International Journal of Innovative Information Systems & Technology Research 14(3):340-352, July-Sept, 2026

© SEAHI PUBLICATIONS, 2026 www.seahipublications.org **ISSN: 2467-8562**

DOI:10.5281/zenodo.22806956

Context-Aware Activity Recognition Framework for Smart Home Network and Environment using Deep Learning

V. C. Amadi-Peter, O. E. Taylor, V. T. Emmah

Department of Computer Science, Faculty of Science, Rivers State University, Port Harcourt, Nigeria

ABSTRACT

Smart homes generate continuous streams of ambient sensor data that can reveal intimate details about residents' daily routines. However, existing Human Activity Recognition (HAR) systems often fail to leverage contextual information, struggle with overlapping activities in multi-resident settings, and may expose sensitive behavioral data without sufficient protection. To address these gaps, this study proposes a Context-Aware Activity Recognition Framework (CAARF) for smart home network and environment. CAARF integrates three key components. First, it introduces a hybrid CNN–LSTM model that fuses encoded temporal, spatial, and environmental contextual features to improve recognition under real-world sensor noise and variability. Second, it presents a Transformer-based multi-label architecture that uses multi-head self-attention and an auxiliary resident attribution head to detect concurrent and overlapping activities performed by multiple occupants at the same time. Third, it adds an Elliptic Curve Cryptography (ECC) privacy-preservation layer combining Elliptic Curve Diffie-Hellman (ECDH) for session key agreement, Advanced Encryption Standard in Galois/Counter Mode (AES-GCM) for efficient symmetric encryption, and Elliptic Curve Digital Signature Algorithm (ECDSA) for integrity and authenticity verification. The system design follows an object-oriented approach, and the implementation uses Python for model development and MySQL for device and activity data management. The framework is trained and evaluated on two publicly available benchmark datasets. The CNN–LSTM model is trained on the CASAS Aruba dataset, while the Transformer-based model is trained on the ARAS two-resident smart home dataset. Results show strong HAR performance as the CNN-LSTM model achieves 96.4% accuracy, 95.1% precision, 94.8% recall, and 94.9% F1-score. The Transformer model achieved 91.7% micro F1, 88.3% subset accuracy, and 0.082 Hamming Loss. The privacy module introduces low overhead, with 2.3 ms encryption latency, 2.1 ms decryption latency, and 18.4 KB memory overhead. The CAARF jointly improves contextual understanding, concurrent multi-resident activity recognition, and real-time privacy preservation within an end-to-end framework.

Keywords: Human Activity Recognition, Smart Home, Context-Awareness, CNN-LSTM, Transformer, Multi-Resident Recognition, Elliptic Curve Cryptography, Privacy-Preservation, Internet of Things.

INTRODUCTION

Smart homes can be classified as a living space that use sensors, smart devices and networked systems to monitor, automate and assist our everyday activities (Rock *et al.*, 2024). With the spread of inexpensive sensors (motion detectors, door contacts, smart plugs, temperature and light sensors), it is now practical to collect streams of data that reflect how people move and interact in their homes (Dwivedi *et al.*, 2025). When these data streams are analyzed using intelligent algorithms, the system can automatically recognize activities such as cooking, sleeping, watching TV, taking medication, or leaving the house. This capability, known as Human Activity Recognition (HAR), has become central to applications such as healthcare monitoring, elderly assistance, automated home control, safety supervision, and energy optimization (Kumar *et al.*, 2024). Technically, context-aware systems significantly improve user experience by utilizing contextual knowledge to make informed and intelligent decisions, enabling more intuitive and proactive interactions with technology. These systems can leverage additional information such as time, location, sensor data, and routine patterns to enhance their functionality and responsiveness (Kush, 2025). However, in smart homes, Human Activity Recognition (HAR) remains challenging because

sensor signals are sparse, noisy and strongly dependent on context. Two sequences of sensor events that look similar can mean different things depending on the time of day, the room where they happened, or the resident's usual routine. For example, opening a kitchen cabinet at 8:00 AM likely means preparing breakfast, but a similar event at 11:00 PM may be something else. That is why context awareness is crucial to make HAR accurate and useful. Despite these advances, smart homes face significant vulnerabilities and challenges. Due to the highly interconnectivity nature of smart homes, they are exposed to security threats such as device spoofing, unauthorized access, data interception, and inference attacks (Magara & Zhou, 2024). Attackers can exploit weak authentication mechanisms, unsecured wireless communication, or poorly protected sensor data to gain insights into residents' routines, occupancy patterns, and behaviors. Even seemingly harmless sensor data such as motion or smart plug activity can reveal sensitive personal information, raising serious privacy concerns (Vardakis *et al.*, 2024). In addition, real-world sensor data is often sparse, noisy, and context-dependent, which makes accurate recognition of human activities difficult. Homes with multiple residents introduce further complexity, as sensor signals from different people may overlap and interleave, making it difficult to correctly attribute activities to individuals (Abuhoureyah *et al.*, 2024). Nevertheless, to address these challenges, Machine Learning (ML) and Deep Learning (DL) techniques have been increasingly applied by research authors in context aware HAR. Techniques such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and Transformer-based models have shown significant improvements in activity recognition (Alomar *et al.*, 2025). LSTM-based and CNN-LSTM hybrid models are particularly effective at capturing long-term temporal dependencies and context from sequential sensor data. Transformer models with attention mechanisms excel at identifying overlapping or concurrent activities in multi-resident smart homes, allowing the system to handle real-life scenarios where multiple activities occur simultaneously (Javadi *et al.*, 2025).

Furthermore, while ML and DL approaches have shown significance in improving recognition accuracy, user and data privacy still remains a central concern. Smart home data can reveal intimate patterns of life, such as sleeping times, presence or absence, habits, and lifestyle preferences (Tian *et al.*, 2025). Therefore, sending raw sensor data to external servers or cloud platforms without adequate protection can expose residents to potential surveillance or misuse. Cryptographic techniques have played a critical role in enhancing privacy and security in a multi-tenant environment such as smart home. For example, Elliptic Curve Cryptography (ECC) provides strong encryption with relatively small key sizes, making it efficient for resource-constrained devices commonly used in smart homes (Davies *et al.*, 2024). By encrypting sensitive data during storage or transmission and combining ECC with symmetric encryption for bulk data, smart home systems can protect residents from unauthorized access while still enabling intelligent analytics and activity recognition (Yusoff *et al.*, 2024).

The goal of this study is to develop a deep learning framework for context-aware recognition in smart home networks and environments. To achieve this, we propose a Context-Aware Activity Recognition Framework that integrates deep learning for precise recognition with ECC-based encryption for privacy preservation. This dual approach effectively addresses the key challenges faced by modern smart home ecosystems.

Many traditional smart home systems lack true context awareness. Sensor data in isolation often fails to capture the full meaning of activities, which are highly dependent on contextual factors such as time, location, environmental conditions, and resident routines (Ali *et al.*, 2025). Further, recognizing overlapping and concurrent activities in multi-resident homes remains a difficult problem, as sensor activations from one resident can overlap with those of another (Anguita-Molina *et al.*, 2025); traditional single-label classification models struggle with such multi-resident scenarios, leading to misclassification and incorrect attribution of activities. Furthermore, privacy and data security limitations hinder smart home widespread adoption, as many existing solutions either fail to protect sensitive data adequately or rely on weak security measures, leaving residents vulnerable to surveillance, profiling, and cyber-attacks (Yaacoub *et al.*, 2025).

The aim of this study is to develop a Context-Aware Activity Recognition Framework for Smart Home Network and Environment using Deep Learning. The objectives of the study are outlined as follows: (i) design a context-aware model using hybrid Long-Short Term Memory (LSTM) and Convolutional Neural Network (CNN); (ii) design a multi-resident activity recognition model using Transformer-based attention architecture; (iii) integrate a robust privacy-preservation mechanism into the framework to protect sensitive data using Elliptic Curve Cryptographic (ECC); (iv) implement the system using the Python programming language and a MySQL database for proper device management; (v) test and evaluate the developed system using standard performance metrics; and (vi) compare the efficiency of the developed system with existing baseline models.

2. Related Works

Context-aware computing refers to the capability of a system to sense, interpret, and respond to contextual information such as location, time, environmental conditions, user preferences, and activity patterns (Magade & Sharma, 2024). It

extends beyond simple sensor readings by incorporating additional layers of situational understanding that allow systems to adapt their behavior intelligently and autonomously. Context awareness forms the foundational principle behind intelligent environments such as smart homes, where the meaning of sensor events cannot be interpreted correctly without considering the surrounding circumstances. Contextual information improves decision-making accuracy by giving meaning to otherwise ambiguous or incomplete sensor signals, enabling the system to react in a way that aligns with the user's needs and the environmental state (Violos *et al.*, 2025).

In smart home environments, context-awareness is particularly essential because sensor events are often sparse, noisy, and extremely dependent on the circumstances in which they occur. A single motion sensor trigger may represent very different activities depending on the time of day, the resident involved, or the room in which it occurred (Lu *et al.*, 2024). By embedding temporal, spatial, and behavioral context within the recognition process, these models can distinguish between activities that appear identical in raw data but differ in meaning when context is considered. CNNs extract high-level spatial features from structured data (Li *et al.*, 2025); when applied to smart home sensor matrices or event windows, CNNs capture local activation patterns that correspond to micro-level activity cues. LSTMs are a class of Recurrent Neural Networks designed to capture long-term temporal dependencies in sequential data (Mienye *et al.*, 2024), addressing the vanishing gradient problem through memory cells and gating mechanisms. Hybrid CNN-LSTM models combine CNN's spatial feature extraction with LSTM's temporal modeling; this integration is theoretically ideal for HAR because activities have both spatial correlations (sensor activation patterns across rooms) and temporal structure (sequences unfolding over time) (Akinola *et al.*, 2024). Transformer models are built on the self-attention mechanism and learn global dependencies in sequences without relying on recurrence (Hosseinzadeh & Sadeghzadeh, 2025); multi-head attention enables the model to focus on multiple segments of sensor data simultaneously, which is essential for multi-resident environments where activities overlap.

Multi-resident activity recognition is grounded in the theories of multi-label classification, concurrency modeling, and sensor disambiguation, which collectively address the complexity that arises when multiple occupants interact with the same smart home environment (Singh *et al.*, 2025). Unlike traditional single-resident HAR systems that assume only one person is active at a time, real homes often involve multiple individuals performing different activities sometimes simultaneously, sometimes in overlapping sequences, and often within shared physical spaces, which greatly increases the ambiguity and difficulty of interpreting sensor data.

Chen *et al.* (2024) proposed the AttCLHAR framework designed to address the challenge of limited annotated sensor data in smart home HAR. The framework was built on the SimCLR contrastive learning paradigm, extended with a self-attention mechanism and a Sharpness-Aware Minimization (SAM) optimizer to improve model generalization. Their architecture consisted of two stages, namely a pre-training stage and a fine-tuning stage, both sharing a common encoder module comprising two 1D-CNN layers with ReLU activation, one LSTM layer for temporal dependency modeling, and a self-attention layer for selective time-step weighting. They trained and evaluated their framework on the publicly available CASAS Aruba and Milan smart home datasets, demonstrating competitive performance in single-resident activity classification under semi-supervised and transfer learning conditions. However, the AttCLHAR framework exhibits several notable limitations. The system provides no explicit context-awareness, as sensor events are processed as raw binary sequences without incorporating temporal, spatial, or environmental contextual features. It is designed exclusively for single-resident environments and employs a single-label classification head that cannot recognize concurrent or overlapping activities performed by multiple occupants. Furthermore, the framework integrates no data security or privacy-preservation mechanism, leaving sensitive behavioral data entirely exposed to unauthorized access and inference attacks.

Kang *et al.* (2024) proposed a novel and robust HAR algorithm that combined a Transformer architecture with Random Forest (RF) techniques. The proposed algorithm is designed to extract and integrate multimodal features across the time domain, frequency domain, and various statistical metrics, constructing both one-dimensional and two-dimensional feature sets through feature transformation. The Transformer component utilized self-attention mechanisms to capture long-range dependencies and extract global contextual information, while the RF component employed random feature selection and sampling to increase model diversity. Their experimental results demonstrated that the Transformer-RF model outperformed state-of-the-art algorithms, achieving an impressive accuracy of up to 94.17% across both one-dimensional and two-dimensional feature sets.

Chen *et al.* (2022) proposed a novel deep learning method called TRANS-BiGRU, which combined a Transformer-based architecture and a bidirectional Gated Recurrent Unit (BiGRU) to efficiently learn and recognize various activities performed by multiple residents. To evaluate the effectiveness of the model, they compared it with state-of-the-art methods, including Ensemble2LSTM (Ens2-LSTM), bidirectional GRUs (Bi-GRU), and traditional machine learning models such as support vector machines (SVM). The experimental findings, derived from the CASAS and ARAS public datasets, demonstrated that TRANS-BiGRU significantly outperforms existing models in the complex activity recognition task involving multiple residents.

The reviewed literature presented on context-aware HAR, it is an obvious fact that many studies have applied ML and DL to improve context-awareness in smart homes. However, while these studies demonstrated the effectiveness of integrating context, they largely assume single-resident environments and struggle under overlapping activity conditions. Most of these studies fail to generalize to multi-resident scenarios, where overlapping activities degrade performance significantly. Researchers such as Shinde *et al.* (2025) attempted to separate user-specific sensor streams using probabilistic models, but these approaches were computationally intensive and fragile in real-world applications.

Technically, several studies have highlighted privacy as a pressing concern that is leading to a major barrier to smart home adoption. A single data breach can enable adversaries to gain access to sensitive information such as occupancy patterns and personal routines (Aswathy & Tyagi, 2022). Researchers such as Werner *et al.* (2019) identified inference attacks as a major threat in the smart home ecosystem.

Poh *et al.* (2019) proposed PrivHome, a privacy-preserving scheme for smart home systems that facilitates authentication, secure data storage, and queries. This scheme ensures data confidentiality and authentication, preventing unauthorized access and modifications to data exchanged among devices, service providers, gateways, and users. Notably, it introduces privacy-preserving queries, allowing users to query data without revealing its content to third parties, a feature not previously addressed in smart homes.

Yusoff *et al.* (2024) presented a robust and secure lightweight communication proxy aimed at enhancing the scalability and security of MQTT-based IoT networks. Building on a mutual authentication protocol tailored for resource-constrained environments, the solution incorporated ECC to significantly bolster device authentication, data confidentiality, and energy efficiency, achieving an 87.68% increase in data confidentiality and up to 77.04% energy savings during publish/subscribe communications in smart homes.

Davies *et al.* (2024) investigated the performance, security, and privacy implications of using ECC to secure data transmission at the edge of IoT networks and devices. Their experimental results confirmed the efficiency of ECC, achieving an average throughput of 5 Mbps, which supports real-time data transmission, with average encryption and decryption response times of 0.7 and 0.6 milliseconds respectively.

Nevertheless, given the review presented on privacy and security studies in the smart home ecosystem, it is clear that several studies have highlighted that privacy and security concerns are major factors or barriers to smart home adoption, often because data breaches allow adversaries to infer user and device sensitive information. However, while cryptographic solutions have been applied to IoT devices, only a few studies have implemented ECC due to its mathematical complexity. Existing works demonstrate that ECC provides efficient security for resource-constrained devices, but integration with HAR systems remains limited.

Although activity recognition in smart homes has attracted extensive research attention, several important knowledge gaps still limit the effectiveness and real-world applicability of existing systems. These gaps are most evident in the areas of context modeling, multi-resident activity handling, and privacy preservation.

Many existing HAR models lack true context-awareness. Studies such as Lu *et al.* (2024) and Nezhadettehad *et al.* (2025) show that most activity recognition techniques rely heavily on raw sensor events without fully integrating temporal routines, spatial information, or environmental context. As a result, current systems struggle to interpret noisy, sparse, or ambiguous sensor data, leading to reduced accuracy in realistic home environments.

There is a significant gap in recognizing overlapping and concurrent activities in multi-resident homes. Most HAR systems, including the AttCLHAR framework by Chen *et al.* (2024), are designed for single-occupant scenarios and assume that only one activity occurs at a time. However, Singh *et al.* (2025) and Alizadegan *et al.* (2023) highlighted that real homes involve multiple individuals performing interleaved or simultaneous activities, which current models fail to separate or attribute correctly. Only a limited number of studies explore multi-label or attention-based architectures, and even fewer apply Transformer models that can selectively attend to disjoint sensor patterns.

Privacy-preservation in smart home HAR remains underdeveloped. Several authors, including Alshamsi *et al.* (2024) and Karim *et al.* (2024), stressed that many smart home systems transmit or store plaintext sensor data, exposing residents to behavioral inference attacks and unauthorized data access. Although lightweight cryptographic techniques have been proposed for IoT systems, studies by Yusoff-Zainatul *et al.* (2024) note that ECC, despite its high security and low computational cost, is rarely integrated into activity recognition pipelines. This creates a gap where HAR systems are accurate yet insecure, leaving sensitive behavioral data vulnerable.

Finally, the literature lacks integrated frameworks that simultaneously address context-awareness, multi-resident concurrency, and privacy preservation. Most prior studies focus on these issues individually, resulting in fragmented solutions that are not suitable for full-scale deployment in real smart home environments. This research addresses these gaps by developing a context-aware, multi-resident–capable, and ECC-secured activity recognition framework, thereby providing a more practical, accurate, and privacy-preserving solution for smart home environments.

METHODOLOGY

3.1 Research Design

This study adopts the Design Science Research (DSR) methodology to guide the development and evaluation of the proposed CAARF. DSR is a problem-solving paradigm widely used in information systems and computing research that focuses on the creation, evaluation, and contribution of artifacts intended to address specific real-world problems. For the system design, an Object-Oriented Design (OOD) methodology is adopted as the central design approach, organizing the framework around objects that encapsulate both data and behavior.

3.2 System Analysis and Architecture

The baseline system analysed in this study was due to its application to ambient sensor-based human activity recognition (HAR) in smart-home environments. The framework combines SimCLR-based self-supervised learning with a 1D-CNN, LSTM and self-attention architecture, using the Sharpness-Aware Minimization (SAM) optimizer to improve generalization. It was evaluated on CASAS smart-home datasets using pre-training and fine-tuning strategies. However, AttCLHAR does not explicitly incorporate contextual information such as time, location, or environmental conditions, and its single-label formulation does not address concurrent activities in multi-resident environments. In addition, the framework does not include an integrated security or privacy-preservation mechanism. These limitations provide the basis for the proposed CAARF, which incorporates context-aware recognition, multi-resident activity recognition, and security mechanisms within a unified smart-home framework.

The proposed model is designed as a modular improvement over the AttCLHAR baseline, comprising three complementary components: a context-aware recognition module based on a hybrid CNN-LSTM architecture, a Transformer-based multi-resident activity recognition module and an ECC-based privacy-preservation mechanism.

The framework operates as a sequential end-to-end pipeline that begins with raw sensor data acquisition and concludes with secure storage of recognized activity labels, structured into four operational components: the Data Acquisition and Preprocessing module, the Context-Aware Recognition module, the Multi-Resident Activity Recognition module, and the Privacy-Preservation mechanism module, as shown in Fig. 1.

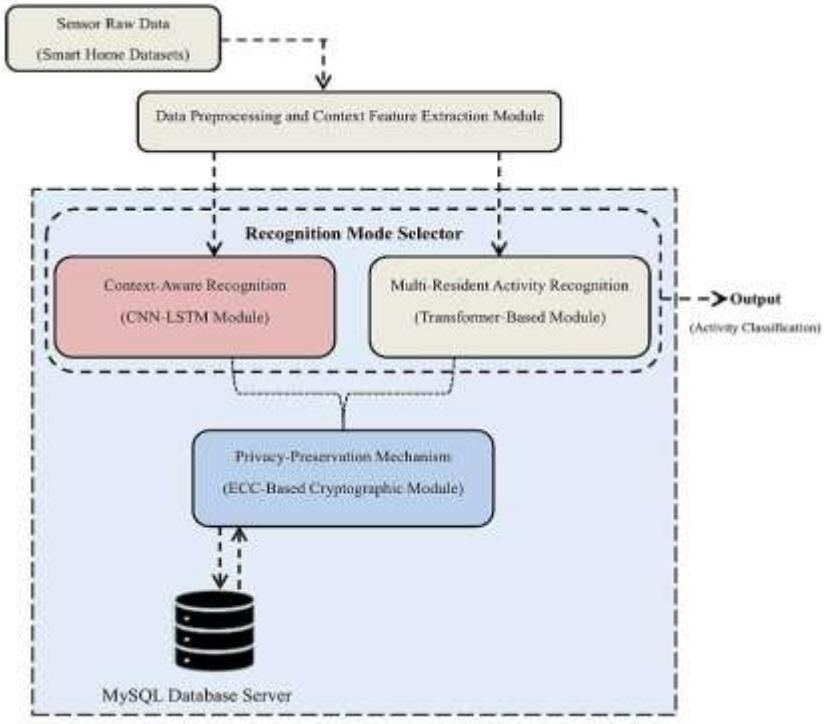


Fig. 1. Component interaction and architectural overview of the proposed CAARF pipeline, from raw sensor acquisition through context-aware and multi-resident recognition to ECC-based privacy preservation and secure storage.

These contextual features are combined with the sensor activation sequence and processed using a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architecture, illustrated in Fig. 2. Collectively, these components extend conventional sensor-based HAR by incorporating contextual information, concurrent multi-resident recognition, and integrated privacy protection within a unified smart-home framework.

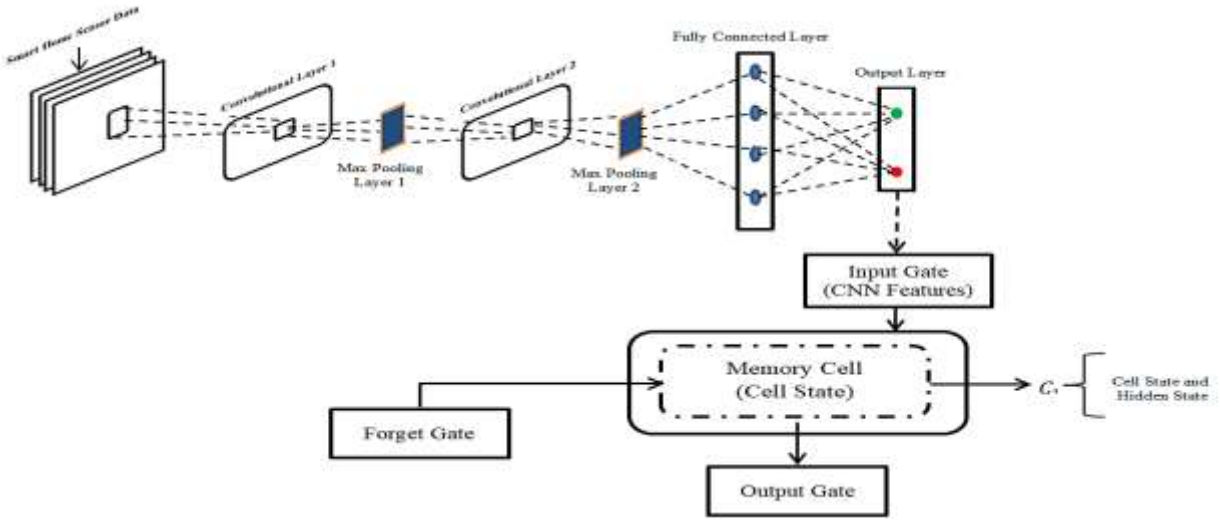


Fig. 2. Architecture of the hybrid CNN-LSTM Context-Aware Recognition Module, showing convolutional feature extraction followed by LSTM temporal gating.

The Multi-Resident Activity Recognition Module represents the second deep learning component of the proposed framework, addressing the more complex challenge of recognizing simultaneous activities performed by multiple residents within the same smart home environment. This module employs a Transformer-based deep learning architecture, illustrated in Fig. 3, which relies on self-attention mechanisms rather than recurrence, allowing the model to examine relationships between all time steps within a sensor window simultaneously. This module was trained using the ARAS two-resident smart home dataset, which contains sensor data from homes occupied by two individuals performing concurrent daily activities.

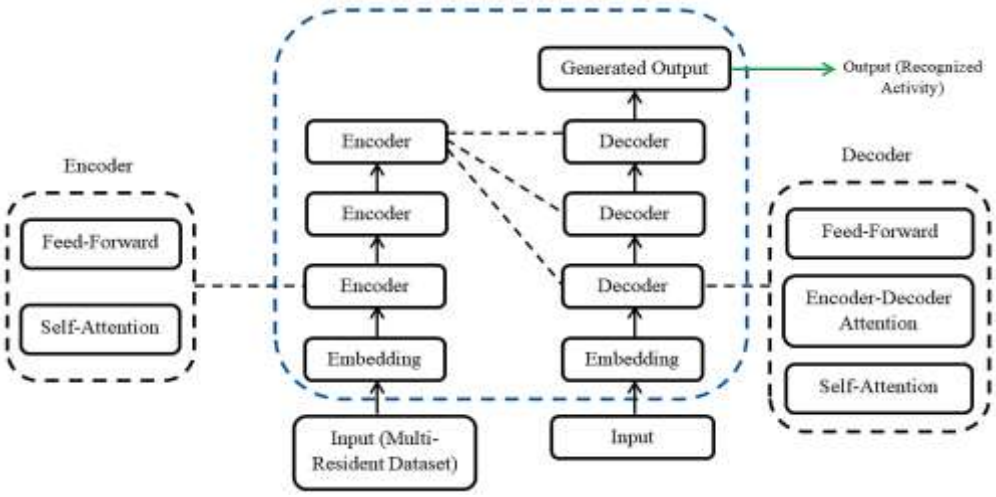


Fig. 3. Transformer-based Multi-Resident Activity Recognition Module, with encoder-decoder self-attention producing the recognized concurrent activity output.

3.3. Implementation, Datasets and Preprocessing

The proposed framework was implemented using Python 3.0 as the primary programming language because of Python's extensive ecosystem of scientific and machine learning libraries, its readability, and its broad adoption in the deep learning research community. TensorFlow/Keras was used for training the deep learning models, and NumPy, Pandas, and Scikit-learn for supporting data preprocessing, feature scaling and evaluation. The privacy-preservation component was implemented using the Python Cryptography package (PyCA), which provided the cryptographic primitives required for ECDH key exchange, ECDSA, and AES-GCMA Flask-based web application was incorporated to provide an interactive interface for accessing the system functions, while MySQL was employed as the database

management system for storing model-related data and system records. For the CNN-LSTM model, the dataset was divided into 70% training, 15% validation, and 15% testing data. The model was trained for 50 epochs using the Adam optimizer with a learning rate of 0.001 and categorical cross-entropy as the loss function. Module performance was evaluated using accuracy, precision, recall, and F1-score for the single-label CNN-LSTM module, and micro-averaged F1-score, subset accuracy, and Hamming loss for the multi-label Transformer module. The privacy-preservation module was evaluated using encryption latency, decryption latency, and memory overhead to assess the efficiency and suitability of the implemented cryptographic mechanism for real-time smart home environments.

3.4. Evaluation Metrics

The results obtained from the context demonstrated that the developed cryptographic framework

Component	Evaluation metrics
Context-Aware CNN-LSTM (single resident)	Accuracy, Precision, Recall, F1-score and prediction confidence
Transformer-based Multi-Resident (multi-label)	Accuracy, Precision, Recall, F1-score, Hamming Loss, and prediction confidence
ECC Privacy-Preservation Mechanism	Encryption time, decryption time, and memory overhead

4.1 RESULTS AND DISCUSSION

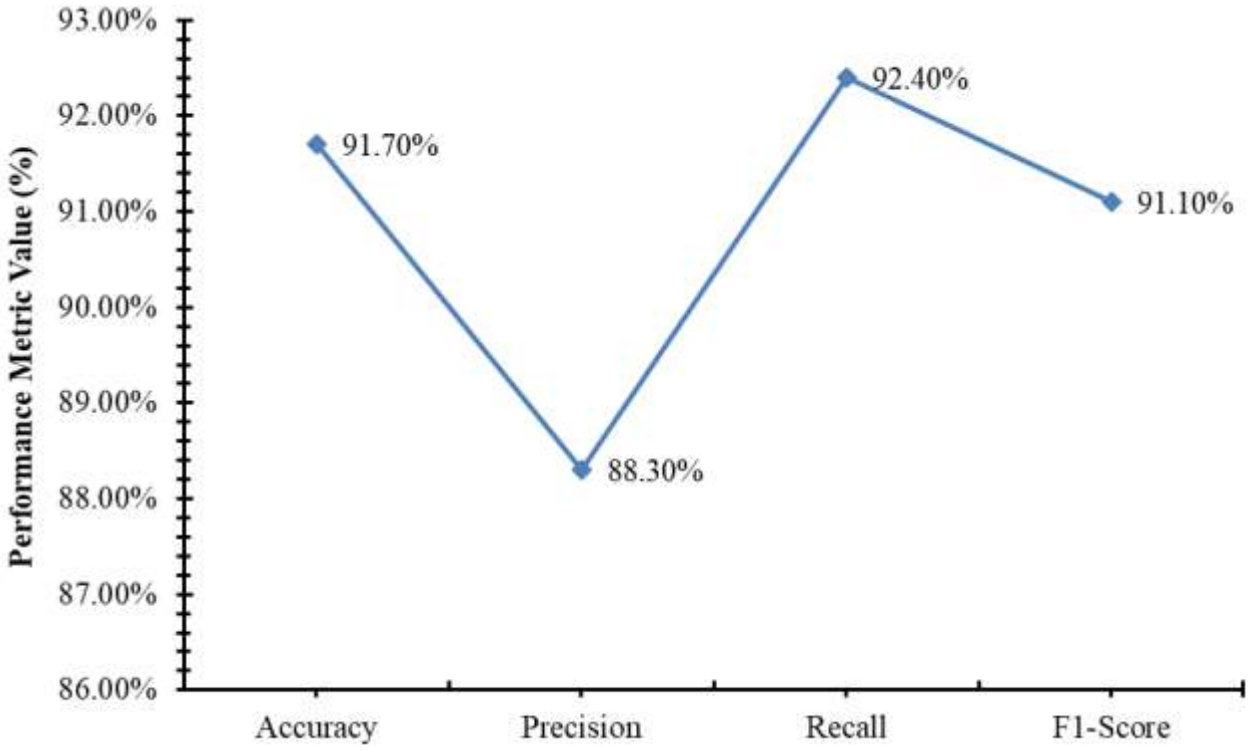
Timestamp	Room Context	Sensor Context Triggered	Predicted Activity	Confidence
5/10/2026 10:33	Kitchen	Kitchen PIR + Kettle Plug	Cooking	94.20%
5/10/2026 10:50	Front Door	Front Door + No Interior PIR	Leaving Home	96.10%
5/11/2026 20:00	Living Room	LivingRoom PIR + Smart TV Plug	Watching TV	91.40%
5/13/2026 8:22	Dining Room	Kitchen PIR + DiningRoom PIR	Eating	83.30%
5/13/2026 22:12	Bedroom	Bedroom PIR	Sleeping	97.80%
5/15/2026 9:00	Bathroom	Bathroom PIR + Medication Cabinet	Taking Medication	93.70%
5/16/2026 7:35	Bathroom	Bathroom PIR + Shower	Personal Hygiene	90.04%
5/17/2026 12:00	Living Room	LivingRoom PIR + Smart TV Plug	Watching TV	93.90%
5/17/2026 9:15	Front Door	Front Door + No Interior PIR	Leaving Home	96.50%
5/17/2026 20:02	Dining Room	Kitchen PIR + DiningRoom PIR	Eating	97.10%

The results presented in Table 4.1 demonstrate the effectiveness of the developed Context-Aware Recognition Module in accurately recognizing single-resident daily activities using contextual sensor information obtained from PIR motion sensors, smart plugs, and environmental triggers. The confidence values obtained from the predictions ranged from 83.3% to 97.8%, indicating a high level of recognition accuracy across most activities.

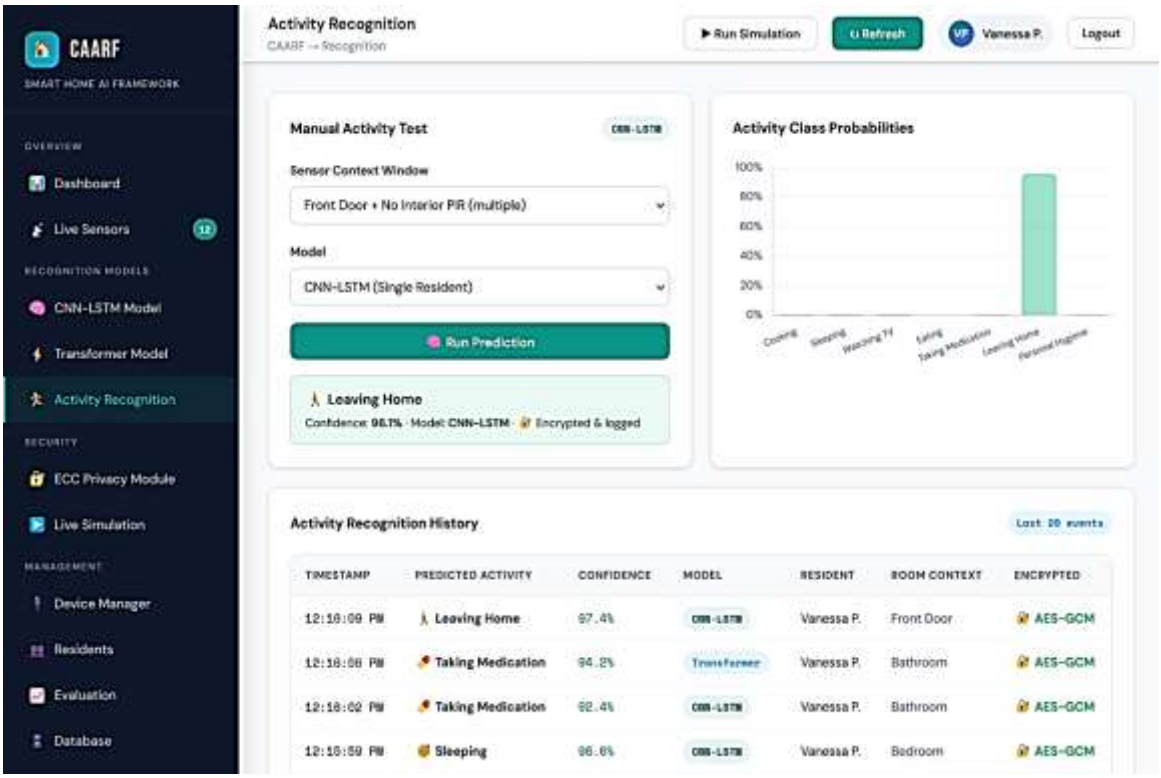
Table 4.2 Result of the Transformer-Based Module for Multi-Resident

Timestamp	Resident A Activity	Resident B Activity	Sensor Context Triggered	Predicted Activities
5/18/2026 7:12	Cooking	Watching TV	Kitchen PIR + LivingRoom PIR + Smart TV Plug	Cooking + Watching TV
5/18/2026 9:45	Leaving Home	Sleeping	Front Door + Bedroom PIR	Leaving Home + Sleeping
5/19/2026 13:20	Eating	Cooking	DiningRoom PIR + Kitchen PIR + Kettle Plug	Eating + Cooking
5/20/2026 18:10	Watching TV	Personal Hygiene	LivingRoom PIR + Bathroom PIR + Shower	Watching TV + Personal Hygiene
5/25/2026 22:40	Sleeping	Watching TV	Bedroom PIR + LivingRoom PIR + Smart TV Plug	Sleeping + Watching TV

The results presented in Table 4.2 indicate that the developed Transformer-based model achieved high recognition in handling concurrent and overlapping activities within multi-resident smart home environments. The confidence scores ranged from 91.9% to 97.2%, demonstrating the robustness and reliability of the model in distinguishing multiple activities occurring simultaneously.



A line graph representation of the performance metric (Accuracy, Precision, Recall, and F1-Score) values achieved in multi-label classification by the transformer-based module is captured in Figure 4.4.



For visualization purpose, Figures 4.1 capture the screenshot interface of the hybrid CNN-LSTM context-aware activity recognition module.

4.1.2 Comparative Analysis with the Existing System

A comparative analysis was conducted between the developed CAARF and existing HAR systems discussed in the literature, using key evaluation criteria including recognition accuracy, F1-score, multi-resident support capability, context-awareness, privacy-preservation integration, and dataset applicability.

Table 4.3. Comparative Analysis with Existing Systems

Model	Accuracy	F1-Score	Multi-Resident	Context-Aware	Privacy/ECC	Dataset
CAARF CNN-LSTM (Proposed)	96.4%	94.9%	Single Resident	Full	ECC P-256	CASAS Aruba
CAARF Transformer-based (Proposed)	88.3%	91.7%	Multi-Resident	Full	ECC P-256	ARAS
AttCLHAR (Chen *et al.*, 2024)	93.1%	91.4%	Single Only	None	No Security	CASAS
TRANS-BiGRU (Chen *et al.*, 2022)	91.8%	90.2%	Partial	None	No Security	CASAS/ARAS
Transformer-RF (Kang *et al.*, 2024)	94.2%	92.1%	Single Only	Partial	No Security	UCI-HAR

The comparative results demonstrate that the developed CAARF CNN-LSTM model achieved the highest overall activity recognition accuracy of 96.4% and an F1-score of 94.9% among the evaluated single-resident activity recognition systems. The superior performance of the developed model was primarily attributed to the integration of contextual learning with hybrid spatial-temporal deep learning mechanisms. Unlike traditional activity recognition systems that rely primarily on raw sensor activations, the developed CNN-LSTM framework incorporated room context, PIR sensor relationships, appliance interaction

patterns, and temporal behavioral dependencies during activity recognition, significantly reducing contextual ambiguity and improving recognition consistency across different smart home conditions.

Table 4.5 Performance Evaluation of the Privacy-Preservation Module

Performance Metric	Computed Value
Encryption Latency	2.3 ms
Decryption Latency	2.1 ms
Memory Overhead	18.4 KB

Key model performance results:

CNN-LSTM: 96.4% accuracy, 95.1% precision, 94.8% recall, and 94.9% F1-score.
Transformer: 91.7% accuracy, 88.3% precision, 92.4% recall, 91.1% F1-score, and 0.082 Hamming Loss.
ECC security: 2.3 ms encryption time, 2.1 ms decryption time, and 18.4 KB memory overhead.

The computed values presented in Table 4.5 indicate that the developed privacy preservation module achieved low computational overhead during encryption and decryption operations. The ECC-based privacy-preservation mechanism was evaluated using encryption latency, decryption latency, memory overhead, and cryptographic key size. The implemented NIST P-256 ECC mechanism achieved an encryption latency of 2.3 ms, decryption latency of 2.1 ms, and memory overhead of 18.4 KB, with a 256-bit ECC key providing approximately 128-bit equivalent security. Both encryption and decryption latencies remained below the 5 ms target, demonstrating low computational overhead and suitability for resource-constrained smart-home IoT environments.

VI. CONCLUSION

This study developed a Context-Aware Activity Recognition Framework (CAARF) for smart-home environments to address limitations related to context awareness, concurrent multi-resident activity recognition, and privacy preservation. The framework integrates a context-aware hybrid CNN-LSTM model, a Transformer-based multi-label recognition model, and an ECC-based security mechanism. The CNN-LSTM model achieved 96.4% accuracy, 95.1% precision, 94.8% recall, and 94.9% F1-score on the CASAS Aruba dataset, demonstrating the benefit of incorporating temporal, spatial, and environmental contextual information. The Transformer-based module achieved a micro-F1 score of 91.7% and Hamming Loss of 0.082 on the ARAS dataset, demonstrating its capability to recognize concurrent activities in multi-resident environments. The ECC-based security mechanism achieved 2.3 ms encryption latency, 2.1 ms decryption latency, and 18.4 KB memory overhead, indicating low computational overhead. Overall, the results demonstrate that CAARF provides an integrated approach to context-aware, multi-resident, and privacy-preserving smart-home activity recognition.

Future research should extend the framework through federated learning to strengthen privacy while enabling collaborative model training across multiple homes. The Transformer-based module should also be evaluated with three or more residents and on larger, more diverse multi-resident datasets. Deployment on physical IoT edge devices, such as Raspberry Pi-class hardware, is recommended to validate real-world computational and cryptographic performance. Further improvements could investigate multimodal sensor fusion, including wearable and smart-meter data, to enhance contextual disambiguation. Finally, the ECC security mechanism should be evaluated alongside post-quantum cryptographic approaches to assess its long-term resilience against emerging security threats.

REFERENCES

F. Abuhoureyah, K. S. Sim, and Y. C. Wong, “Multi-user human activity recognition through adaptive location-independent WiFi signal characteristics,” *IEEE Access*, vol. 12, pp. 112008–112024, 2024.

D. Akinola, A. O. Oyedemi, and M. O. Ajinaja, “A deep learning-based hybrid CNN-LSTM model for human activity recognition,” *Int. J. Sci. Res. in Computer Science and Engineering*, vol. 12, no. 6, 2024.

Ali, T. Montanaro, I. Sergi, S. Carrisi, D. Galli, C. Distante, and L. Patrono, “An innovative IoT and edge intelligence framework for monitoring elderly people using anomaly detection on data from non-wearable sensors,” *Sensors*, vol. 25, no. 6, p. 1735, 2025.

K. Alomar, H. I. Aysel, and X. Cai, “CNNs, RNNs and Transformers in human action recognition: a survey and a hybrid model,” *Artificial Intelligence Review*, vol. 58, no. 12, pp. 1–44, 2025.

O. Alshamsi, K. Shaalan, and U. Butt, “Towards securing smart homes: a systematic literature review of malware detection techniques and recommended prevention approach,” *Information*, vol. 15, no. 10, p. 631, 2024.

M. Á. Anguita-Molina, P. J. Cardoso, J. M. Rodrigues, J. Medina-Quero, and A. Polo-Rodríguez, "Multi-occupancy activity recognition based on deep learning models fusing UWB localisation heatmaps and nearby-sensor interaction," *IEEE Internet of Things Journal*, vol. 12, no. 11, pp. 16037–16052, 2025.

H. Chen, C. Gouin-Vallerand, K. Bouchard, S. Gaboury, M. Couture, N. Bier, and S. Giroux, "Enhancing human activity recognition in smart homes with self-supervised learning and self-attention," *Sensors*, vol. 24, no. 3, p. 884, 2024.

D. Chen, S. Yongchareon, E. M.-K. Lai, J. Yu, Q. Z. Sheng, and Y. Li, "Transformer with bidirectional GRU for nonintrusive, sensor-based activity recognition in a multiresident environment," *IEEE Internet of Things Journal*, vol. 9, no. 23, pp. 23716–23727, 2022.

N. Davies, O. E. Taylor, V. I. E. Anireh, and E. O. Bennett, "Adaptive hybrid case-based neuro-fuzzy model for intrusion detection and prevention for smart home network," *International Journal of Computer Sciences and Engineering*, vol. 10, no. 5, pp. 01–10, 2024.

D. Dwivedi, S. Tiwari, A. Bhushan, A. K. Singh, and R. K. Yadav, "Analyzing the energy efficiency and sustainability implications of IoT tools in smart homes," *Int. J. Inf. Eng. Electron. Bus.*, vol. 17, no. 1, pp. 31–48, 2025.

S. Javadi, D. Riboni, L. Borzì, and S. Zolfaghari, "Graph-based methods for multimodal indoor activity recognition: a comprehensive survey," *IEEE Transactions on Computational Social Systems*, vol. 12, no. 5, pp. 3729–3746, 2025.

Y. Kang, Z. Wang, X. Sun, H. Wang, R. Lu, D. Zou, et al., "Sensor-integrated transformer-RF model for HAR," in *Proc. 2024 IEEE 30th Int. Conf. Parallel and Distributed Systems (ICPADS)*, 2024.

M. Karim, S. Khalid, A. Aleryani, J. Khan, I. Ullah, and Z. Ali, "Human action recognition systems: A review of the trends and state-of-the-art," *IEEE Access*, vol. 12, pp. 36372–36390, 2024.

P. Kumar, S. Chauhan, and L. K. Awasthi, "Human activity recognition (HAR) using deep learning: Review, methodologies, progress and future research directions," *Archives of Computational Methods in Engineering*, vol. 31, no. 1, pp. 179–219, 2024.

J. C. Kush, "Integrating sensor technologies with conversational AI: enhancing context-sensitive interaction through real-time data fusion," *Sensors*, vol. 25, no. 1, p. 249, 2025.

D. Mienye, T. G. Swart, and G. Obaido, "Recurrent neural networks: A comprehensive review of architectures, variants, and applications," *Information*, vol. 15, no. 9, p. 517, 2024.

G. S. Poh, P. Gope, and J. Ning, "PrivHome: Privacy-preserving authenticated communication in smart home environment," *IEEE Transactions on Dependable and Secure Computing*, vol. 18, no. 3, pp. 1095–1107, 2019.

L. Y. Rock, F. P. Tajudeen, and Y. W. Chung, "Usage and impact of the internet-of-things-based smart home technology: a quality-of-life perspective," *Universal Access in the Information Society*, vol. 23, no. 1, pp. 345–364, 2024.

R. Hosseinzadeh and M. Sadeghzadeh, "Attention mechanisms in Transformers: A general survey," *Journal of AI and Data Mining*, vol. 13, no. 3, pp. 359–368, 2025.

K. Magade and A. Sharma, "Significant role of IoT in Cyber-Physical Systems, Context Awareness, and Ambient Intelligence," in *The Next Generation Innovation in IoT and Cloud Computing with Applications*, CRC Press, 2024, pp. 16–34.

G. Shinde, A. Ravi, E. Dey, S. Sakib, M. Rampure, and N. Roy, "A survey on efficient vision-language models," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 15, no. 3, e70036, 2025.

D. Singh, E. Merdivan, J. Kropf, and A. Holzinger, "Class imbalance in multi-resident activity recognition: an evaluative study on explainability of deep learning approaches," *Universal Access in the Information Society*, vol. 24, no. 2, pp. 1173–1191, 2025.

H. Khan and A. S. Stillwell, "Patterns tell human stories: towards connecting residential water use to occupant behavior in a permanent supportive housing context," *Environmental Research: Infrastructure and Sustainability*, vol. 5, pp. 1–20, 2025.

Y. J. Tian, V. Duong, E. Buhr, N. A. Felber, D. R. Schwab, and T. Wangmo, "Monitored and cared for at home? Privacy concerns when using smart home health technologies to care for older persons," *AJOB Empirical Bioethics*, vol. 16, no. 2, pp. 61–76, 2025.

S. Aswathy and A. K. Tyagi, "Privacy breaches through cyber vulnerabilities: Critical issues, open challenges, and possible countermeasures for the future," in *Security and Privacy-Preserving Techniques in Wireless Robotics*, CRC Press, 2022, pp. 163–210.

G. Vardakis, G. Hatzivasilis, E. Koutsaki, and N. Papadakis, "Review of smart-home security using the internet of things," *Electronics*, vol. 13, no. 16, p. 3343, 2024.

J. Violos, G. Mamanis, I. Kompatsiaris, and S. Papadopoulos, "Cognition and context-aware decision-making systems for a sustainable planet: a survey on recent advancements, applications and open challenges," *Discover Sustainability*, vol. 6, no. 1, pp. 1–43, 2025.

J. Werner, J. Mason, M. Antonakakis, M. Polychronakis, and F. Monrose, "The severest of them all: Inference attacks against secure virtual enclaves," in Proc. 2019 ACM Asia Conference on Computer and Communications Security, 2019.

J. P. A. Yaacoub, H. N. Noura, O. Salman, and K. Chahine, "Toward secure smart grid systems: risks, threats, challenges, and future directions," Future Internet, vol. 17, no. 7, p. 318, 2025.

Z. Y. M. Yusoff, M. K. Ishak, L. A. Rahim, and M. S. M. Asaari, "Improving smart home security via MQTT: Maximizing data privacy and device authentication using elliptic curve cryptography," Computer Systems Science & Engineering, vol. 48, no. 6, 2024.

Y. M. Yusoff-Zainatul, M. K. Ishak, and L. A. Rahim, "Securing IoT edge device communication with efficient ECC middleware for resource-constrained systems," Bulletin of Electrical Engineering and Informatics, vol. 13, no. 6, pp. 4285–4293, 2024.

T. Magara and Y. Zhou, "Internet of things (IoT) of smart homes: privacy and security," Journal of Electrical and Computer Engineering, vol. 2024, no. 1, art. 7716956, 2024.