

A Smartphone Sensors-Based Personalized Human Activity Recognition System for Sustainable Smart Cities

Authors:

Abdul Rehman Javed , Raza Faheem b, Muhammad Asim, Mirza Omer Beg, Thar Baker

Presented by:

Basma Adawy, Samayandys Sisa Ruiz

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Introduction

Rapid urbanization by 2050: 66% of the world population will live in cities.

Smart cities aim to improve urban life through sustainability and healthier environments.

Problem Statement:

Current activity recognition systems lack accuracy in recognizing complex activities.

Objective:

Develop a novel framework for Human Activity Recognition (HAR) using smartphone sensors and Google Fit API.

Key Contribution:

A deep recurrent neural network (DRNN) model for accurate activity recognition.

Importance of Human Activity Recognition (HAR)



Why HAR Matters:

Essential for healthcare, fitness, skill assessment, and independent living.

Helps in detecting diseases like Parkinson's and Dementia.

Supports sustainable urban development by promoting healthier lifestyles.



Challenge

Limited accuracy in existing HAR systems.

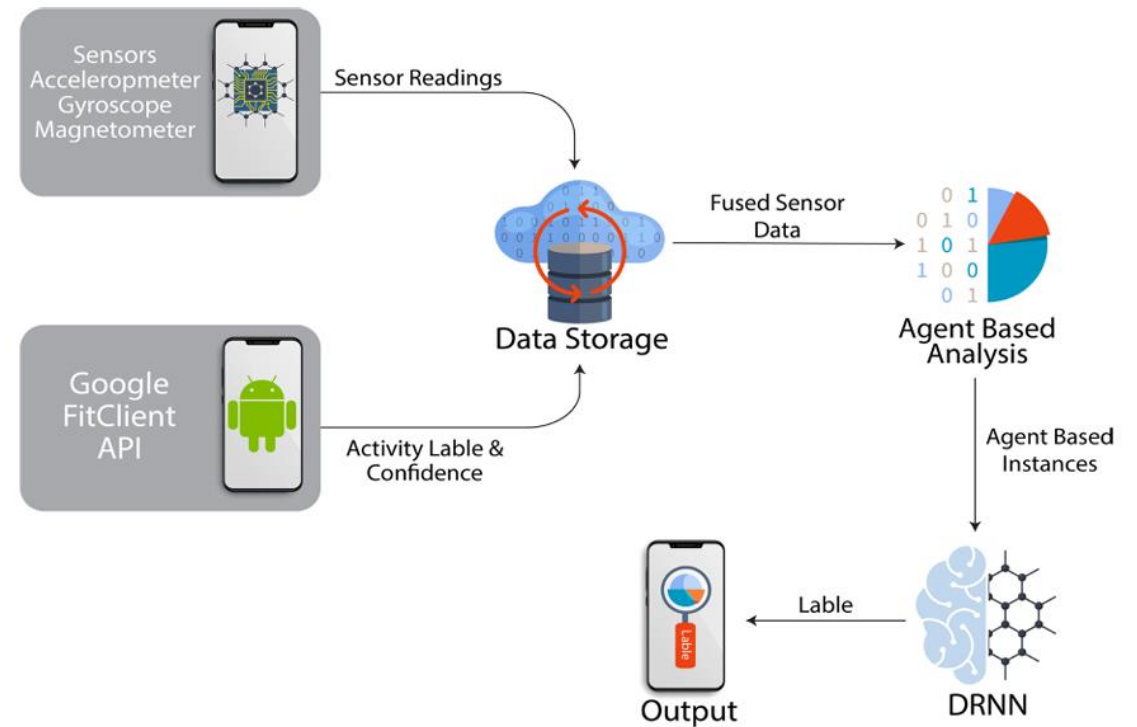
Proposed Framework

Overview:

- Combines smartphone sensors (accelerometer, gyroscope, magnetometer) with Google Fit API.
- Uses a Deep Recurrent Neural Network (DRNN) for activity classification.

Key Components:

- **Smartphone Sensing:** Collects raw sensor data.
- **Google Fit API:** Tracks physical activities (walking, running, cycling, etc.).
- **Agent-Based Analysis (ABA):** Filters and fuses data for improved accuracy.
- **DRNN Model:** Classifies activities with high precision.



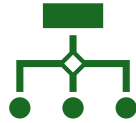
Methodology



Data Collection:

12 participants, 5 activity classes (In-Vehicle, Tilting, Still, On Foot, Walking).

Smartphone sensors collect data at 30 samples/second.



Feature Extraction:

Raw data transformed into a feature matrix with 11 axes (3 sensors x 3 axes + Google Fit).



Model Training:

DRNN with LSTM units for time-series data.

Hyperparameters: Learning rate (0.001), batch size (64), 50 epochs.



Evaluation Metrics:

Accuracy, Precision, Recall, F-Score, AUC.

Deep Recurrent Neural Network (DRNN)

Why DRNN?

- Effective for time-series data.
- Captures temporal dependencies in sensor data.

Architecture:

- Input Layer: 10 dimensions (sensor data + Google Fit).
- Hidden Layers: LSTM units.
- Output Layer: 5 dimensions (activity classes).

Key Features:

- Softmax activation function.
- Categorical Cross-Entropy loss function.
- Adam optimizer for gradient descent.

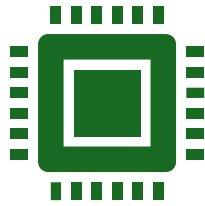
Experimental Setup



Dataset:

12 participants, 5 activities, 130,000 sensor readings.

Smartphones used: Oppo F3, Samsung J7, Huawei Honor, etc.



Environment:

Ubuntu 18.04, NVIDIA GeForce 1080 GPU, 128GB RAM.



Evaluation:

5-fold cross-validation.

80% training, 20% testing.

Results

Accuracy:	With ABA: 99.43% Without ABA: 94%
Comparison with Other Models:	DRNN outperforms Adaboost, Naive Bayes.
Confusion Matrix:	Minimal confusion between Tilting and Still activities. High accuracy for Walking, In-Vehicle, and On Foot.

Performance Metrics

Precision, Recall, F-Score, AUC:

- **In-Vehicle:** Precision (99.9%), Recall (97.7%), F-Score (98.9%), AUC (99.6%)
- **Walking:** Precision (99.7%), Recall (99.4%), F-Score (99.7%), AUC (99.8%)

Average Performance:

- Precision (98%), Recall (98%), F-Score (98%), AUC (99.4%)

Parameter Tuning

Hyperparameter Optimization:

- Learning rate: 0.001
- Batch size: 64
- Epochs: 50

Grid Search:

- Analyzed different combinations of layers, learning rates, and batch sizes.

Best Model:

- Achieved 99% accuracy at the 27th epoch.



Conclusion

Key Findings:

- The proposed framework achieves high accuracy (99.43%) in recognizing complex activities.
- Integration of Google Fit enhances system robustness.
- DRNN outperforms traditional machine learning models.

Future Work:

- Extend to more activities and larger datasets.
- Compare with meta-heuristic algorithms for feature selection.

Reference

- You can find the presented paper here
https://www.sciencedirect.com/science/article/abs/pii/S2210670721002560?casa_token=fM0l0SHQ0u0AAAAA:dGjrLvliE5XllgyKuO7qtNZDOR7IJ8ObgDs7TeRUAQ7Nc8hGHGFq4BVz0QgRWnG3Dk_HRUU



Thank you

