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Efficient Human Activity Recognition Using Accelerometer Data and Random Forest for Mobile Computing

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Abstract

Human Activity Recognition (HAR) functions as a fundamental technology in mobile and pervasive computing systems to provide context-based services in healthcare and fitness applications as well as smart environments. The majority of current HAR approaches require either sophisticated algorithms or multiple input devices which prevents their immediate deployment on mobile platforms. This research develops a compact single-sensor HAR system based on smartphone accelerometer information. The Random Forest algorithm uses training data to identify six different activities including Walking, Jogging, Upstairs, Downstairs, Standing and Sitting. The pipeline uses data cleaning and normalization followed by supervised learning which results in 89% accuracy and F1-scores reaching 0.99 for dynamic activities. The study demonstrates that minimal hardware can enable efficient and accurate HAR operations which suits real-world mobile computing environments

Index Terms: Human Activity Recognition, Accelerometer Data, Mobile Computing, Random Forest, Pervasive Systems

1. Introduction

Modern smartphones and wearable devices have driven fresh opportunities for mobile and pervasive computing throughout recent years. These devices include various embedded sensors which continuously track user movements and environmental conditions through accelerometers and gyroscopes and GPS modules. The technological expansion has driven the development of numerous intelligent applications which span health monitoring and fitness tracking along with smart homes and personalized services [1,2].

Human Activity Recognition (HAR) stands out as one of the most promising applications because it uses sensor data to classify user activities such as walking or sitting or jogging. The classification of human activities through sensors proves valuable for monitoring health in real time and supporting rehabilitation and delivering services that adjust to specific situations. Real-time physical activity recognition strengthens pervasive systems' intelligence by enabling them to modify their functions based on user requirements [3].

Machine learning (ML) techniques maintain their effectiveness in Human Activity Recognition (HAR) because they can learn patterns from unprocessed sensor data. The performance of traditional classifiers including Random Forests and Support Vector Machines and k-Nearest Neighbors reaches high levels when they have enough labeled data for activity classification tasks [4,5]. These models are computationally efficient and interpretable, making them suitable for resource-constrained mobile devices.

Practical implementation of HAR systems encounters multiple obstacles in their deployment. Sensor data contains noise and the distribution of classes remains unbalanced and the system struggles to differentiate activities that produce comparable movement patterns like walking and jogging [6]. The selection of proper preprocessing techniques that include scaling and cleaning affects the accuracy of classification results. The development of a successful HAR model demands thorough evaluation of both the data processing approach together with the learning methodology.

This research develops a lightweight and interpretable HAR system based on accelerometer data collected from a smartphone. The dataset contains six different activity classes which include Walking, Jogging, Upstairs, Downstairs, Standing, and Sitting while each class has different sample amounts. The study uses standard preprocessing methods including label encoding and feature scaling to train a Random Forest classifier which assesses its ability to distinguish between these activities.

Our method operates differently from deep learning techniques because it does not need big datasets or extensive computing resources while achieving fast results and mobile deployment capabilities. The Random Forest model offers a middle ground between precision and transparency which makes it suitable for environments that require swift decisions with clear explanations [7]. The analysis of model strengths together with weaknesses happens through confusion matrices and classification metrics for complete evaluation. This research establishes a practical starting point for upcoming HAR studies that focus on mobile and pervasive computing environments [8].

2. Related Work

The field of Human Activity Recognition (HAR) emerged as a primary research focus in mobile computing and pervasive systems because it allows applications to become intelligent through contextual awareness. The initial research in HAR used manually created rules and threshold-based heuristics which processed accelerometer or gyroscope sensor data [9]. The basic methods showed perfect sensitivity to both user differences and sensor noise. The development of supervised machine learning techniques brought a scalable adaptive solution for classifying complex human activities. Machine learning algorithms have extensively processed raw sensor streams to produce real-time activity labels [10].

Tr Decision Trees together with Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN) and Naive Bayes have proven effective for HAR tasks when appropriate feature engineering is implemented [11, [12]. Random Forest classifiers exhibit excellent potential because they deliver robust performance with minimal variance while processing nonlinear sensor data patterns. The efficient training process of Random Forests combined with simple hyperparameter requirements makes them suitable for mobile applications that operate with restricted computational capabilities [13].

HAR systems use Deep learning methods such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to learn time-series data features automatically [14]. The models eliminate manual feature extraction needs and typically produce better accuracy results. The models require significant computational resources along with large memory consumption and extensive labeled data which makes them unsuitable for operation on devices that have limited resources such as smartphones and wearable devices [15].

Multiple research investigations have examined hybrid models which utilize both traditional and deep learning methods. CNN-LSTM models function as effective tools to analyze spatial and temporal movement patterns in motion data [16]. Research studies suggest transfer learning and federated learning approaches as methods to decrease model retraining requirements on fresh devices and user groups. These innovative methods present challenges for implementation in lightweight mobile systems because they need complex development processes and extensive infrastructure support [17].

Sensor modality also plays a key role in HAR systems. While some studies incorporate multimodal data from accelerometers, gyroscopes, magnetometers, and GPS, others focus on single-sensor systems to reduce data redundancy and energy consumption [18]. Accelerometer-only models, such as those in [19]. have demonstrated strong classification performance, especially when the sampling rate is high and features are well-engineered. Our work aligns with this direction by focusing solely on accelerometer data for its balance between simplicity and effectiveness.

Preprocessing methods and windowing strategies significantly impact HAR performance. Many works apply fixed-size sliding windows to extract statistical or frequency-domain features [20]. However, there is no consensus on the optimal window length or feature set, as these often depend on the dataset and application. Some studies also apply normalization or standardization to improve model convergence. Our study adopts a standard preprocessing pipeline involving label encoding and feature scaling, as demonstrated to be effective in various HAR benchmarks [21].

Research interest in lightweight HAR solutions continues to grow yet no study exists which thoroughly evaluates traditional classifiers using real-world client-specific datasets. The research community has emphasized the importance of evaluating basic models on unaltered sensor data which originates from everyday mobile device usage [22]. Our research fills this research gap through an evaluation of accelerometer-based activity classification which operates on authentic six-activity-labeled dataset. Using Random Forest delivers both easy-to-understand results combined with minimal resource requirements and establishes a solid foundation for subsequent developments which incorporate temporal analysis or combination of multiple sensors.

3. Proposed Methodology

The methodology for building the Human Activity Recognition system uses accelerometer data from mobile devices which this section explains in detail. The workflow follows a sequence that starts with data acquisition then moves through data preprocessing and feature scaling followed by model training and finally performance evaluation. The framework aims to create an efficient real-time Human Activity Recognition system which operates on smartphones and embedded platforms.

A. System Workflow Overview

The methodology exists as a visual representation in Fig. 3 which displays a colored block diagram depicting a realistic data flow architecture. The sequence starts with the “Sensor Data Collection” block which takes direct readings from smartphone accelerometer sensors. The following block “Data Cleaning & Label Encoding” implements preprocessing steps to eliminate Z-axis reading semicolons and convert activity categories into numerical values.

The dataset undergoes normalization through a single “Feature Scaling” block because performing this operation once prevents unnecessary repetition. The normalized dataset undergo a division into training and testing subsets as demonstrated in the “Train-Test Split” block which maintains the same distribution of classes. The next block, “Random Forest Classifier,” consists of an ensemble of decision trees that performs activity class predictions. The process reaches “Performance Evaluation” to validate results through statistical metrics and confusion matrices.

The block-oriented structure of Fig.1 presents a structured pipeline which prevents both repetition and circular dependencies between its components. The modular design of each stage permits future enhancements including sensor integration and classifier alternatives.

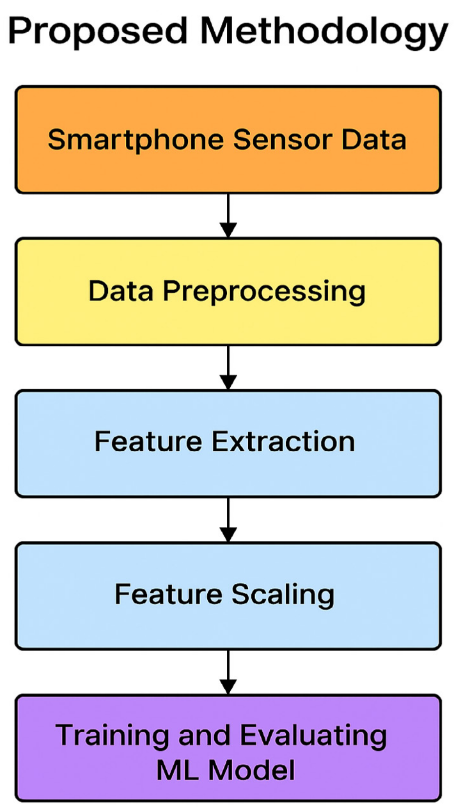

Figure 1: ***Block diagram illustrating the complete workflow for human activity recognition using smartphone accelerometer data.***

B. Data Cleaning and Label Encoding

The initial dataset needed data preparation procedures to correct its structural irregularities. The Z-axis values existed in string format with trailing semicolons so a programmatic approach first eliminated these characters before converting values into floating-point numbers. The dataset underwent label encoding to transform activity categories into numerical values. The step converts target variables into numbers so supervised learning algorithms can utilize them.

C. Feature Scaling and Modeling

The Z-score normalization method serves to stop one axis from having excessive power in the model because of its range or unit differences:

$$z = \frac{x - \mu}{\sigma}$$

The input value or μ represents the data point while the feature mean is and standard deviation is . The standardization process moves every feature to zero mean and unit variance which improves both classification performance and convergence.

The dataset was divided into training and testing groups through a stratified sampling approach which allocated 70% of data for training and 30% for testing. The method guarantees equal distribution of all activity classes between both dataset partitions. By maintaining data diversity and avoiding class bias the stratified split enables fair model evaluation of all classes.

The Random Forest classifier became the preferred choice because it can model intricate decision boundaries and work with multiple classes. The classifier constructs multiple decision trees which make predictions that the ensemble uses majority voting to determine the final output class.

$$\hat{y} = mode(\{T_1(x), T_2(x), \ldots, T_n(x)\})$$

Each prediction from the ith decision tree is expressed as $T_i(x)$. The model parameters, such as the number of trees, were kept at default to maintain simplicity and generality. Random Forests also offer feature importance estimates, which can be used in future work for dimensionality reduction.

D. Experiment Setup

The experiment ran on a Windows 10 machine that contains 16 GB RAM along with an Intel Core i5-1165G7 processor running at 2.80 GHz with four physical cores and eight logical processors. Python served as the programming language for implementation and the system used these packages for the project: PyTorch for loading and quantizing the GPT-J-6B model and Transformers (by Hugging Face) for handling model architecture and tokenization and Matplotlib and Seaborn for generating visualizations and comparative plots and Pandas for tabular data management and metric tracking.

Table 1: Tools and technologies used in the experiments.

Tools	Description
OS	Window 10
RAM	16 GB
CPU	Intel® Core™ i5-1165G7 CPU @ 2.80 GHz, 4 Core(s), 8 Logical Processor(s)
Language	Python
Packages	Sklearn, Transformer, Matplotlib, and Seaborn.
Data	CSV (Comma-Separated Values) format managed using Pandas

E. Performance Evaluation

The model outputs are evaluated using four standard classification metrics: Accuracy, Precision, Recall, and F1-Score. These are calculated using the confusion matrix with the following equations:

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall:

$$Recall = \frac{TP}{TP + FN}$$

F1 Score:

$$F1\,Score = 2 \times \frac{Precision \cdot Recall}{Precision + Recall}$$

Where:

- TP: True Positives
- TN: True Negatives
- FP: False Positives
- FN: False Negatives

Visualization tools such as confusion matrices and correlation heatmaps are employed to support quantitative results and interpret model behavior.

4. Results & Analysis

This section presents the evaluation results and in-depth analysis of the Random Forest model trained using smartphone accelerometer data. The effectiveness of the model is assessed through precision, recall, F1-score, and confusion matrix.

A. Overall Performance

The Random Forest classifier achieved strong performance across the six activity classes. Table 2 shows the overall metrics:

Table 2: Random Forest Performance Metrics (Overall)

Metric	Accuracy	Precision	Recall	F 1 Score
Result	0.89	0.79	0.78	0.78

These results indicate that the model provides reliable predictions with a balanced trade-off between precision and recall. The model particularly excelled in detecting dynamic activities such as Jogging, Upstairs, and Downstairs.

B. Class-wise Analysis

A deeper breakdown of performance per activity class is provided in Table 3:

Table 3: Class-wise Precision, Recall, and F1-Score for Human Activity Recognition Using Random Forest

Activity Label	Precision	Recall	F1-Score
0 (Walking)	0.58	0.49	0.53
1 (Jogging)	0.90	0.88	0.89
2 (Upstairs)	0.99	0.99	0.99
3 (Downstairs)	0.99	0.99	0.99
4 (Standing)	0.56	0.47	0.51
5 (Sitting)	0.75	0.85	0.80

As observed, the model performed best on Upstairs and Downstairs, achieving near-perfect F1-scores of 0.99. Jogging also achieved a high F1-score of 0.89. In contrast, lower performance was observed for Walking (0.53) and Standing (0.51), primarily due to the high similarity in sensor patterns between these static activities.

C. Confusion Matrix Interpretation

The confusion matrix shown in Fig. 2 illustrates the class-wise distribution of true versus predicted values. Misclassifications were most frequent between Walking and Sitting, and between Standing and Sitting, which suggests overlapping motion profiles or transitional ambiguity during data capture.

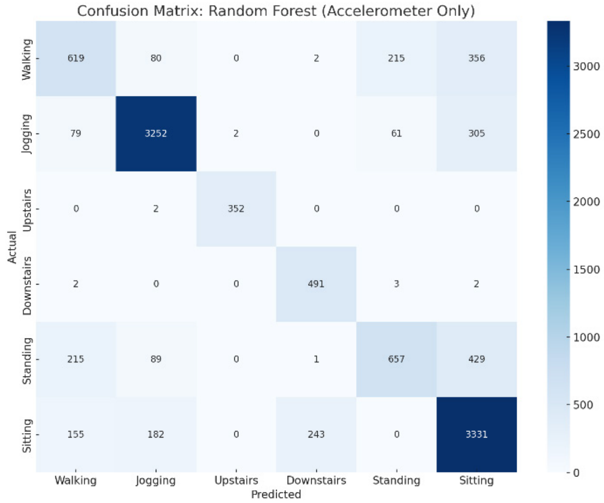

Figure 2: Confusion Matrix: Random Forest (Accelerometer Only)

From the matrix, we observe:

- Class 1 (Jogging) had the highest true positive count (3252), confirming the model's strength in identifying dynamic activities.
- Class 4 (Standing) and Class 5 (Sitting) show frequent overlap, likely due to static posture similarity.
- Class 2 and Class 3 (Upstairs and Downstairs) are accurately distinguished due to differing step patterns.

D. Outcome

The performance analysis reveals clear patterns in the classification capabilities of the Random Forest model. As shown in Figure 3, dynamic activities such as Jogging, Upstairs, and Downstairs achieved the highest precision, recall, and F1-scores, all around 0.99. This confirms the model's reliability in distinguishing motion-rich behaviors.

Conversely, performance on static or transitionally subtle activities like Walking and Standing was notably lower, with F1-scores of 0.53 and 0.51 respectively. These results suggest that acceleration patterns for these two activities may be less distinguishable, leading to frequent misclassifications especially with Sitting.

Figure 5 highlights these differences clearly, where taller bars for dynamic activities contrast sharply against the shorter bars for static ones. Despite this, Sitting achieved relatively high recall (0.85) and F1-score (0.80), indicating the classifier's ability to reliably detect seated postures.

Figure 3: Bar chart comparison of precision, recall, and F1-score per activity class.

5. DISCUSSION

The performance of the Random Forest classifier on the accelerometer dataset highlights its efficacy in distinguishing between complex and dynamic physical activities. Activities like Upstairs, Downstairs, and Jogging achieved exceptionally high F1-scores, indicating that motion-intensive classes are more distinguishable due to their unique acceleration patterns. This suggests that accelerometer-only models can effectively classify a range of human activities in real-time applications. Nonetheless, performance on Walking and Standing reveals notable challenges, as static activities exhibit less variation in signal dynamics.

The classification errors which occur among Walking, Sitting, and Standing arise from similar body positions and transitional movement patterns. The activities share similar accelerometer signal ranges which makes it challenging for classifiers to correctly differentiate them. The current limitation stresses the importance of incorporating temporal data into sensor interpretation processes. The absence of contextual movement sequence in short-duration motion data makes it difficult to identify fundamental motion patterns particularly for low-intensity or transitional activities.

The future research should employ temporal modeling approaches alongside sensor fusion methods for overcoming current system constraints. The integration of gyroscope and magnetometer data provides rotational movement information which accelerometer signals do not capture. Deep learning models that process sequences including Long Short-Term Memory (LSTM) and Temporal Convolutional Networks (TCNs) can improve classification results through their understanding of motion sequences. These improvements will reduce the performance difference between recognizing high-motion and static activities.

6.Conclusion

The research introduces a straightforward yet powerful technique which uses accelerometer data for Human Activity Recognition on smartphones with a Random Forest algorithm. The approach focused on three key aspects which include simplicity, efficiency and modularity to enable convenient deployment across mobile and distributed computing platforms. The system achieved excellent results when identifying fast-moving activities including Jogging, Upstairs and Downstairs by obtaining F1-scores that reached 0.99. The classifier achieved 89% accuracy in real-time applications on devices with limited resources by using basic preprocessing steps and maintaining a single model structure.

The model could not differentiate between Holding and Walking because their sensor patterns remained too similar for accurate recognition. The research identifies possible future improvements through the integration of multiple sensors together with temporal analysis methods. The system's current limitations would improve when additional sensors are integrated or deep learning models are deployed to enhance overall system durability. The proposed pipeline presents a suitable base for mobile HAR systems which advances machine learning applications in pervasive computing domains.

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