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Development of an Adaptive Machine Learning Framework for Real-Time Sensing and Recognition of Human Activities

Ms. Asra Khalid[1], Dr. Pawan Meena[2]
[1]MTech Scholar, RITS, Bhopal
[2]Guide, RITS, Bhopal

Abstract: *Human Activity Recognition (HAR) plays a vital role in applications such as healthcare monitoring, smart environments, human–computer interaction, and safety systems. While traditional HAR systems achieve good accuracy under controlled conditions, their performance often degrades in real-world deployments due to user variability, sensor noise, and concept drift. This paper presents the development and evaluation of an adaptive machine learning framework for real-time sensing and recognition of human activities. The proposed framework integrates streaming sensor data processing, lightweight deep learning models, and online adaptation mechanisms to maintain high recognition accuracy over time. Experiments conducted on benchmark wearable sensor datasets demonstrate that the adaptive framework consistently outperforms non-adaptive baselines, particularly in cross-subject and long-term evaluation scenarios. The results confirm the effectiveness of adaptive learning in addressing real-world challenges in real-time HAR systems.*

Keywords: *Human activity recognition, adaptive learning, real-time sensing, wearable sensors, online machine learning.*

1. Introduction

Human Activity Recognition using sensor data has gained significant attention due to the proliferation of wearable devices and smart environments. Conventional HAR systems rely on offline-trained models that assume static data distributions. However, in real-world settings, changes in user behavior, sensor placement, and environmental conditions cause performance degradation over time.

To address these limitations, adaptive machine learning frameworks have been proposed, enabling models to update continuously during deployment. This paper focuses on the **development and experimental evaluation** of an adaptive framework designed for real-time activity recognition using wearable sensors. The main objectives of this work are:

1. To design a real-time sensing and recognition pipeline suitable for resource-constrained devices.
2. To integrate online learning and personalization mechanisms.
3. To experimentally evaluate the impact of adaptation on recognition accuracy, latency, and robustness.

2. System Architecture and Framework Design

2.1 Overall Architecture

The proposed framework consists of five main components:

1. **Sensor Data Acquisition Module** Collects real-time data from wearable inertial sensors (accelerometer and gyroscope).
2. **Preprocessing and Segmentation Module** Performs noise filtering, normalization, and sliding window segmentation on streaming data.
3. **Feature Representation Module** Uses both statistical features and learned representations from raw sensor signals.
4. **Activity Recognition Model** A lightweight deep learning classifier deployed on the edge device.

5. **Adaptive Learning Module**
   Updates the model incrementally based on new labeled or pseudo-labeled samples.

2.2 Real-Time Processing Pipeline

Sensor data are processed using overlapping sliding windows of fixed duration. Each window is classified immediately, enabling low-latency predictions. Adaptation is triggered periodically when performance degradation is detected or when new labeled samples become available.

3. Dataset and Experimental Setup

3.1 Datasets Used

Experiments were conducted using publicly available benchmark datasets:

- **UCI Human Activity Recognition Dataset**
  Includes six daily activities recorded using smartphone inertial sensors.
- **WISDM Dataset**
  Contains accelerometer data for multiple users performing common activities.

These datasets are widely used and provide sufficient diversity for evaluating cross-subject generalization.

3.2 Data Preprocessing

- Sampling rate normalization
- Noise filtering using a low-pass filter
- Sliding window segmentation (2.56 s window with 50% overlap)
- Z-score normalization

3.3 Experimental Protocol

Three evaluation settings were considered:

1. **Subject-dependent evaluation**
   Training and testing on the same users.
2. **Cross-subject evaluation**
   Training on a subset of users and testing on unseen users.
3. **Online adaptive evaluation**
   Initial training followed by incremental updates during testing.

4. Model Implementation

4.1 Baseline Model

The baseline system uses a non-adaptive deep learning model trained offline:

- 1D Convolutional Neural Network
- Two convolutional layers followed by a fully connected layer
- Softmax output for multi-class classification

4.2 Adaptive Model

The adaptive model extends the baseline by incorporating:

- Incremental weight updates using mini-batch online learning
- Learning rate scheduling to prevent catastrophic forgetting
- Limited replay buffer containing recent samples

The adaptive updates are computationally lightweight and suitable for real-time execution.

5. Performance Metrics

The following metrics were used for evaluation:

- **Accuracy**
- **Precision**
- **Recall**
- **F1-score**
- **Inference latency**
- **Model update time**

Accuracy and F1-score are emphasized due to class imbalance in activity data.

6. Experimental Results

6.1 Baseline Performance

Evaluation Setting	Accuracy (%)	F1-score
Subject-dependent	94.8	0.95
Cross-subject	86.3	0.87

The baseline model performs well in subject-dependent settings but shows noticeable degradation in cross-subject evaluation.

6.2 Adaptive Framework Performance

Evaluation Setting	Accuracy (%)	F1-score
Cross-subject (adaptive)	91.7	0.92
Online long-term (adaptive)	90.9	0.91

The adaptive framework significantly improves performance when tested on unseen users and over extended time periods.

6.3 Impact of Online Adaptation

- Accuracy improvement of **5–6%** over the non-adaptive model
- Reduced error accumulation during long-term deployment
- Stable performance under simulated sensor drift

6.4 Latency Analysis

- Average inference time per window: **12 ms**
- Average model update time: **< 30 ms**
- Total latency remains within real-time constraints for wearable applications

7. Discussion

The results clearly demonstrate that adaptation is essential for real-world HAR systems. While offline-trained models perform well in controlled settings, their accuracy declines when exposed to new users and changing conditions. The proposed adaptive framework mitigates this issue by continuously refining the model during deployment.
Key observations include:

- Lightweight adaptation mechanisms provide substantial gains without heavy computational overhead.
- Personalization improves recognition of user-specific activity patterns.
- Careful control of update frequency prevents overfitting and catastrophic forgetting.

8. Limitations

Despite promising results, several limitations remain:

- Dependence on labeled or semi-labeled data for adaptation
- Evaluation limited to inertial sensor datasets
- No explicit handling of adversarial or malicious sensor inputs

Addressing these limitations will be part of future work.

9. Conclusion

This paper presented the development and experimental evaluation of an adaptive machine learning framework for real-time sensing and recognition of human activities. By integrating online learning and personalization into a real-time HAR pipeline, the proposed system achieves higher accuracy and robustness than traditional non-adaptive models. Experimental results on benchmark datasets validate the effectiveness of adaptation, particularly in cross-subject and long-term scenarios. The findings highlight the importance of adaptive learning for deploying reliable human activity recognition systems in real-world environments.

10. Future Work

Future research directions include:

- Incorporating self-supervised and active learning techniques
- Extending the framework to multimodal sensing (vision, RF, physiological data)
- Implementing federated learning for privacy-preserving adaptation
- Deploying and evaluating the framework on real wearable hardware

References

[1] Ł. Czekaj, “Real-Time Sensor-Based Human Activity Recognition for Exercise Classification Using Deep Learning,” *Sensors*, vol. 24, no. 12, p. 3891, 2024.

[2] D. Navakauskas, “Wearable Sensor-Based Human Activity Recognition: XAI and Neural Network Interpretability,” *Sensors*, vol. 25, no. 14, p. 4420, 2025.

[3] B. A. Khan, “Deep Learning-Based Human Activity Recognition Using Dilated CNN-LSTM Architectures,” *Appl. Sci.*, vol. 15, no. 22, 2025.

[4] L. Sakalauskas, “Adaptive Learning Approach for Human Activity Recognition Using Hidden Markov Models,” *Appl. Sci.*, vol. 15, no. 14, 2025.

[5] S. Kundu, M. Mallik, and J. Saha, “Smartphone Based Human Activity Recognition Irrespective of Usage Behavior Using Deep Learning,” *Int. J. Inf. Technol.*, vol. 17, pp. 69–85, 2025.

[6] T. S. Qureshi, R. et al., “A Systematic Literature Review on Human Activity Recognition: Challenges and Trends,” *Artif. Intell. Rev.*, 2025.

[7] L. S. Songare, H. P. Singh, S. Bhayal, P. Baniya, A. S. Rajput and P. Lakkadwala, "Laptop Price Estimation Using Data-Driven Predictive Analytics," *2025 IEEE International Conference on Advances in Computing Research On Science Engineering and Technology (ACROSET)*, INDORE, India, 2025, pp. 1-6, doi: 10.1109/ACROSET66531.2025.11281104.

[8] A. Mewada, A. S. Yadav, H. P. Singh, P. Nigam, M. A. Ansari and S. Ahmad, "Smart Censorship: Real-Time Obscene Content Detection Using Skin Pixel Aggregation and Humanoid Shape Recognition," *2025 IEEE Madhya Pradesh Section Conference (MPCON)*, Jabalpur, India, 2025, pp. 743-747, doi: 10.1109/MPCON66082.2025.11256623.

[9] Avani Trivedi et al., "Development of Mental Health Prediction App for the Depression Assistance Based on AI Chatbot," 2025 International Conference on Engineering Innovations and Technologies (ICoEIT), Bhopal, India, 2025, pp. 1369-1374, doi: 10.1109/ICoEIT63558.2025.11211786.

[10] K. N. Singh, H. P. Singh, S. Mohod, S. Adekar, A. Budholiya and R. Kushwah, "Technological Approach for Safe Transportation Through Elderly and Impaired Drivers," 2025 International Conference on Engineering Innovations and Technologies (ICoEIT), Bhopal, India, 2025, pp. 120-125, doi: 10.1109/ICoEIT63558.2025.11211795.

[11] H. P. Singh, A. Sharma, S. Chouhan, P. Rane, A. H. Pilay and N. Singh, "Hand Interaction in VR: A Comparative Evaluation of Techniques and Performance," *2025 International Conference on Engineering Innovations and Technologies (ICoEIT)*, Bhopal, India, 2025, pp. 1435-1440, doi: 10.1109/ICoEIT63558.2025.11211762

[12] Singh, Harsh Pratap, et al. "AVATRY: Virtual Fitting Room Solution." 2024 2nd International Conference on Computer, Communication and Control (IC4). IEEE, 2024.

[13] Singh, Nagendra, et al. "Blockchain Cloud Computing: Comparative study on DDoS, MITM and SQL Injection Attack." 2024 IEEE International Conference on Big Data & Machine Learning (ICBDML). IEEE, 2024.

[14] Singh, Harsh Pratap, et al. "Logistic Regression based Sentiment Analysis System: Rectify." 2024 IEEE International Conference on Big Data & Machine Learning (ICBDML). IEEE, 2024.

[15] H. Sharen, “WISNet: A 1D-CNN Approach for Complex Human Activity Recognition,” *Expert Syst. Appl.*, 2024.

[16] I. Charabi, “DeepF-SVM: A Hybrid Deep Learning Model for Enhanced Human Activity Recognition,” *Inf. Sci.*, 2025.

[17] M. Xu et al., “DCAM-Net: DeepConvAttentionMLPNet for Human Activity Recognition without Pre-trained Models,” *Sci. Rep.*, 2025.

[18] M. Maray et al., “Intelligent Deep Learning for HAR in IoT-Edge-Cloud Continuum,” *Sci. Rep.*, vol. 15, p. 29640, 2025.