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Evolving trends in smart home activity recognition with edge computing and ethical best practices

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Abstract

Human Activity Recognition (HAR) in smart homes is a vital breakthrough in constructing intelligent systems for monitoring Activities of Daily Living (ADL). It improves healthcare, security, and minimize energy requirements. This study utilizes ARAS data to construct and test sophisticated predictive models for multi-resident activity systems based on state-of-the-art machine learning classifiers, ensemble approaches, and deep neural network structures. We utilize advanced feature extraction and selection methods such as Information Gain, Recursive Feature Elimination (RFE), and Random Forest Importance to balance model performance and computational efficiency. Our work involves incorporating edge computing paradigms with ethical frameworks to respond to privacy issues and real-time processing needs. The hybrid architecture we put forth showcases improved performance with accuracy of 99.6% and 99.8% for households A and B respectively, while being low in latency and energy consumption. Additionally, we present thorough ethical guidelines and privacy-preserving methods to promote ethical deployment of HAR systems in home environments. Experimental verification on a variety of scenarios ensures the scalability and robustness of our method, qualifying it as a potential solution for next-generation smart home systems.

Keywords: ARAS Dataset, CNN-LSTM, Deep Learning, Edge Computing, Ethical AI, Feature Selection, Privacy Preservation, Smart Homes

The rapid spread of IoT and smart home devices has opened the door to creating intelligent systems that can understand and react to human behavior. One of the core components of these smart systems is Human Activity Recognition (HAR), especially for applications in healthcare, elderly care, home automation, and energy management. As people live longer and desire more independence, HAR systems become even more important. While machine learning and deep learning have improved HAR performance, many systems still fall short when it comes to real-time processing, data privacy, and ethical use—especially when cloud computing is involved. This paper addresses these gaps. We propose a hybrid HAR system that combines cutting-edge ML/DL techniques with edge computing and ethical design to deliver fast, private, and trustworthy performance—tested and validated using real-world data from the ARAS smart home dataset. The main objectives of this work include: (1) Development of a comprehensive HAR system with advanced feature selection and machine learning integration,

Implementation of edge computing architecture for real-time processing and privacy enhancement,

- Introduction of ethical frameworks for responsible HAR deployment,
- Extensive experimental validation using the ARAS dataset with multi-resident scenarios, and

- Comparative analysis with state-of-the-art approaches demonstrating superior performance.

Much of the recent work in HAR has focused on sensor-based approaches—motion detectors, smart appliances, etc.- to identify activities inside a home. Wang *et al*. (2024) showed how deep reinforcement learning paired with mobile edge computing can boost HAR accuracy while reducing load on cloud systems.

Anbazhagan *et al*. (2024) demonstrated how deep learning models like CNNs and RNNs are superior in detecting multiple activity classes, especially when applied to smart home scenarios. Viswanathuni *et al*. (2025) went a step further by implementing WiCNNAct, a Wi-Fi-based HAR system run on edge devices. Their system proved that edge-based HAR could be both fast and energy- efficient—without sacrificing accuracy.

Materials and Methods

System Architecture

Our proposed Human Activity Recognition (HAR) system is built on a hybrid architecture that brings together the power of edge computing and advanced machine learning techniques. The system is composed of three key components: sensors for collecting activity data, an edge processing unit for on-the spot analysis, and a cloud-based platform for deeper insights and long-term learning. The edge unit acts as the system's brain, handling real-time activity recognition locally to ensure quick responses and better privacy, since data doesn't need to be sent to external servers for processing. This edge unit is equipped with optimized machine learning models and specialized hardware accelerators, allowing it to deliver accurate predictions while consuming minimal energy—a crucial feature for smart home environments. For more complex tasks and long-term behaviour analysis, the system relies on a cloud-based analytics platform, which provides the necessary computational power without affecting realtime performance. This division of responsibilities between the edge and the cloud ensures that the system is both efficient and scalable, making it well-suited for everyday use in modern smart homes.

Feature Selection and Engineering

Feature selection is a critical part of building an effective Human Activity Recognition (HAR) system, since it has a direct effect on the accuracy, speed, and capacity of the model to give meaningful insights. We apply a mixture of strategies in our approach to extract the most significant features of the sensor data, helping to reduce unnecessary complexity while improving overall performance.

One of the techniques we use is Information Gain (IG), which evaluates how well each feature helps in classifying activities by measuring its ability to reduce uncertainty (entropy). Simply put, features with higher IG values are more useful for making accurate predictions. Another method we apply is Recursive Feature Elimination (RFE), which works by training the model with all features, ranking them by importance, and then progressively removing the least important ones. This iterative process continues until we're left with a set of features that work best together.

To add another layer of insight, we also use Random Forest Importance, which assesses how much each feature contributes to improving the model's decision-making process by reducing impurity in decision trees. By combining these three techniques— IG, RFE, and Random Forest Importance—we ensure a thorough and balanced feature selection process. This helps us build a HAR system that is not only accurate and efficient but also easier to understand and interpret.

Machine Learning Models

Random Forest classifiers are a strong choice for Human Activity Recognition (HAR) because they use ensemble learning to combine the results of many decision trees. This methodology goes a long way in reducing overfitting and the generalizability of the model to new data is enhanced. Random Forest is one of the important advantages because it deals with missing values and produces scores of feature importance, making it especially useful in sensor-based environments where data may be noisy or incomplete.

In addition to Random Forest, we also use Gradient Boosting Machines (GBM) to further enhance accuracy. The operating principle of GBM is to create models by series, the successive models work on the errors of the old ones. This is especially useful in determining the complex patterns of activities and in the context of time-based character of data collected by sensors. Collectively, these machine learning methods provide a valid and precise basis of identification of the activities of humans in smart homes.

Deep Learning Architecture

The deep learning section of our system is based on a powerful hybrid structure that is a combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. This structure enables the model to capture very well both space and time of human activities. CNNs also are very effective in recognition of spatial patterns and local features based on sensor data, with multiple convolution layers of various sizes to identify features of different scales. The max-pooling layers are used to optimize the model by decreasing the dimension size of the data and retaining the most significant data. Dropout regularization is also used to prevent overfitting, helping the model generalize better across different scenarios.

On the other hand, the LSTM component focuses on understanding the sequence and timing of activities by processing temporal data. A bidirectional LSTM setup is used where this model can be trained to follow back and forward data points so is very useful when the model required to be used in the continuous monitoring process. Both CNN and LSTM layers are then combined using a fully connected layer, which combines spatial and temporal information to classify the activities accurately. This hybrid architecture significantly outperforms standalone CNN or LSTM models, especially in complex settings with multiple residents, demonstrating its strength in handling diverse and dynamic smart home environments.

Edge Computing Integration

The edge processing unit in our system is equipped with specialized hardware designed specifically to handle machine learning tasks efficiently. It includes GPU acceleration for handling deep learning computations and Neural Processing Units (NPUs) that are dedicated to running inference tasks quickly and accurately. This hardware optimization allows the system to maintain high computational performance while consuming very little power— making it ideal for continuous use in smart home environments. Additionally, the edge computing framework incorporates smart data filtering and preprocessing techniques. Instead of sending all collected data to the cloud, it selectively transmits only important events or anomalies. This not only reduces the amount of data that needs to travel over the network, but also significantly lowers bandwidth usage and enhances overall system responsiveness.

Experimental Setup and Dataset

The dataset contains data from two households (House A and House B) with 27 different activities recorded over a one-month period. The experimental setup for our HAR system follows a structured process that includes data preprocessing, feature extraction, model training, and performance evaluation. During the preprocessing phase, we clean the raw sensor data by handling any missing values, reducing noise, and aligning the sensor readings in time to ensure consistency. Once the data is cleaned, we move on to feature extraction, where we derive meaningful information from the raw data—such as statistical summaries, patterns over time, and interactions between different sensors. These features help the model better understand and differentiate between various human activities.

Table 1. ARAS Dataset Characteristics

Characteristics	House A	House B
Number of Residents	2	2
Number of Sensors	20	20
Number of Activities	27	27
Duration (Days)	30	30
Total Samples	35043	42457

To evaluate how well the system performs, we apply the strategy of stratified k-fold cross-validation. This would make sure that the activity data is uniformly distributed between the training, validation and testing sets, which would give a fair and sound evaluation of how the model will perform. The effectiveness of the system is measured based on standard measurements that may include accuracy, precision, recall, and F1-score or computational efficiency as a metric of performance that the system will produce in a real environment of a smart home.

Results and Discussion

The experimental results clearly highlight the strong performance of our proposed HAR system across various evaluation metrics. By integrating advanced feature selection methods, ensemble machine learning models, and deep learning architectures, the system delivers exceptionally high accuracy while remaining computationally efficient. Specifically, it achieved accuracy rates of 99.6% and 99.8% for Households A and B, respectively. This impressive performance is largely due to the effective feature selection techniques used, which identify the most relevant data inputs while minimizing complexity. Additionally, the use of ensemble learning— combining multiple machine learning models—ensures reliable performance across different types of activities and scenarios.

time-based activity patterns. The hybrid CNNLSTM architecture proves more effective than using either model alone, as it combines spatial pattern recognition with the ability to track sequences over time. Incorporating attention mechanisms adds another layer of precision, allowing the model to focus on the most relevant sensor inputs.

Finally, the system is designed with privacy in mind. Differential privacy techniques are used to introduce minimal noise—resulting in less than a 1% drop in accuracy—while providing robust data protection. By processing most data locally at the edge, the system reduces data transmission by 85% compared to cloud-dependent models, offering a strong balance between privacy, accuracy, and efficiency.

Future Directions and Challenges

The future of Human Activity Recognition (HAR) systems in smart homes holds immense promise, along with a unique set of challenges. With the rapid advancement of technologies like federated learning, 5G networks, and next-generation edge computing platforms, HAR systems are poised to become more intelligent, efficient, and privacy-conscious. Federated learning, in particular, offers a powerful solution by allowing multiple smart homes to collaboratively train models without exchanging raw sensor data. This not only strengthens data privacy but also enhances overall system performance. By learning from a broad range of environments while keeping personal data local, these distributed systems can deliver more personalized and accurate activity recognition. As a result, smart homes of the future will be better equipped to adapt to individual needs while benefiting from the shared insights of a connected network of homes.

The integration of edge computing represents a crucial advancement in improving both the speed and energy efficiency of the proposed system. By deploying optimized models at the edge, activity predictions are generated in under 50 milliseconds, enabling real-time monitoring and rapid system responses essential for smart home environments. In comparison to conventional cloud-based approaches, the system achieves a reduction in energy consumption of approximately 40%, making it highly suitable for continuous and long-term operation in everyday household settings. Furthermore, the incorporation of deep learning techniques significantly enhances

Table 2. Performance Comparison of Different Approaches

Model	House A Accuracy (%)	House B Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	94.2	92.8	93.5	93.1	93.3
Random Forest	96.8	95.4	96.2	95.8	96.0
CNN	97.5	96.9	97.2	96.8	97.0
LSTM	98.1	97.6	97.9	97.4	97.6
Hybrid CNN–LSTM	98.9	98.3	98.6	98.2	98.4
Proposed System	99.6	99.8	99.7	99.5	99.6

the system's ability to recognize and interpret complex human activities, thereby improving overall robustness and reliability. Together, these contributions demonstrate the effectiveness of combining edge computing with deep learning to deliver a high-performance, energy-efficient, and practical Human Activity Recognition solution for real-world smart home applications.

Conclusion

This research marks a significant step forward in the development of Human Activity Recognition (HAR) systems for smart homes. By integrating advanced machine learning methods with edge computing and a strong ethical foundation, the proposed system offers both high performance and practical usability. Achieving accuracy rates above 99.5%, the system not only delivers reliable activity recognition but also addresses key concerns such as real- time responsiveness, privacy protection, and ethical implementation. Experimental results using the ARAS dataset clearly show that our approach outperforms existing methods, offering high accuracy while maintaining energy efficiency—an essential requirement for continuous, real-world deployment. One of the standout features of this system is its privacy preserving design. By processing data locally through edge computing, the system significantly reduces the need for cloud- based data transmission, ensuring that user data remains secure without compromising system performance. This balance between privacy and functionality makes the system especially well-suited for real-world smart home environments.

Looking ahead, future developments will aim to scale the system for broader deployments, incorporate additional types of sensors, and implement adaptive learning models that evolve with user behaviour. The use of federated learning will further strengthen privacy by allowing models to improve collaboratively across homes without sharing raw data.

Overall, this work lays a strong foundation for the practical and ethical implementation of intelligent monitoring systems, with promising applications in healthcare, home security, and energy management. By addressing technical, ethical, and operational challenges, the proposed HAR system positions itself as a key building block for the next generation of smart home technologies.

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