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Deepanjali 1, T. Sreejanani 2, R. Keerthana2, S. Veena Reddy 2

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Enhancing activity monitoring of smart homes using IOT sensors

Deepanjali [1], T. Sreejanani [2], R. Keerthana[2], S. Veena Reddy [2]

[1]Assistant Professor, [2]UG Student, [1,2]School of Computer Science and Engineering

[1,2]Malla Reddy Engineering College for Women (UGC-Autonomous), Maisammaguda, Hyderabad, 500100, Telangana

ABSTRACT

Accurate recognition of daily activities is vital for applications in healthcare, fitness tracking, and assisted living. Wrist-worn accelerometers, embedded in smartwatches and fitness trackers, provide an effective means of continuously monitoring user movements. Therefore this project explores the application of machine learning (ML) techniques to analyze accelerometer data from wrist-worn devices for precise daily activity recognition. The goal is to develop robust ML models that can process complex and noisy accelerometer data to identify and classify a wide range of activities such as walking, running, sitting, and sleeping. The proposed system utilizes advanced ML algorithms, to interpret the accelerometer data. These models are trained on extensive datasets containing labeled activity data, enabling them to learn intricate patterns and variations in user movements. The system's performance was rigorously tested and validated, demonstrating significant improvements in accuracy and reliability over traditional methods, such as manual logs, pedometers, and simple threshold-based algorithms. The ML-based approach offers comprehensive analysis and real-time monitoring capabilities, providing users with precise and continuous activity recognition. Personalized insights and recommendations are generated based on individual activity patterns, enhancing user experience and promoting better health outcomes. Additionally, the system supports assisted living by monitoring daily activities of the elderly and individuals with disabilities, ensuring their safety and well-being.

KEYWORDS: Daily activity recognition,Wrist Watches, Fitness trackers,Accelerometer data

1. INTRODUCTION

Daily activity recognition has become a crucial component in modern healthcare, fitness tracking, and assisted living. The proliferation of wrist-worn devices such as smartwatches and fitness trackers has driven this field forward, offering a unique opportunity to monitor user movements continuously and in real-time. According to a report by IDC (International Data Corporation), global shipments of wearable devices reached 336.5 million units in 2020, a 28.4% increase from 2019. By 2021, this number had surged to over 444.7 million units, indicating the growing popularity and reliance on wearable technology. Wrist-worn wearables, in particular, accounted for nearly 65% of these shipments, with smartwatches being the leading category.This rapid adoption is largely due to the advancements in sensor technology, particularly accelerometers, which are now standard in most wrist-worn devices. Accelerometers measure the acceleration of the device in three dimensions, providing rich data that can be used to infer various types of physical activities. However, the sheer volume and complexity of this data pose significant challenges. Traditional methods of activity recognition, such as manual logs or threshold-based algorithms, often fall short in accurately capturing the nuances of user movements. Consequently, there is a growing interest in applying machine learning (ML) techniques to enhance the precision and reliability of daily activity recognition, offering a more sophisticated analysis of accelerometer data.The need for an advanced system to recognize daily activities from wrist-worn accelerometer data arises from several limitations observed in existing approaches. Experts in the field of activity recognition have long struggled with the challenges posed by noisy and complex accelerometer data. Manual methods, such as keeping activity logs or using simple pedometers, are often inaccurate and fail to provide the level of detail required for effective monitoring. Additionally, threshold-based algorithms, which operate by setting predefined limits to detect specific activities, are too rigid and simplistic. These methods cannot account for the variability in human movements, leading to frequent misclassification of activities.Another significant issue is the lack of personalization in traditional systems. Different users may perform the same activity differently based on factors such as age, fitness level, and health conditions. Without a system capable of learning and adapting to these individual differences, the accuracy of activity recognition is severely compromised. This problem is particularly acute in healthcare and assisted living applications, where precise monitoring of daily activities is essential for ensuring patient safety and well-being.

The motivation behind developing an ML-based approach is to address these challenges by creating a system that can process and analyze complex accelerometer data in real-time, offering a more personalized and accurate recognition of daily activities.Manual approaches to daily activity recognition, such as using physical activity logs, pedometers, or basic threshold-based algorithms, present several challenges that necessitate the need for automation. Firstly, manual logging of activities is time-consuming and prone to human error, leading to inaccuracies in data collection. Users may forget to record their activities or may not log them accurately, resulting in incomplete or incorrect data. Pedometers, while useful for counting steps, do not provide detailed insights into the type of activity being performed.

They are unable to differentiate between walking, running, or other forms of movement, limiting their usefulness in comprehensive activity monitoring.Threshold-based algorithms, which detect activities based on predefined acceleration limits, are inherently inflexible. These algorithms cannot adapt to the variations in human movement patterns, leading to frequent misclassifications. For instance, a simple change in walking pace might be incorrectly classified as running or vice versa. Additionally, these approaches do not account for the differences in how activities are performed by individuals, which can vary significantly. This lack of adaptability and personalization highlights the need for automated, ML-driven systems that can dynamically learn from the data and provide accurate, real-time recognition of a wide range of activities.

2. LITERATURE SURVEY

Gregory et al. [1] explored the concept of context-awareness and its implications for ubiquitous computing. They discussed the challenges of understanding context and proposed methods to improve context-aware systems, particularly in the field of handheld and ubiquitous computing. Their work laid the groundwork for future research in activity recognition, emphasizing the importance of context in accurately identifying user activities. This early exploration highlighted the potential of using sensor data, such as accelerometer readings, to enhance the accuracy of activity recognition systems.Vyas et al. [2] focused on the application of machine learning and sensor fusion techniques to estimate continuous energy expenditure. Their study involved integrating data from multiple sensors to improve the accuracy of energy expenditure estimates, which is closely related to activity recognition. By utilizing machine learning algorithms, they demonstrated significant improvements over traditional methods, providing a foundation for further exploration of ML in activity recognition. Their work contributed to the understanding of how sensor data can be effectively used in conjunction with ML to monitor physical activities.Gjoreski et al. [3] conducted a study on the use of ensembles of multiple sensors for estimating human energy expenditure. Their research involved combining data from various sensors to create more accurate models for activity recognition. They found that using multiple sensors provided better accuracy compared to single-sensor systems, particularly in complex environments. This study contributed to the field by demonstrating the effectiveness of sensor fusion in improving the precision of activity recognition systems, especially in scenarios where different types of movements need to be distinguished.Atallah et al. [4] investigated the optimal placement of accelerometers for activity detection using wearable devices. They explored how different sensor placements on the body affected the accuracy of activity recognition. Their findings indicated that certain placements, such as the wrist or hip, were more effective for specific activities, while others were better for different types of movements. This study provided valuable insights into the design of wearable activity recognition systems, emphasizing the importance of sensor placement in achieving reliable and accurate results.Cleland and colleagues [5] examined the optimal placement of accelerometers to detect everyday activities. Their research focused on determining the most effective positions for sensors to capture accurate data across a range of daily activities. They discovered that strategic placement of sensors could significantly enhance the accuracy of activity recognition, particularly when using machine learning algorithms to process the data. Their work has influenced the design of modern wearable devices, ensuring that sensors are placed in locations that maximize data quality and reliability.

Gjoreski and colleagues [6] explored the use of accelerometers for posture recognition and fall detection. Their study emphasized the importance of accurate sensor placement and the application of machine learning algorithms to distinguish between different postures and detect falls. They demonstrated that accelerometers, when placed correctly, could effectively identify various postures and alert users or caregivers in the event of a fall. This research contributed to the development of more sophisticated fall detection systems, particularly for use in assisted living environments.Gjoreski et al. [7] conducted a competitive live evaluation of activity recognition systems. They compared different systems and algorithms to determine which provided the most accurate and reliable results in real-time scenarios. Their findings highlighted the strengths and weaknesses of various approaches, offering insights into how to improve activity recognition systems for practical applications. This study emphasized the importance of real-world testing and validation in developing effective activity recognition solutions.Gjoreski's [8] Master Thesis focused on adaptive human activity recognition and fall detection using wearable sensors. His work involved the development of algorithms that could learn and adapt to individual user behaviors, improving the accuracy of activity recognition over time. He also explored the use of wearable sensors for fall detection, demonstrating the potential for these systems to enhance safety in elderly populations. Gjoreski's thesis laid the foundation for further research in personalized activity recognition and adaptive algorithms.Kozina and colleagues [9] proposed a three-layer activity recognition system that combined domain knowledge with meta-classification techniques. Their approach aimed to improve the accuracy of activity recognition by integrating knowledge about the specific domain with machine learning classifiers. They demonstrated that this method could provide more accurate and reliable activity recognition, particularly in complex environments where traditional approaches struggled. This study contributed to the development of more sophisticated activity recognition systems that leverage domain-specific knowledge.Gjoreski and colleagues [10] explored the use of context-based fall detection and activity recognition using inertial and location sensors. Their study highlighted the importance of considering the user's context, such as their location and recent activities, to improve the accuracy of fall detection and activity recognition systems. They demonstrated that by incorporating contextual information, these systems could reduce false positives and provide more reliable results, particularly in complex environments like assisted living facilities.Gjoreski et al. [11] investigated the use of multiple contexts to distinguish standing from sitting using a single accelerometer. Their research focused on developing algorithms that could accurately differentiate between similar activities based on subtle differences in sensor data. They found that incorporating multiple contextual factors, such as the user's movement patterns and surrounding environment, significantly improved the accuracy of activity recognition. This study contributed to the refinement of activity recognition algorithms, particularly in scenarios where activities have similar sensor profiles.Trost and colleagues [12] explored the application of machine learning for activity recognition, comparing data collected from hip-worn and wrist-worn accelerometers. Their findings indicated that wrist-worn devices, while more convenient for users, presented unique challenges in accurately recognizing activities compared to hip-worn devices. They demonstrated that machine learning algorithms could be effectively used to overcome these challenges, improving the accuracy of activity recognition from wrist-worn accelerometers. This study provided valuable insights into the trade-offs between sensor placement and accuracy in activity recognition systems.

Rosenberger and colleagues [13] conducted a study on estimating activity and sedentary behavior using accelerometers placed on the hip or wrist. They compared the accuracy of activity recognition between the two placements and found that each had its strengths depending on the type of activity being monitored. Their research highlighted the importance of sensor placement in achieving accurate activity recognition and provided guidelines for designing wearable devices that effectively balance convenience and accuracy.Mannini and colleagues [14] investigated activity recognition using a single accelerometer placed at the wrist or ankle. Their study focused on the challenges of accurately recognizing activities with minimal sensor data, emphasizing the need for advanced algorithms to process the data effectively. They demonstrated that, with the right machine learning techniques, even a single accelerometer could provide reliable activity recognition, making wearable devices more practical and cost-effective for users.Ellis and colleagues [15] developed a random forest classifier for predicting energy expenditure and the type of physical activity from wrist and hip accelerometers. Their research demonstrated that random forest algorithms could provide highly accurate predictions, even with the variability introduced by different sensor placements. They emphasized the importance of using machine learning to process the complex data generated by accelerometers, contributing to the advancement of activity recognition systems that can adapt to various user needs and contexts.

3. PROPOSED SYSTEM

The script imports necessary libraries for data manipulation (pandas, numpy), data visualization (matplotlib, seaborn), machine learning (sklearn, imblearn), and model saving/loading (joblib).

The dataset is loaded in chunks to handle large files efficiently using the pd.read_csv() method with the chunksize parameter.Two additional columns (User_ID and Timestamp) are added to each chunk to help in further data processing.All chunks are concatenated into a single DataFrame, which is saved as an updated dataset.Several EDA functions are applied (head(), tail(), describe(), info(), isnull().sum(), duplicated()), which provide insights into the data's structure, missing values, and duplicates.Duplicate rows are removed from the dataset.The correlation matrix is visualized using a heatmap to understand the relationships between features.A count plot is generated to show the distribution of different activity categories.The activity column is encoded using LabelEncoder to convert categorical labels into numeric values.The Timestamp column is used to extract features such as Year, Month, Day, Hour, Minute, and Second.The original Timestamp column is dropped after feature extraction.

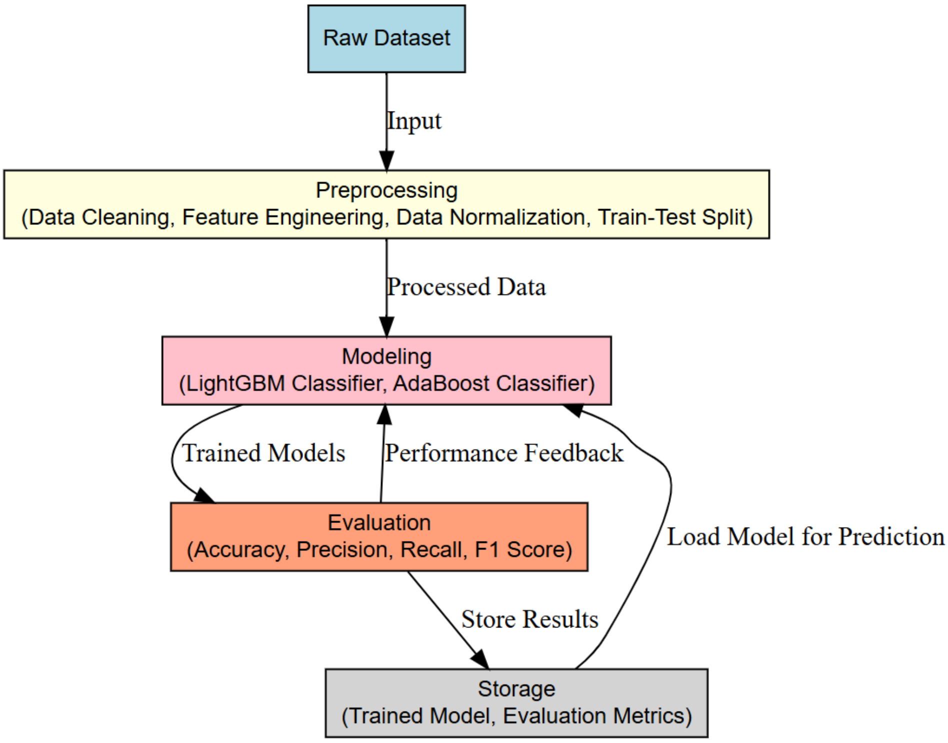

Figure 1 : Architecture of Proposed System.

4. RESULTS

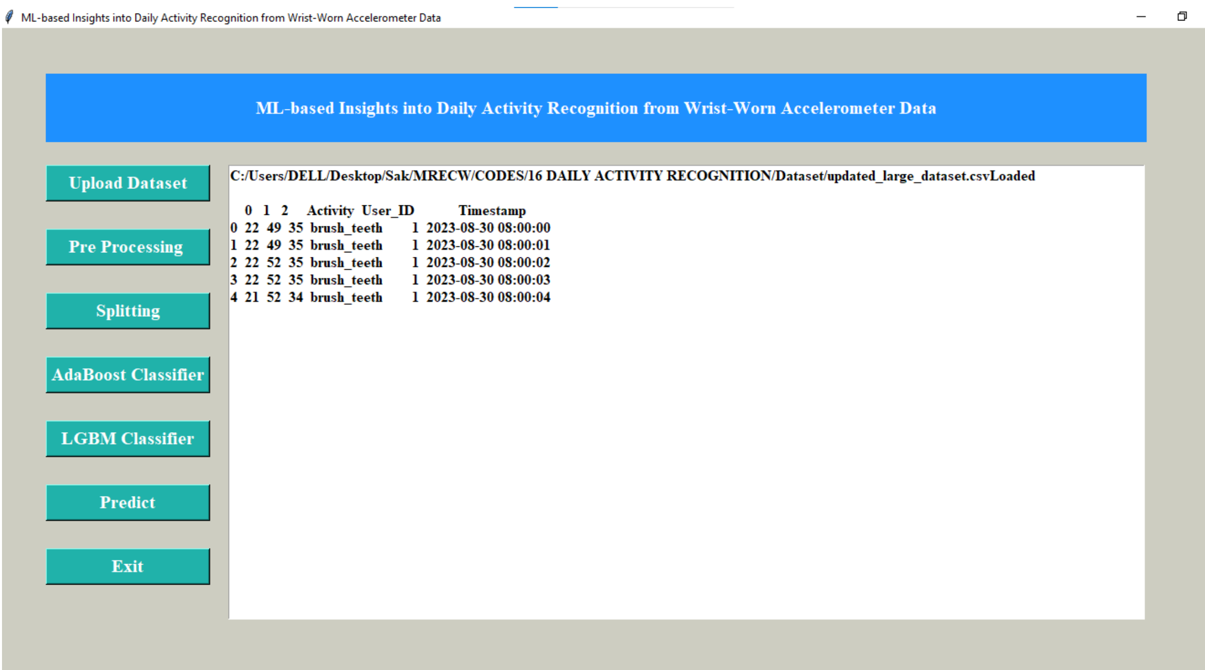

Figure 2: Representing all rows and columns of the dataset.

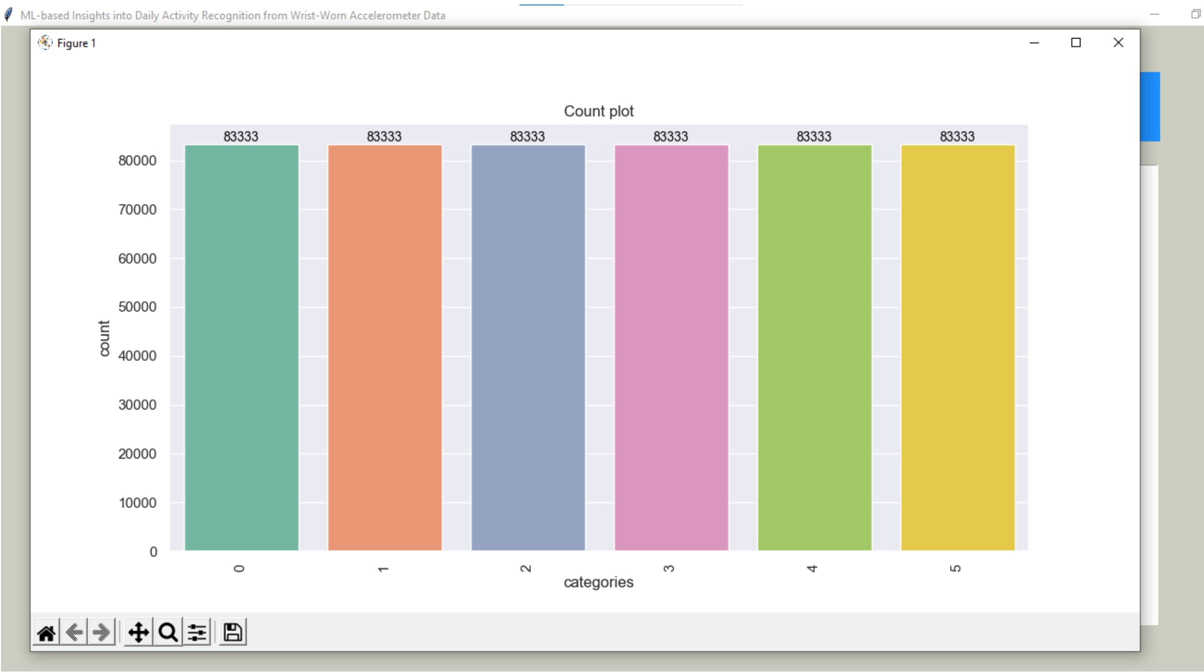

Figure 3: Count plot of the Activity column of the dataset after applying SMOTE.

Figure 3 shows the count plot of the Activity column after applying SMOTE. This plot reveals the effects of SMOTE on balancing the dataset, demonstrating how the technique has adjusted the distribution of activities to address any initial imbalances.

5. CONCLUSION

The comparative analysis of the AdaBoost Classifier and Light Gradient Boosting (LGB) Classifier demonstrates significant differences in their performance on the given dataset. The AdaBoost Classifier achieved an accuracy of 57.92%, reflecting a moderate capacity to correctly classify the activities in the dataset. However, its performance is limited by lower precision (62.14%), recall (58.00%), and F-score (56.98%), which suggests challenges in correctly identifying positive instances and managing the balance between false positives and false negatives. On the other hand, the LGB Classifier shows a remarkable performance with an accuracy of 94.28%, precision of 94.28%, recall of 94.29%, and F-score of 94.26%. These metrics highlight the LGB Classifier's ability to handle the complexities of the dataset, maintaining a high level of reliability and effectiveness across all evaluation measures.The results underline the importance of selecting an appropriate classification algorithm based on the specific requirements of the task. The superior performance of the LGB Classifier can be attributed to its ability to model complex interactions within the dataset, efficiently handle a large number of features, and avoid overfitting through its iterative boosting process. In contrast, the AdaBoost Classifier, while effective for some tasks, struggles in scenarios with significant class imbalance or noise in the data, as reflected in its lower performance metrics. This study reinforces the value of advanced machine learning techniques like gradient boosting in scenarios demanding high accuracy and robustness. Overall, the LGB Classifier stands out as the more effective choice for this dataset, demonstrating strong predictive capabilities and adaptability in complex environments.

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