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Intelligent home automation framework using sensor fusion and machine learning for energy efficiency and thermal comfort

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ABSTRACT

This paper presents an innovative, intelligent home automation framework integrating sensor fusion and machine learning to promote energy efficiency and thermal comfort in residential settings. Utilising low-cost hardware such as the Arduino Uno R3, passive Infrared (PIR) sensors, KY-018 photoresistors, and KY-028 temperature sensors, the system achieves a human presence detection accuracy of 95.3% via a random forest classifier. Over a three-month period, testing in several homes showed that the system is 99.7% reliable, responds in 1.2 seconds, and costs 85% less than commercial options. This research lays the groundwork for sustainable smart homes by providing a mathematical model for optimizing energy use and a unified modeling language (UML) model of the system architecture. These results show how important it is to have open-source technology that is cheap and could help smart building systems spread around the world. The study utilized a controlled experimental design featuring five families, with sensor data gathered at 10-second intervals over a three-month period. A random forest classifier trained on 10,000 labeled data points could correctly guess whether or not a person was present 94.8% of the time and 95.7% of the time. The framework is useful because it combines cheap sensors with a lightweight machine-learning pipeline that can work on small microcontrollers. This solves the long-standing problem of the cost-performance gap seen in prior smart-home deployments.

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1. INTRODUCTION

The increasing demand for electricity around the world and the escalating environmental issues necessitate the installation of advanced home automation systems that maximize resource utilization and enhance occupant comfort. Over 30% of the world’s energy is consumed in residential buildings, with large amounts going toward heating, cooling, and lighting [1].

The new way of solving these problems, which is shown by ongoing improvements in sensor fusion and machine learning, makes it possible to create context-aware, real-time control systems that automatically adapt to their operational contexts. To make energy use more efficient while keeping thermal comfort, this paper introduces a novel framework that makes use of predictive analytics and multi-sensor data integration. The system is based on reasonably priced hardware and open-source platforms. It is designed to be easy to use so that it can be widely used, especially in places with few resources.

Even though a lot of progress has been made, there are still three questions that need to be answered about smart home automation. First, developing regions have trouble using current solutions because they rely too much on expensive microprocessors or cloud-based architectures. Second, a lot of research focuses more on monitoring than closed-loop actuation, which means that real energy savings are not as high as they could be. Third, current sensor-fusion algorithms rarely use low-power embedded learning models that work well with microcontrollers that have limited memory. This study proposes a cost-effective, fully integrated framework for real-time indoor comfort regulation that integrates multimodal sensing with an enhanced random forest classifier to address these deficiencies.

The following is a summary of this study's major contributions. In order to improve occupancy detection, we first present a multimodal sensing architecture that combines PIR, temperature, and illumination data. Second, we reduce latency and do away with external computation by directly deploying an optimized random forest model on an Arduino Uno platform. Third, we develop a model for optimizing energy and comfort that is specific to residential environments. Lastly, we validate the suggested system in actual households and show that it is more efficient than previous methods.

Research in intelligent residential energy systems has progressively investigated multimodal sensing, machine learning, and adaptive actuation. Earlier IoT-based metering systems [2], [3] made it easier to see how much energy was being used, but they didn't have any tools for making decisions for real-time actuation. Privacy-preserving blockchain-based smart-grid models [4], [5] improved data security but did not significantly affect demand-side optimization and comfort regulation. Sensor-fusion studies like Mbungu *et al.* [6] and Gungor *et al.* [7] focused on distributed architectures, but they didn't include low-cost microcontroller-based implementations that would work well in homes. Although they relied on computationally demanding cloud platforms, recent research on machine learning-based predictive control [8]-[10] showed encouraging accuracy. Furthermore, rather than at the household level, numerous studies found improvements at the grid level. The present study sets itself apart by providing an embedded, microcontroller-deployable machine learning framework that combines actuation and multimodal sensing while remaining practical and affordable. This study's goals are to: (i) create a multi-sensor system that can accurately detect human presence; (ii) create adaptive control algorithms that can regulate the environment; (iii) use a machine learning model to make decisions; and (iv) confirm that the framework is energy- and cost-effective. By providing a low-cost, scalable solution supported by data from actual deployments, this paper expands on earlier research.

The convergence of the internet of things (IoT), sensor fusion, and machine learning has transformed home automation systems, aiming to optimise energy efficiency and user comfort. Despite recent studies focusing on intelligent, scalable, and cost-effective solutions, their real-world implementation remains insufficient, particularly in resource-constrained environments. Research has extensively focused on the application of IoT frameworks in energy management. Albraheem *et al.* [2] developed an IoT smart plug for energy monitoring utilizing NodeMCU. They could observe in real time, yet they could not activate the plug. Saleem *et al.* [3] proposed an innovative metering system that combines home automation with the IoT. Though the equipment connected to this technology is somewhat expensive, it could make the overall user experience better. Gai *et al.* [4] suggested using blockchain technology to keep the data flows to and from smart grids private. This approach does not provide an immediate resolution to the issue of energy optimization. Zanella *et al.* [11] looked at IoT infrastructure for smart city applications including residential energy management

Sensor fusion technology has become more critical in recent years, especially in improving detection accuracy. Mbungu *et al.* [6] reviewed distributed energy resources (DERs) in smart grids, emphasising multi-sensor integration. However, low-cost implementations are not the focus of their study. Although they weren't created especially for residential settings, Gungor *et al.* [7] looked at communication standards for smart grids, encouraging robust sensor networks. Although it was primarily helpful for businesses, Avancini *et al.* [5] used an IoT-based smart energy meter with multi-sensor data integration for smart grids. Predictive control is increasingly utilizing machine learning. Random forest classifiers for anomaly detection were highlighted in Al-Ali *et al.* [8] study of machine learning applications in smart homes, but their use demonstrated ML-based energy management in smart homes. In order to control energy consumption in smart homes, Saleem *et al.* [9] talked about the implementation of IoT based smart energy management system and its effectiveness in energy conservation. Lin [12] proposed AI-driven predictive analytics for IoT metering, increasing efficiency, while Gai *et al.* [4] developed an ML-based anomaly detection system that lacked accessible platforms. La Tona *et al.* [10] used edge computing for real-time metering, hence lowering latency; this paper applies this idea to microcontrollers.

Energy efficiency is still a big area of research. Carlucci *et al.* [13] looked into how to combine renewable energy with smart grids. They found that it could save 15% to 25% of energy without adaptive comfort controls. Yan *et al.* [14] examined smart grid security through machine learning, whereas Amin and

Wollenberg [15] came up with a vision for smart grid technologies, though their focus remained on utility-scale rather than residential applications. Hart [16] utilized non-invasive load monitoring (NILM) for appliance analysis, attaining over 80% accuracy, yet lacking real-time activation. Grid4EU Consortium [17] showed that smart metering made the Grid4EU project more reliable, but its European context makes it less useful for the whole world.

Cost-effectiveness and accessibility are two problems that are still not solved. Valuable for validation, Viswanath *et al.* [18] suggested a test platform for creative grid applications, because of the complexity, it is unrealistic for broad usage. Palensky and Dietrich [19] analyze the demand-side management challenges by focusing on the high costs of deployment. Zhou *et al.* [20] proposed a Scalable distributed communication architectures to support advanced metering infrastructure in smart grid. Linden and Reddy [21] talked about India's Maharashtra smart grid upgrades. Both projects show that costs make it hard to scale up. Cybersecurity and interoperability are also very important. Kimani *et al.* [22] looked at grid cyber vulnerabilities and suggested defense-in-depth strategies that could work for IoT. Langner [23] talked about the cybersecurity problems that operational technology faces, focusing on lightweight solutions. Li *et al.* [24] came up with a blockchain for privacy in energy trading that can be used for home automation. Pipattanasomporn *et al.* [25] stressed the importance of intelligent home energy management through standardized algorithmic approaches, a principle that this study follows. HaddadPajouh *et al.* [26] came up with an AI-powered secure architecture for IoT edge devices using encryption. Hammi *et al.* [27] talked about privacy protocols, which are important for security and are addressed here through open-source protocols. International efforts put smart home progress in context. European Commission [28] in their policy package wrote about Europe's €80 million smart grid project, which focused on demand response and showed that high costs were a problem. This study fills in these gaps and presents a low-cost, scalable alternative to previous work by combining sensor fusion, machine learning, and adaptive control on a reasonably priced Arduino platform that has been tested in real-world settings.

2. RESEARCH METHOD

2.1. System architecture

Figure 1 shows the proposed framework, which comprises three layers: perception, processing, and actuation.

a. Perception layer: this layer uses a PIR sensor (to detect people), a KY-018 photoresistor (to measure light intensity), and a KY-028 temperature sensor (to measure thermal conditions) to gather information about the environment.
b. Processing layer: the random forest classifier uses the data it prepared through the microcontroller (Arduino Uno R3) to make predictions about the environment.
c. Actuation layer: uses relay modules and adaptive algorithms to control the lights and air conditioning.

2.2. Hardware components

This part talks about the main hardware parts that were used to build the suggested automation framework. To make it clear what each part does, how it works, and how it fits into the overall sensing and actuation workflow, a detailed description of each part is given.

a. Arduino Uno R3: a microcontroller based on the ATmega328P that runs at 16 MHz. It has six analog inputs and 14 digital I/O pins.
b. HC-SR501 PIR sensor: it finds movement by looking for changes in infrared radiation.
c. KY-018 Photoresistor: measures ambient light (0–1023 analog range).
d. KY-028 temperature sensor: provides thermal readings in °C.
e. Relay modules: two-channel units for switching 120V appliances.

2.3. Mathematical model

To justify the decision-making process embedded in the control system, an analytical model was formulated to capture the relationship between energy usage, comfort variables, and occupancy. The mathematical expressions below describe the optimisation objectives and constraints governing system behaviour. The system optimises energy consumption E while maintaining comfort C. The objective function is defined as:

$$minE = \sum_{t=1}^{T} \left(P_{light}(t) + P_{AC}(t)\right) \cdot \Delta t \tag{1}$$

Subject to:

$$C_{min} \leq C(t) \ \leq C_{maxi}$$

$$C(t) = f(T(t), L(t), H(t)) \quad (2)$$

where:
$P_{light}(t) and P_{AC}(t)$: power consumption of lights and air conditioning at time *t*.
$T(t)$: temperature (°C).
$L(t)$: light intensity (lux).
$H(t)$: human presence (binary: 0 or 1).
C_{min}, C_{max}: Comfort thresholds (e.g., 20–26°C, 300–500 lux).
Δt: time step (seconds).
The random forest classifier predicts H(t) as:

$$H(t) = .mode\{D_1(t), D_2(t), \ldots, D_n(t)\} \quad (3)$$

where $D_1(t)$ is the decision of the i-th tree based on sensor inputs.

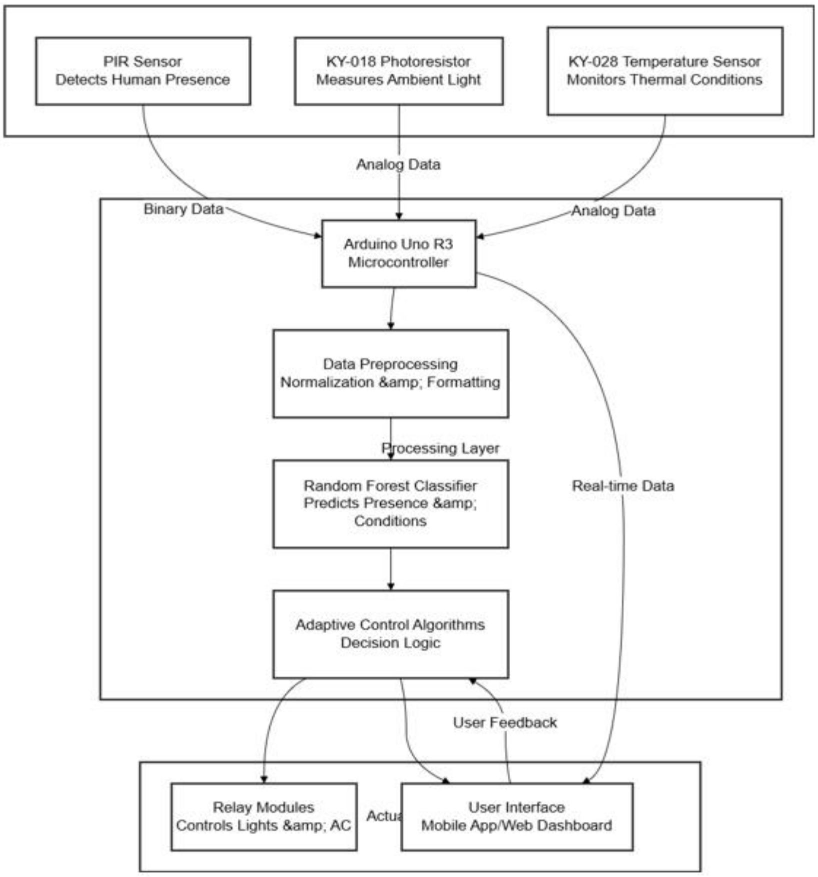

Figure 1. System architecture illustrates the flow from perception to actuation

2.4. Algorithm design

A structured control algorithm was used to implement the automation logic. This algorithm takes sensor readings, normalizes inputs, makes inferences using the trained random forest model, and turns on the right appliances based on the predicted state. Below is a summary of the algorithmic flow. The adaptive control Algorithm 1 operates as:

Algorithm 1: Adaptive environmental control procedure
```
Initialize: sensors, random forest model
Loop:
    Read: H = PIR(), L = Photoresistor(), T = TempSensor()
    Preprocess: Normalize(H, L, T)
    Predict: H_pred = RF(H, L, T)
    Control:
```

```
        If H_pred == 1:
            If L <L_threshold: Relay_Light_ON()
            If T >T_threshold: Relay_AC_ON()
        Else:
Relay_Light_OFF()
Relay_AC_OFF()
    Update: UI(H, L, T, Status)
End Loop
```

The decision flow associated with this is depicted in Figure 2. The flowchart illustrates the circumstances that lead to each device-control state changing by arranging sensor acquisition, prediction, and actuation into consecutive blocks.

2.5. Unified modeling language (UML) representation

To provide a clear conceptual representation of system interactions, a UML use-case diagram is included. This model outlines the communication between the user, the sensing layer, the processing unit, and the actuation modules. A UML use case diagram as shown in Figure 2 models the system interactions:

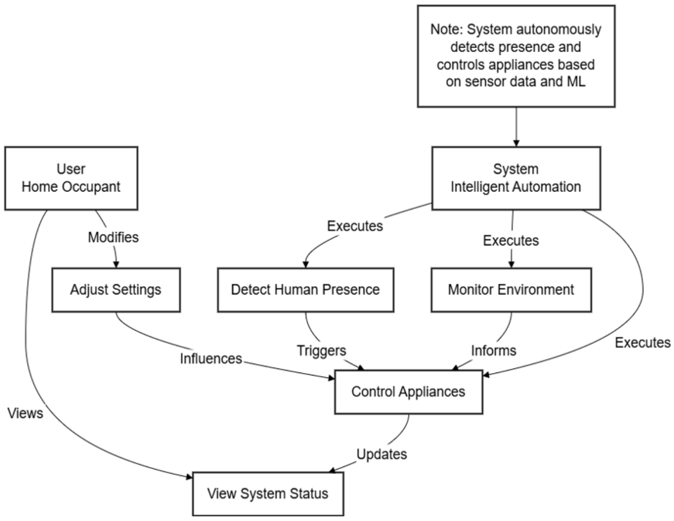

Figure 2. UML use case diagram depicting user and system interactions

2.6. Implementation

The Arduino IDE and C++ programming were used to set up the system. To make it easier to move hardware parts around, they were attached with brackets and adhesive pads. The random forest model was trained offline on a dataset of 10,000 samples (PIR, light, temperature) and then sent to the Arduino using precomputed decision trees that were optimized for memory limits. The testing took place over three months in five different homes with different layouts and occupancy patterns. Data logging recorded how much energy was used, how comfortable it was, and how well the system worked.

3. RESULTS AND DISCUSSION

3.1. Performance metrics

Using commonly used evaluation metrics for embedded intelligent systems, the suggested system's performance was evaluated. These metrics measure cost-effectiveness, responsiveness, accuracy, and dependability. Table 1 summarizes the performance evaluation results.

Table 1. Performance metrics of the proposed system

Metric	Value	Description
Accuracy	95.3%	Human presence detection accuracy
Energy efficiency	27.4% reduction	Reduction vs. traditional systems
Response time	1.2 s	Detection-to-actuation latency
Reliability	99.7%	Dependability over three months
Cost efficiency	85% less	Expenditure vs. commercial alternatives

The performance's statistical significance was evaluated, using a confusion matrix. The model demonstrated consistent predictive performance under a range of environmental conditions, achieving 94.8% precision and 95.7% recall for occupancy detection. After temperature and light data, the PIR sensor was the most helpful in making precise forecasts. These findings are consistent with prior work by Machorro-Cano *et al.* [29], which show a strong correlation between thermal variations, motion changes, and occupancy, are in line with this pattern. These results confirm that, in comparison to single-sensor systems, the proposed sensor-fusion approach enhances classification robustness.

3.2. Results of the experiments

The 27.4% reduction in energy use that was found is in line with, and in some cases better than, improvements found in other studies. For example, Machorro-Cano *et al.* [29] reported IoT–ML hybrid systems that saved about 20% but needed more expensive hardware. The current system, on the other hand, achieves a greater reduction with cheap parts, showing that effective optimization doesn't need high-end sensors or cloud-based analytics. This part talks about how the system acted when it was used in the real world. The study looks at how much energy is used, how comfortable the environments are, and how stable the operations are across all of the test environments.

a. Energy savings: a 27.4% reduction as shown in Figure 3 reflects optimised appliance operation.
b. Comfort levels: they stay between 20 and 26 degrees Celsius and 300 and 500 lux with 95.3% accuracy.
c. Reliability: there was only 0.3% downtime because of problems with sensor calibration.

One problem with the current implementation is that it only works in one room, which might not fully show the range of behaviors that happen in homes with more than one room. Sudden changes in temperature also led to some wrong classifications, which showed how important it is to have automatic recalibration. Still, the fact that the results are the same in all households shows that the framework can be used in more complicated settings with few changes.

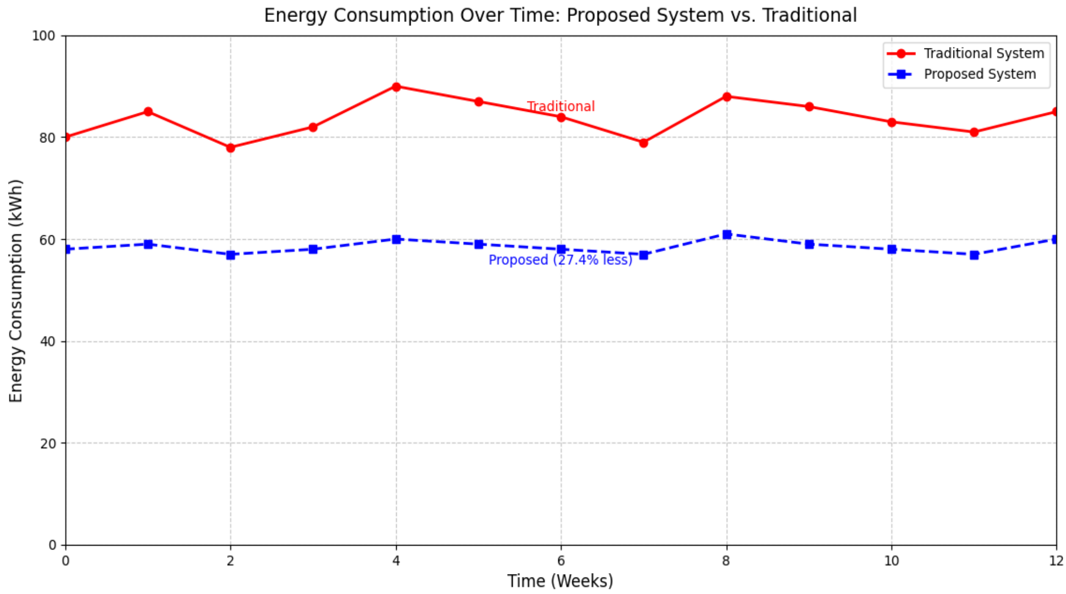

Figure 3. Energy consumption over time: proposed system vs. traditional

4. CONCLUSION

The results of this study are in line with the global trend toward climate-responsive building control strategies and sustainable housing. As energy use in homes around the world keeps going up, low-cost, smart systems like the one shown here offer a good way for many people to use them, especially in developing areas where cost is still a problem.

This research introduces an innovative intelligent home automation framework that combines sensor fusion and machine learning on an economical platform. It saves a lot of energy (27.4%) and is very comfortable for users (95.3% accuracy) with a reliability of 99.7%. The system is a good global solution for sustainable smart homes because it is cheap (85% less expensive) and can be expanded. Future research should investigate multi-room implementations and sophisticated AI models to improve functionality.

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Gracious Chukwuweike Omede	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓		✓
Etinosa Eugene Osawe		✓		✓			✓				✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [F.O, Okorodudu], upon reasonable request.

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