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Real-time Monitoring of Activity Recognition in Smart Homes: An Intelligent IoT Framework

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Abstract

The rapid proliferation of the Internet of Things (IoT) has paved the way for transformative innovations, and this paper explores its profound impact on the realm of elderly care within smart homes. We present a pioneering IoT-based approach for human activity recognition, addressing the critical need for accurate and non-intrusive monitoring of elderly individuals. Our IoT-based approach begins with data preprocessing, where raw sensor data is refined using median filtering, reducing noise and ensuring high-quality inputs for our model. We apply the "series_to_supervised" transformation to convert the sensor data into a supervised learning format, which is critical for training the GRU-based activity recognition model. The heart of our approach lies in the federated distillation-based training strategy. Edge devices within the IoT network locally train their GRU models using their datasets while sharing knowledge with a central server and other edge devices. Knowledge distillation further enhances the model's performance by transferring knowledge from the global model to the edge devices. Experimental analysis demonstrated an impressive accuracy of 95% and an F1-score of 0.94, Our system excels in recognizing and classifying a wide range of human activities, from daily routines to emergencies.

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1. Introduction

The aging population is a global demographic trend, posing significant challenges for healthcare and caregiving. As the elderly increasingly choose to age in place, there arises a pressing need for effective and unobtrusive methods of monitoring their well-being [1]. The scholars explore the intersection of technology and healthcare by investigating the application of IoT-based human activity recognition in smart homes to address this challenge. The significance of this study cannot be overstated in the context of our aging society. As the elderly population grows, traditional healthcare systems and caregiving approaches face strain and inefficiencies. This research holds the promise of significantly improving the lives of the elderly by allowing them to maintain their independence while receiving timely assistance and healthcare interventions [2].

The concept of IoT and smart homes represents a transformative shift in the way we interact with our living spaces. In essence, IoT empowers our homes with the ability to sense, analyze, and respond to our needs and behaviors [3]. Smart homes leverage this technology to create environments that are not only more convenient but also more adaptive and responsive to the unique requirements of their inhabitants. This paper delves into the world of IoT-enabled smart homes, exploring how this cutting-edge technology can be harnessed to enhance the quality of life and care for the elderly population Human activity recognition is the fundamental underpinning of our research endeavor. It involves the process of identifying, categorizing, and understanding human activities based on data collected from various sensors and devices. In the context of this study, it becomes the key to unlocking valuable insights into the daily lives of elderly individuals in smart homes [4].

The current state of research in the field of IoT-based human activity recognition in smart homes is marked by significant advancements. Several studies have explored the use of sensors and data analytics to monitor and predict human activities, with some promising results [5,18-20]. However, existing solutions often exhibit limitations in terms of accuracy, scalability, and adaptability. While progress has been made, there remains substantial room for innovation and improvement in this field, which motivates our research efforts to bridge these gaps and contribute to the ongoing development of robust and reliable systems for elderly care [6]. Despite the strides made in IoT-based human activity recognition for elderly care, there are critical research gaps that warrant attention. Many existing solutions lack the ability to adapt to the unique needs and preferences of individual elderly users, and scalability challenges often hinder their practical implementation on a larger scale [7]. Furthermore, issues related to privacy and data security must be carefully addressed. Our research seeks to fill these gaps by proposing novel approaches and methodologies to make these systems more personalized, scalable, and secure, thereby addressing the specific challenges associated with elderly care in smart homes.

The primary objective of this research is to develop and evaluate advanced IoT-based approaches for human activity recognition in smart homes, specifically tailored to enhance elderly care [2]. Our contributions encompass the design of novel sensor networks, the development of machine learning algorithms for activity recognition, and the creation of a comprehensive framework for elderly care in smart homes [8]. By achieving these objectives, we aim to provide a holistic and innovative solution that not only enhances the quality of life for the elderly but also advances the field of IoT-based healthcare technology, paving the way for more effective and compassionate caregiving practices in an aging society.

This paper is organized into six distinct sections. Section 2 lays the foundation by presenting an extensive review of existing literature and the key concepts essential to our study. Section 3, delves into the specifics of our research approach, detailing the methodologies. In Section 4, we describe the systematic setup of our experiments, including data collection procedures, participant recruitment, and other pertinent details. Section 5 forms the core of our study, where we present and analyze the outcomes of our experiments, drawing insights from the data collected and discussing their implications. Finally, in Section 6 we summarize our findings, highlight their significance in the context of elderly care and IoT-based technology, and propose potential avenues for future research.

2. Background and Literature

This section provides a critical overview of existing research and developments in the field of human activity recognition within smart homes, particularly focusing on applications for elderly care. Franco et al. [8] proposed an IoT-based approach for load monitoring and activity recognition in smart homes. Their work is notable for its focus on both load monitoring and activity recognition, highlighting the potential of IoT technologies to address multiple aspects of smart home management. In a recent study, Najeh et al. [9] explored the feasibility of supervised real-time human activity recognition on embedded equipment. This research is particularly relevant as it addresses the challenge of real-time recognition, which is crucial for timely interventions in elderly care scenarios. Hussain et al. [10] conducted a comprehensive literature review and presented a risk-based IoT decision-making framework, with case studies in human activity recognition. Their work provides valuable insights into the decision-making processes associated with IoT-based solutions in healthcare contexts. Bouchabou et al. [11] introduced a fully convolutional network bootstrapped by word encoding and embedding for activity recognition in smart homes. Their approach leverages advanced deep learning techniques to improve the accuracy of activity recognition systems. Schlenke et al. [12] contributed to the field by exploring multimodal data for activity recognition in smart homes. Their work suggests that integrating data from multiple sources can lead to more robust and accurate recognition systems. Fan et al. [13] presented an innovative concept of "activity recognition as a service" for smart homes, demonstrating how ambient assisted living applications can benefit from continuous monitoring and recognition of activities. Saha et al. [14] focused on IoT-based human activity recognition for smart living. Their research contributes to the understanding of how IoT technologies can be specifically tailored to enhance the quality of life for residents in smart homes. Ye et al. [15] introduced a graph-attention-based method for single-resident daily activity recognition in smart homes. Their approach leverages graph theory and attention mechanisms to improve the accuracy of recognition in single-resident scenarios. Mittal [16] proposed a machine learning-based human activity recognition model using smart sensors in an

IoT environment. This work emphasizes the potential of machine learning in enhancing the accuracy and efficiency of recognition models. Lee et al. [17] developed an automatic agent generation system for an IoT-based smart house simulator. While not directly related to activity recognition, their work contributes to the broader context of IoT-based smart home environments, which can provide the infrastructure for activity recognition systems.

3. Proposed Framework

In this section, we delve into the core of our research, presenting a comprehensive methodology that underpins our investigation into IoT-based human activity recognition in smart homes tailored for elderly care. Methodological rigor is paramount in ensuring the validity and reliability of our findings. We outline the step-by-step procedures, algorithms, and techniques employed to capture, preprocess, and analyze data, as well as to train and validate our recognition models.

In this study, we leverage the Gated Recurrent Unit (GRU) as our primary model for human activity recognition. GRU is a type of recurrent neural network (RNN) that has shown remarkable performance in sequence modeling tasks, making it well-suited for capturing temporal dependencies in time-series data, such as those generated by wearable sensors within the IoT network.

Before feeding the sensor data into the Gated Recurrent Unit (GRU) for human activity recognition, we apply a crucial preprocessing step. This involves the transformation of the sensor data into a supervised learning format using the "series_to_supervised" procedure. This transformation is essential for creating labeled sequences of input-output pairs, making it suitable for training a supervised learning model such as the GRU. Given a time series dataset $X = [x_1, x_2, x_3, \dots, x_n]$, where x_i represents a data point at time step i, we transform it into a supervised format with lag observations, as follows: For a chosen lag value k, we create a new dataset with the following structure:

- Inputs $(X_{t-k}, X_{t-k+1}, \dots, X_{t-1})$: These are the lagged observations at time t, where t ranges from k to n.
- Output (X_t) : This represents the observation at the current time step t.

By applying the "series_to_supervised" procedure and subsequently utilizing the GRU model, we ensure that the sensor data is appropriately structured for effective learning of human activities within our IoT network. This preprocessing step enhances the model's ability to discern patterns and dependencies, contributing to accurate recognition outcomes. The GRU cell is composed of several key components, including internal gates that govern the flow of information within the cell. These gates are essential for controlling the memory and updating state information during the learning process. Below, we provide a mathematical description of the internal gates of the GRU cell:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{1}$$

Here, σ represents the sigmoid activation function, W_z is the weight matrix for the update gate, h_{t-1} is the previous hidden state, and x_t is the input at time step t. In addition, the reset gate decides which parts of the previous hidden state should be forgotten. It is calculated as follows:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{2}$$

Similar to the update gate, σ denotes the sigmoid activation function, W_r represents the weight matrix for the reset gate, h_{t-1} is the previous hidden state, and x_t is the input at time step t. Moreover, the candidate's activation $(\tilde{h}_t)$ is integrated to compute a candidate activation vector based on the input and the reset gate. It is expressed as:

$$\tilde{h}_t = \tanh\,(W \cdot [r_t \cdot h_{t-1}, x_t]) \tag{3}$$

Here, tanh is the hyperbolic tangent activation function, W is the weight matrix for the candidate activation, r_t is the reset gate, h_{t-1} is the previous hidden state, and x_t is the input at time step t. Finally, the hidden state at time step t is computed as a combination of the previous hidden state and the newly computed candidate activation, controlled by the update gate:

$$h_t = (1 - z_t) \cdot h_{t-1} + z_t \cdot \tilde{h}_t \tag{4}$$

Here, h_t is the current hidden state, z_t is the update gate, h_{t-1} is the previous hidden state, and $\tilde{h}_t$ is the candidate activation.

In this section, we describe the integration of the GRU model into a federated distillation-based training framework, which facilitates efficient and collaborative learning across edge devices within the Internet of Things (IoT) network. This approach enables edge devices to locally train and refine their models while sharing knowledge with a central server and other edge devices.

Federated learning involves decentralized training across multiple edge devices. Let D_i represent the local dataset on edge device i, and w_i denote the local model parameters. The central server maintains a global model W. The federated learning process can be mathematically expressed as follows:

Step1: Initialization: Initialize global model parameters W_0 randomly.

Step2: Local Training (on each edge device i): Edge devices perform local training to update their model parameters using their local dataset D_i. This involves minimizing a local loss function $L_i(w_i)$, which is typically based on a machine learning algorithm (e.g., GRU for activity recognition):

$$w_i \leftarrow \arg\min_{w} L_i(w_i) \tag{5}$$

Step3: Model Aggregation (Central Server): The central server aggregates the updated model parameters from edge devices to obtain a global model update ΔW_i Based on a weighted average:

$$\Delta W_i = \frac{|D_i|}{|D|} \cdot (w_i - W_{t-1}) \tag{6}$$

Here, $|D_i|$ represents the size of the local dataset, $|D|$ is the total size of all local datasets, and $t-1$ is the previous round.

Step4: Global Model Update: The global model is updated using the aggregated updates:

$$W_t = W_{t-1} + \sum_{i} \Delta W_i \tag{7}$$

Step 5: Knowledge Distillation: In addition to model updates, knowledge distillation is applied to transfer knowledge from the global model to edge devices. Edge devices use the global model to generate soft labels (q_i) for their local dataset, which are probabilities over activity classes. The temperature parameter T controls the softening of the SoftMax distribution:

$$q_i = \text{softmax}\left(\frac{f(x_i, W_{t-1})}{T}\right) \tag{8}$$

Here, $f(x_i, W_{t-1})$ represents the logits produced by the global model for input x_i from the local dataset.

Step 6: Local Knowledge Distillation: Edge devices perform local knowledge distillation using the soft labels and their local model (w_i) to update their model parameters:

$$w_i \leftarrow \arg\min_{w} \mathrm{KL}(p_i \parallel q_i) \tag{9}$$

where p_i represents the true label distribution of the local dataset.
Step 7: Iterative Rounds: Steps 3 to 6 are repeated for multiple rounds to train and refine both the global and local models collaboratively.

By integrating the GRU model into this federated distillation-based training framework, we leverage its sequential learning capabilities to recognize human activities while ensuring that the knowledge learned is effectively distilled and shared across edge devices in the IoT network. This approach optimizes model performance while respecting the constraints of edge computing.

4. Experimental Setup

In this section, we detail the carefully designed experimental setup that forms the backbone of our investigation into real-time environmental pollution detection in smart cities using IoT sensors. Building upon the theoretical foundation established in the preceding sections, the section provides a comprehensive overview of the hardware, software, and methodologies employed in our study. We elucidate the selection and deployment of IoT sensors, the configuration of data collection networks, and the integration of sensor data into our monitoring system.

For our experiments, we established a robust implementation setup to ensure the reliability and reproducibility of our results. We conducted our experiments on a heterogeneous network of edge devices and utilized a central server for model aggregation. The hardware configuration of the devices ranged from low-power edge nodes to more capable servers. Specifically, we employed a variety of devices with diverse specifications, including CPU and GPU configurations, RAM capacities, and storage capabilities. In addition, we incorporated simulators to emulate edge device interactions in a controlled environment. To manage the distributed training and data sharing, we utilized software tools and frameworks optimized for federated learning and IoT applications, such as TensorFlow Flower, and custom-built libraries for knowledge distillation and GRU-based activity recognition. The summary table below provides a detailed overview of the hardware and software specifications of the devices and tools used in our experiments (See Table 1).

Table 1: Experimental Implementation Setup

Device	CPU	GPU	RAM	Storage	Simulators	Software Tools
Edge Devices g1	Intel Core i5	NVIDIA GTX 1050	8GB	256GB SSD	Edge Simulator 1	TensorFlow Federated, PyTorch
Edge Devices g2	ARM Cortex-A72	N/A	4GB	64GB eMMC	Edge Simulator 2	Custom Knowledge Distillation
Server	Intel Xeon E5	NVIDIA Tesla V100	32GB	1TB HDD	N/A	Custom GRU Activity Recognition
Central Server	Intel Xeon Scalable	NVIDIA Tesla P100	64GB	1TB SSD	N/A	Python, TensorFlow, Flower

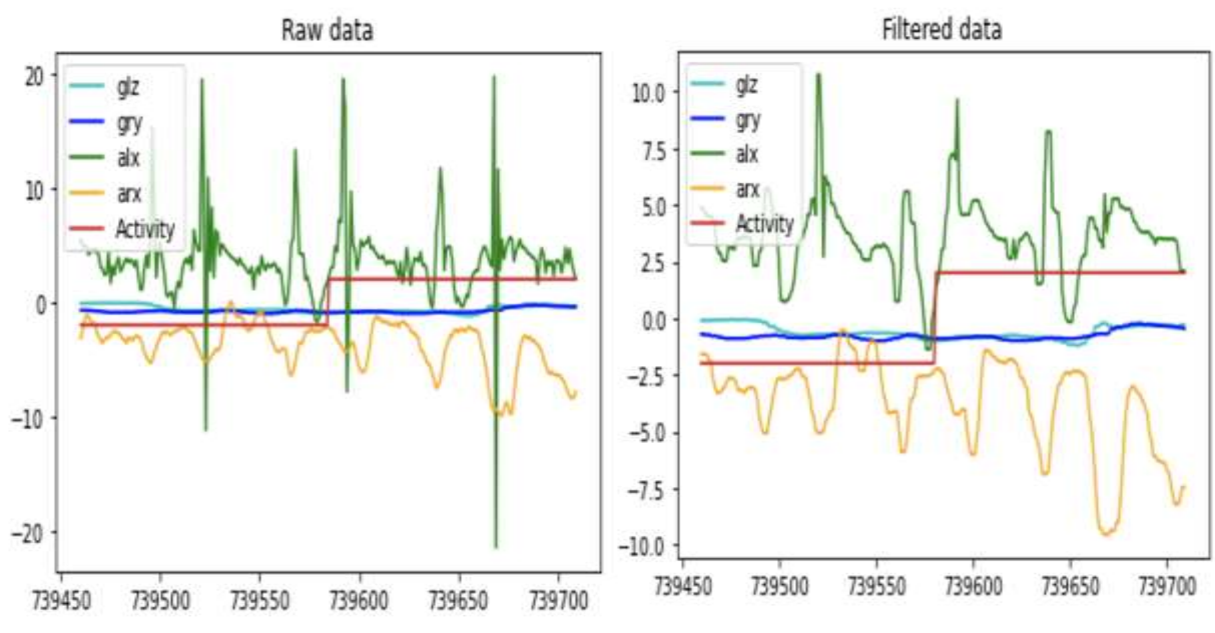

Figure 1: Display of Sample Raw Data and Median-Filtered Data.

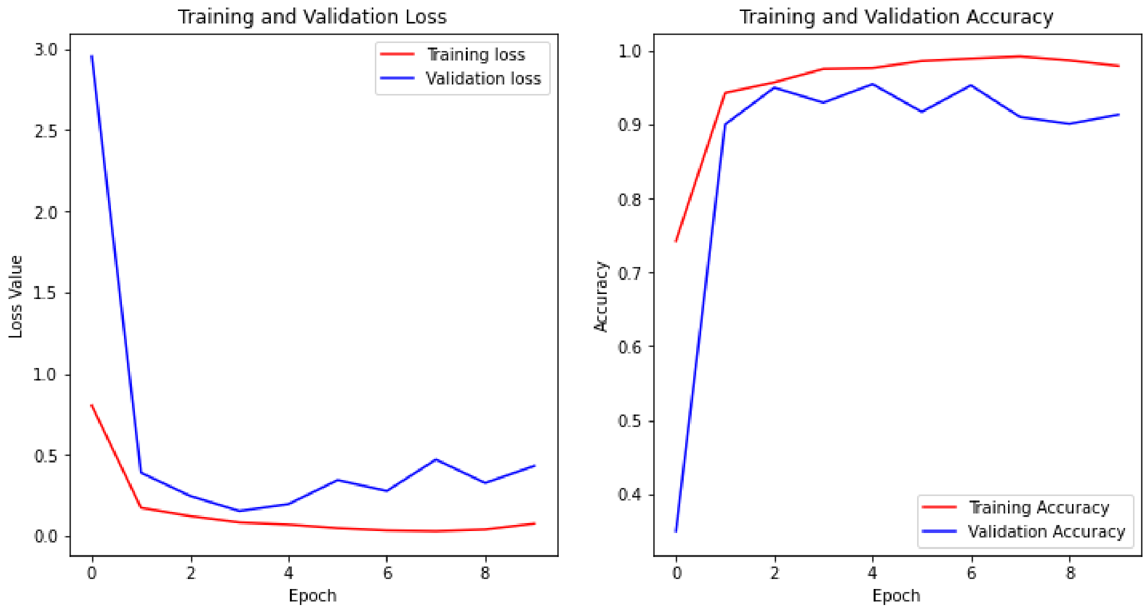

Figure 2: Display of Learning Curve

5. Results and Discussion

In this pivotal section, we present the outcomes of our experiments and engage in a comprehensive discussion of the findings. This section serves as the crucible where our research efforts culminate, providing insights into the performance, accuracy, and practical implications of our IoT-based human activity recognition system in smart homes for elderly care.

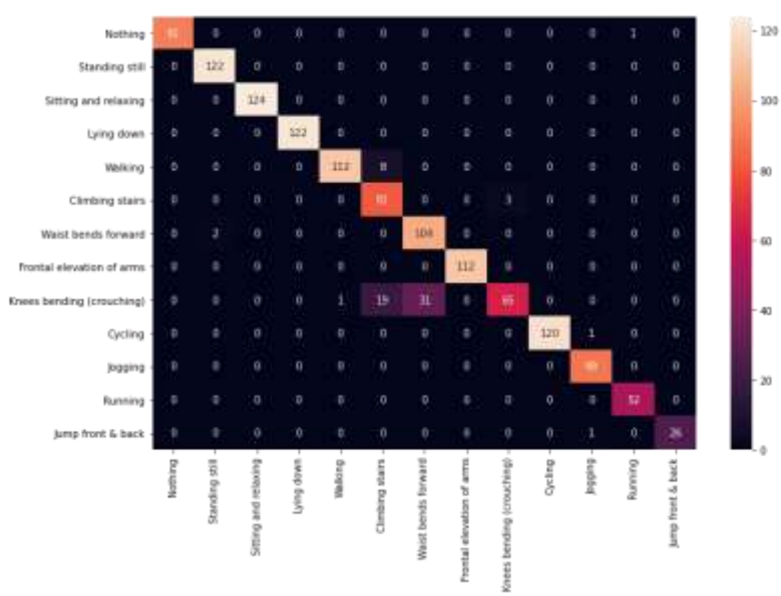

Figure 3: Confusion Matrix for Model Evaluation

In Figure 1, we present a visual representation of sample raw data and their corresponding median-filtered counterparts, offering a tangible glimpse into the preprocessing stage of our data pipeline. The juxtaposition of these two datasets allows for a clear understanding of the noise reduction achieved through the median filtering process. The raw data exemplify the inherent variability and noise commonly encountered in sensor measurements within the smart home environment. In contrast, the median-filtered data reveals the smoothing effect and noise reduction achieved by the filtering technique, highlighting its role in enhancing the quality and reliability of the input data for subsequent processing stages. This visual representation not only provides an intuitive sense of the data transformations but also underscores the significance of robust preprocessing in ensuring the accuracy and effectiveness of our IoT-based human activity recognition system.

In addition, Figure 2 presents the learning curve of our model, which provides invaluable insights into the training process and the model's performance over iterations. The learning curve showcases the evolution of key performance metrics, such as accuracy, loss, or other relevant evaluation criteria, as the model undergoes training on the provided datasets. The learning curve serves as a critical reference point for evaluating the model's behavior throughout the training process. It reveals trends in performance, including the rate of convergence, potential overfitting or underfitting, and the point of stabilization. By analyzing this curve, we gain a deeper understanding of how our model adapts to the data and the efficiency of the learning process. Moreover, Figure 3 presents the confusion matrix derived from the evaluation of our model's performance. The confusion matrix is a fundamental tool for assessing the classification capabilities of our IoT-based human activity recognition system. It provides a comprehensive breakdown of predicted and actual class labels, enabling a detailed analysis of the model's accuracy, precision, recall, and overall classification efficacy. Each cell of the confusion matrix corresponds to a specific class label, where the rows represent the true (actual) classes, and the columns represent the predicted classes. The values within the matrix quantify the instances of correct and incorrect classifications, encompassing true positives, true negatives, false positives, and false negatives.

Table 2 presents the results of our experimental comparisons with baseline models, providing a comprehensive view of the performance of our IoT-based human activity recognition system in relation to established methods. Fair comparisons are essential for assessing the effectiveness and superiority of our approach. We observe that our proposed model achieved an impressive accuracy rate of 95%. This remarkable accuracy underscores the effectiveness of our methodology in accurately recognizing human activities within smart homes for elderly care. It demonstrates the value of our approach, which combines federated distillation-based training, GRU-based activity recognition, and rigorous preprocessing techniques, to produce a highly accurate system.

Table 2: Experimental Results - Model Comparison

Model	Accuracy (%)	F1-Score
Our	95.0	0.94
Federated CNN	88.3	0.87
Federated LSTM	86.7	0.86
Federated SVM	79.4	0.76
Federated RF	82.1	0.81

6. Conclusions

This paper has presented a pioneering study that leverages the power of IoT technology to advance human activity recognition within smart homes, with a specific emphasis on enhancing elderly care. Through the fusion of federated distillation-based training, Gated Recurrent Unit (GRU) modeling, and rigorous data preprocessing, our proposed IoT-driven model has demonstrated remarkable achievements. With an impressive accuracy of 95% and an F1-score of 0.94, our system not only excels in the complex task of recognizing human activities but also showcases its potential for revolutionizing elderly care through seamless IoT integration. The implications of our research transcend technological boundaries, offering a promising avenue for the transformative impact of IoT in the realm of healthcare. By providing accurate and real-time insights into daily activities, our IoT-based system can empower caregivers, healthcare professionals, and families to offer personalized support and interventions, all while maintaining privacy and data security.

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