Burnify

Recognition of human activities for wellness management using a smartphone

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ABSTRACT

Recognition and classification of human activities play a vital role in wellness management systems. This research presents the development and implementation of a smartphone-based human activity recognition (HAR) system utilizing the device's integrated multimodal sensors, including accelerometer, gyroscope, and magnetometer. The study implements different ML Models such as as Adaboost, Random Forest and Long Short-Term Memory (LSTM) neural network architecture to classify five distinct physical activities: walking, running, standing, ascending stairs, and descending stairs. The methodology encompasses systematic data collection from smartphone sensors during various activities, followed by comprehensive data preprocessing and labeling procedures to develop a robust training dataset. The resulting Android application integrates user anthropometric parameters (age, weight, and height) during initial setup to enhance prediction accuracy and provide personalized insights. The system offers real-time activity tracking capabilities and maintains a history of the 10 most recent activities with timestamps. Additionally, the application incorporates a caloric expenditure calculation feature based on recognized activities and user metrics. This research contributes to the field of wellness monitoring by demonstrating the feasibility of implementing a machine-learning model on an Android application for continuous activity recognition and wellness monitoring.

1 Introduction

With the increasing prevalence of sedentary lifestyles and health-related issues, monitoring physical activity has become crucial for maintaining a healthy lifestyle. Human Activity Recognition (HAR) plays a vital role in providing individuals with insights into their daily routines and encouraging healthier behaviors. However, many existing approaches rely on external wearables or infrastructure-heavy solutions, which can be costly and inconvenient for users.

This study addresses these limitations by leveraging smartphone-embedded sensors, specifically the accelerometer, magnetometer, and gyroscope, to develop a lightweight and accessible HAR system. Our approach offers a cost-effective and convenient solution that does not require additional hardware, making it more accessible to a broader population.

A key differentiator of our solution compared to existing methods is the integration of machine learning models such as Adaboost, Random Forest and LSTM which enable accurate activity classification. The system operates in two phases: an offline training phase, where activity data is collected and processed to build predictive models, and an online phase, where real-time activity predictions are made based on incoming sensor data.

Furthermore, our system employs sensor fusion techniques to enhance recognition accuracy by combining data from multiple sensors, ensuring reliable tracking of complex movements. An integrated calorie counter adds further value by estimating energy expenditure based on recognized activities and user-specific factors such as weight, age, and activity intensity.

Key performance metrics such as accuracy and F1-score were analyzed to demonstrate the effectiveness of the proposed solution. The potential of our smartphone-based HAR system is to help users achieve their fitness goals with greater efficiency and reliability.

2 Architecture

The application's functioning can be divided into two main phases: an initial phase involving data collection and model training, and a subsequent phase where real-time activity recognition and calorie estimation are performed based on sensor data.

2.1 Sensor data collection

To ensure accurate human activity recognition, the authors of this study collected sensor data directly from the accelerometer, magnetometer, and gyroscope embedded in a smartphone. During the data collection phase, participants performed various activities while the application continuously recorded sensor readings in real-time. The collected data was then processed and labeled based on the corresponding activities to create a comprehensive dataset used for training the machine learning models.

	acc_X	acc_Y	acc_Z	mag_X	mag_Y	mag_Z	gyro_X	gyro_Y	gyro_Z	activity
0	-0.8865	-1.1522	1.4740	22.5563	-2.8875	-36.1125	-1.0183	-0.2508	1.3144	downstairs
1	-1.5058	-1.3730	1.8943	22.5563	-2.8875	-36.1125	-1.0183	-0.2508	1.3144	downstairs
2	-1.5058	-1.3730	1.8943	22.0125	-1.9875	-36.7125	-1.0183	-0.2508	1.3144	downstairs
3	-1.5058	-1.3730	1.8943	22.0125	-1.9875	-36.7125	-1.0183	-0.2508	1.3144	downstairs
4	-1.5058	-1.3730	1.8943	22.0125	-1.9875	-36.7125	-1.0229	-0.1324	1.2220	downstairs
...	...	...	...	...	...	...	...	...	...	...
371113	-1.4861	1.5890	-2.5617	-18.9000	-4.1438	51.2438	-0.5558	-0.5968	-1.3725	upstairs
371114	-1.4861	1.5890	-2.5617	-18.9000	-4.1438	51.2438	-0.5558	-0.5968	-1.3725	upstairs
371115	-1.4861	1.5890	-2.5617	-18.9000	-4.1438	51.2438	-0.4812	-0.5775	-1.3251	upstairs
371116	-1.2010	1.7466	-2.6828	-18.9000	-4.1438	51.2438	-0.4812	-0.5775	-1.3251	upstairs
371117	-1.2010	1.7466	-2.6828	-18.7125	-3.9563	51.5438	-0.4812	-0.5775	-1.3251	upstairs

371118 rows × 10 columns

The collected raw data, in the form of sensor readings, was then processed and labeled according to the activity being performed at each time. The labeling process included associating each data point with its corresponding activity, such as “walking”, “running”, “standing”, “upstairs” or “downstairs” to create a comprehensive, structured dataset. The accelerometer provided information in the form of three coordinate values (X, Y, Z) representing the linear acceleration, while the magnetometer offered three coordinate values for the magnetic field strength (X, Y, Z). The gyroscope produced three coordinate values (X, Y, Z) representing rotational velocity along the respective axes. This dataset, with labeled sensor readings, was then utilized for training the machine learning models, enabling the system to recognize and classify different human activities based on these multi-dimensional inputs.

2.2 Machine Learning Models

After preprocessing our data (the 9 columns besides our label), the feature extraction was done to get a useful information from the data like the mean, standard deviation, minimum and maximum so the number of outputs from this stage is 36 columns which fed to models like random forest and adaBoost.

Machine learning models such as AdaBoost and Random Forest are employed to train the system. These models are trained using a dataset containing different activities such as walking, running, standing, upstairs and downstairs. The training process involves normalization, feature extraction and data balancing.

How each model works:

2.2.1 Random Forest Model

An ensemble method that combines multiple decision trees to create a robust model. Randomly select subsets of the training data (with replacement) to train each tree. This ensures diversity among the trees and reduces overfitting. For classification, the final prediction is made by majority voting (the most frequent class predicted by the trees).

After the data was cleaned and processed the RF model was applied for the classification task, the data was split into train and test sets using 80:20 ratio, n_estimators=100, and random_state=42.

Statistical features (mean, standard deviation, min, max) were extracted from sliding windows of size 50 with a step size of 25 as the data is time series and fed to the model.

2.2.2 AdaBoost Model

Focuses on correcting errors by giving more weight to misclassified samples. For working with adaboost we needed to use the label encoder to convert the categorical labels to suit the algorithm

The model was trained on the extracted features from the sensors data like in the case of Random Forest.

2.2.3 LSTM Model

Long Short-Term Memory model is a type of Recurrent Neural Network designed to handle sequential data. It is particularly effective for time-series or sequence-based tasks, such as activity recognition using sensor data.

Fixed-length sequences of 200-time steps are created. Each sequence contains 9 features. Labels are assigned based on the most frequent activity in each sequence.

The LSTM model is built using TensorFlow/Keras with two main LSTM layers. The first LSTM layer uses 128 units and processes input data with the shape (N_TIME_STEPS, N_FEATURES). It returns sequences, which are passed to the second LSTM layer with 64 units. After the LSTM layers, there’s a fully connected layer with 64 units and a ReLU activation function to combine features. The output layer is a dense layer with N_CLASSES units and softmax activation for multi-class classification. The model uses categorical cross-entropy as the loss function and accuracy as the evaluation metric.

2.3 Data Processing and Prediction

Once the machine learning models are trained and optimized, the application transitions to the real-time phase, where it continuously monitors the sensor data to classify user activities and estimate calorie expenditure. This phase is key to the application’s functionality, as it requires seamless integration between the device’s sensors, the server, and the machine learning models deployed for real-time processing.

The architecture begins with the Android device, where the application requests the necessary permissions to access the sensors (accelerometer, magnetometer, and gyroscope). Once the permissions are granted, the application begins collecting real-time sensor data. It receives continuous readings from all the available sensors mentioned before, with the data being processed in small windows, every 50 samples collected from the sensors form one data window. The application then sends a POST request to the server, where these 50 samples are processed.

At the server side, the data undergoes feature extraction. For each window of 50 samples, the system calculates several statistical features: the mean, standard deviation, minimum, and maximum values for each of the sensor's three axes. These features are crucial for machine learning models to accurately recognize the current activity. The extracted features are returned as a response to the mobile device through the server's API.

The server-side models are now deployed locally, ensuring that processing is carried out within the user's environment without relying on external cloud services. This setup allows for greater control over computational resources, reduced latency, and enhanced data privacy. The local infrastructure is optimized to handle incoming requests efficiently, enabling seamless and real-time execution of machine learning models for activity recognition.

Once the features are extracted, the machine learning model performs predictions to classify ongoing activities. The results are then returned to the Android device as a response to the POST request. This process happens in real-time, ensuring that the system continuously monitors the sensor data and provides accurate activity recognition and calorie estimation with low latency, allowing for real-time feedback to the user.

2.4 User Interface

The user interface (UI) of the application is designed to be simple and intuitive, comprising three main pages managed by a bottom navbar for easy navigation: DataScreen, TodayScreenActivity, and Settings.

2.4.1 DataScreen

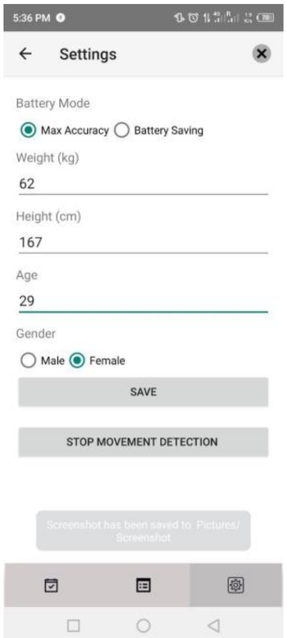
The DataScreen provides an overview of the activities currently being performed by the user. It displays real-time activity recognition data, showing which activity the user is engaged in at any given moment. Below this, a list of recent activities is shown, providing users with a quick reference to their past actions. This helps the user track their activity history and provides valuable context for ongoing or future activity recognition.

2.4.2 TodayScreenActivity

TodayScreenActivity focuses on displaying the user’s daily progress. Two main charts are featured:
A calories burned chart, which shows the total calories expended throughout the day. This provides the user with a visual representation of their energy expenditure, allowing them to track their fitness goals. A histogram of activities, which visually represents the different activities performed by the user throughout the day and the corresponding duration spent on each activity. This histogram allows users to see how their time is distributed across various activities, offering insights into their daily routines and physical activity levels.

2.4.3 Settings

The Settings screen allows users to customize their experience by selecting their preferred sampling mode (Max Accuracy or Battery Saving) and entering personal details such as weight, height, and age. Additionally, users have the option to stop the sensor sampling, providing full control over when the sensors are actively collecting data. This flexibility ensures that users can tailor the app's functionality according to their specific needs and preferences, whether they prioritize accuracy, battery life, or data collection.



The bottom navbar is designed to be easily accessible, enabling users to switch between these pages with ease. The layout of the UI is optimized for user experience, ensuring that key information is readily available while maintaining a clean and organized interface.

3 Experimental results

This section presents the experimental evaluation of our human activity recognition system, which comprises two main components: the performance analysis of our trained models and the implementation results from our Android application. We evaluate the effectiveness of different machine learning approaches including Random Forest and Adaboost for activity classification, followed by an analysis of the application's real-world performance in tracking user activities and calculating caloric expenditure.

3.1 Model Training Results

We evaluated three different machine learning models (Random Forest, AdaBoost and LSTM) on their ability to classify five distinct activities: downstairs, running, standing, upstairs, and walking. The performance metrics for each model were assessed using precision, recall, F1-score, and support values.

The Random Forest model achieved exceptional performance with:

```
Classification Report:

              precision    recall  f1-score   support

  downstairs       1.00      0.99      0.99       680
     running       0.99      1.00      0.99       631
    standing       1.00      0.99      1.00       702
    upstairs       0.99      1.00      0.99       712
     walking       1.00      0.99      0.99       705

    accuracy                           0.99      3430
   macro avg       0.99      0.99      0.99      3430
weighted avg       0.99      0.99      0.99      3430

Model saved as 'movement_detection_rf_model.pkl'
```

The Adaboost model showed significantly lower performance:

```
Classification Report:

              precision    recall  f1-score   support

  downstairs       0.48      0.39      0.43       680
     running       0.87      0.79      0.83       631
    standing       0.83      0.79      0.81       702
    upstairs       0.55      0.62      0.58       712
     walking       0.58      0.69      0.63       705

    accuracy                           0.65      3430
   macro avg       0.66      0.66      0.66      3430
weighted avg       0.66      0.65      0.65      3430

Model saved as 'movement_detection_adaboost_model.pkl'
```

The LSTM model showed significantly lower performance:

```
              precision    recall  f1-score   support

           0       0.87      0.89      0.88       419
           1       0.96      0.83      0.89       250
           2       0.98      0.94      0.96       462
           3       0.83      0.89      0.86       332
           4       0.84      0.86      0.85       437

    accuracy                           0.89      1900
   macro avg       0.90      0.88      0.89      1900
weighted avg       0.89      0.89      0.89      1900
```

3.2 Application results

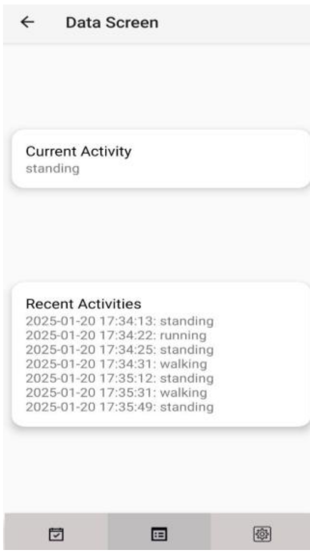
The Android application features several key screens that provide users with comprehensive activity tracking and wellness monitoring capabilities.

Activity Tracking Screen

The main data screen displays two primary components

1. ***Current Activity***: Shows the user's present activity state in real-time (e.g., "standing")
2. ***Recent Activities***: Maintains a chronological log of the last five activities with precise timestamps, allowing users to track their activity transitions throughout the day

(e.g., "2023-01-20 17:34:22 walking", "2023-01-20 17:34:25 standing")

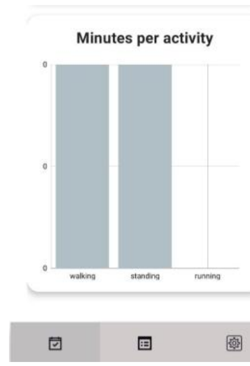


Today's Overview Screen

This screen provides daily activity analytics through two main visualizations.

1. ***Calories Burned Graph:*** Displays a line graph showing caloric expenditure over time which includes clear axis labelling for time and calorie measurements. And shows the total calories burned for the day (e.g., "Total Calories Burned: 16.33 kcal")

2. ***Minutes per Activity*:** Features a bar chart visualization showing time spent in different activities**.** It separates activities by type (walking, standing, running) and provides a clear comparison of duration across different activities



The application's interface is designed for intuitive navigation with a bottom navigation bar featuring three main sections, making it easy for users to switch between different views of their activity data.

4 Conclusion

This project successfully demonstrated the development and implementation of a smartphone-based Human Activity Recognition (HAR) system for wellness management. By utilizing built-in smartphone sensors, the solution eliminates the need for additional wearable devices while maintaining high recognition accuracy. The system effectively classifies five distinct physical activities using various machine learning models, with Random Forest outperforming both AdaBoost and LSTM models in terms of accuracy.

The developed Android application integrates real-time tracking with practical wellness features, enabling both activity recognition and detailed analysis. Personalized metrics, such as age, height, weight, and sex, enhance the accuracy of calorie expenditure calculations, offering valuable insights into users' physical activity patterns. The intuitive user interface, featuring current and recent activity tracking, ensures ease of monitoring and user engagement.

This project contributes to the field of mobile health monitoring by demonstrating that activity recognition systems can be effectively implemented using widely available smartphone sensors, making wellness monitoring more accessible to the general public. Future work could focus on expanding the range of recognized activities, refining energy consumption models, and improving system usability and performance. The positive experimental results suggest that smartphone-based HAR systems can play a significant role in promoting active lifestyles and supporting personal health management.

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