness monitoring, security, and accessibility, with the possibility of integrating with other smart devices or platforms. The project will focus on creating a reliable, efficient, and user-friendly solution while considering privacy and ethical considerations related to data collection and usage.

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