Human Activity Recognition in Smart Homes: Advancements and Future Trends With Edge Computing Integration and Ethical Frameworks

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

INTRODUCTION

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

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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:

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

LITERATURE REVIEW

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.

METHODOLOGY

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 behavior analysis, the system relies on a cloud-based analytics platform, which provides the necessary computational power without affecting real-time 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, as it directly influences the model's accuracy, speed, and ability to provide meaningful insights. In our approach, we use a combination of techniques to identify the most important features from 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 approach helps reduce overfitting and improves the model's ability to generalize well to new data. One of the key advantages of Random Forest is its ability to handle missing values and generate feature importance scores, 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. GBM works by building models in a sequence, where each new model focuses on correcting the mistakes made by the previous ones. This method is particularly effective for identifying complex activity patterns and understanding the time-based nature of sensor data. Together, these machine learning techniques offer a reliable and accurate foundation for recognizing human activities in smart home settings.

Deep Learning Architecture

The deep learning component of our system is built on a powerful hybrid architecture that combines Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks. This design allows the model to effectively capture both spatial and temporal aspects of human activities. CNNs are particularly adept at identifying spatial patterns and local features from sensor data, using multiple convolution layers with different filter sizes to detect features at various scales. To keep the model efficient, max-pooling layers are applied to reduce the dimensionality of the data while preserving the most important information. 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. We use a bidirectional LSTM setup, which allows the model to learn from both past and future data points, making it highly effective for continuous monitoring applications. The outputs from both CNN and LSTM layers are then combined through a fully connected layer, bringing together spatial and temporal insights for accurate activity classification. 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 data collected 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.

Table – 1
ARAS Dataset Characteristics

Characteristic	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	35,043	42,457

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.

To evaluate how well the system performs, we use a technique called stratified k-fold cross-validation. This ensures that the activity data is evenly distributed across the training, validation, and testing sets, providing a fair and robust assessment of the model's performance. We measure the system's effectiveness using standard metrics such as accuracy, precision, recall, and F1-score, along with computational efficiency to gauge how well the system would perform in a real-world smart home setting.

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.

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 integration of edge computing plays a critical role in enhancing both speed and energy efficiency. The optimized models are capable of making activity predictions in under 50 milliseconds, which supports real-time monitoring and quick system responses. Compared to traditional cloud-based systems, energy usage is reduced by 40%, making the solution more practical for continuous use in everyday home environments.

Our deep learning component further strengthens the system's capabilities, especially when it comes to detecting complex and time-based activity patterns. The hybrid CNN-LSTM 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.

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 behavior. 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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