IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Ai-Driven Smart Home System For Dynamic Appliance Control Using Environmental And Occupancy Data

[1] Ch. Divya Tejaswini, [2]P. Santhi Raju, [3]J. Chaitanya Adi Shekhar, [4]J. Subhash, [5]V. Simhadri

[1]Student(22551A0469), [2]Student(22551A04A2), [3]Student(22551A0483), [4]Student(22551A0482),[5]Asst Prof

ELECTRONICS AND COMMUNICATION ENGINEERING,

GODAVARI INSTITUTE OF ENGINEERING AND TECHNOLOGY(AUTONOMOUS), RAJAHMAHENDRAVARAM

Abstract: Through this project, we aim to develop a Raspberry Pi-based smart home automation system that intelligently controls appliances by analyzing environmental conditions, occupancy status, and time of day using machine learning techniques. The system monitors indoor climate and evaluates ambient lighting conditions using environmental and light intensity data. For occupancy detection, the system replaces traditional IR sensors with a camera-based approach using Convolutional Neural Networks implemented via OpenCV, enabling more accurate and real-time detection of human presence within the monitored space. Additionally, time-based features including hour of the day and day/night classification are incorporated to enhance decision-making accuracy. A machine learning model is trained on historical data encompassing temperature, humidity, occupancy status and temporal features to predict optimal control actions for household appliances such as lights, fans, and air conditioners. The Raspberry Pi serves as the central controller, interfacing with sensors and the camera, and executing automation decisions in real time

Keywords - Smart home automation, IoT, AI, ML, Raspberry Pi, CNN, Occupancy detection, environmental monitoring, OpenCV, computer vision, sensor fusion, dynamic appliance control, energy efficiency, predictive automation, real-time decision making, temperature and humidity sensors, light intensity detection, home appliance control, time-based feature analysis, and adaptive control system.

I. Introduction

Smart homes represent a modern evolution of residential environments where interconnected devices, sensors and appliances communicate to improve comfort, security and energy efficiency. With advancements in IoT, AI and wireless technologies, home automation has shifted from manual control to intelligent, self-adapting systems capable of analyzing usage patterns and responding automatically. Conventional systems operate using fixed schedules or user commands, which limits adaptability and often leads to unnecessary power consumption.

AI-driven automation addresses this limitation by enabling context-aware control using real-time data such as temperature, humidity, light intensity and occupancy. Automated decision-making allows appliances like lights and fans to operate only when needed, reducing wastage and improving convenience. Increasing global energy demand and the need for sustainable living further highlight the importance of intelligent household control mechanisms.

This project proposes an AI-based smart home system that monitors environmental conditions and detects occupancy to dynamically control appliances. By integrating machine learning with sensor-generated data, the system aims to provide efficient power management, enhance comfort and create a responsive home environment. The developed model focuses on predictive automation rather than rule-based switching, making it more adaptive, scalable and suited for real-world deployment.

II. LITERATURE SURVEY:

Sugannivas V. & Shanthi H. J. (2025) proposed a dual-mode home automation system implemented using Arduino and Proteus simulation. The model integrates HC-05 Bluetooth communication to operate appliances locally without internet dependency. Their work demonstrates reliable device switching and easy microcontroller-based implementation, making it suitable for low-cost residential automation. However, the system functions purely on user commands and lacks smart decision-making, energy optimization, and real-time environmental adaptability.

Yadlapalli S. et al. (2025) introduced a voice-based IoT home automation system that connects appliances to cloud-supported assistants such as Alexa and Google Assistant. The framework enables hands-free control through speech commands, improving accessibility for elderly and physically challenged users. The work highlights seamless device integration with smartphones and voice interfaces, although execution depends heavily on network availability and does not include predictive automation or autonomous switching based on occupancy.

Karthikeyan P. et al. (2025) developed an intelligent home automation system incorporating IoT-based appliance control along with embedded home security. Sensor-generated data was used for monitoring environmental conditions and detecting intrusion events. The model provides improved safety through alert-based response mechanisms while managing basic automation functions. Despite its effectiveness, the system mainly relies on rule-based triggers and does not use AI for adaptive behaviour or energy-efficient decision processes.

Gurumurthy P. et al. (2025) proposed an IoT-driven automation system aimed at simplifying household appliance management. Their approach prioritised cost-effectiveness and basic network-controlled switching using microcontrollers. The system demonstrated functional reliability and ease of deployment, making it suitable for small-scale smart homes. However, the design lacks environmental awareness, real-time sensor analytics, and machine learning-based optimization, resulting in limited automation intelligence.

Warad S. et al. (2025) implemented a cloud-enabled home automation architecture supporting remote appliance control, data logging, and multi-device synchronization. Their system enhances accessibility through online dashboards and cloud-stored activity records, allowing monitoring beyond local network boundaries. Although the solution improves scalability and device management, continuous internet requirement introduces latency and dependency, and the system does not incorporate AI-driven automated response behavior.

Vijaya Bhasker Reddy et al. (2024) designed an AI-integrated IoT home automation system using Arduino, DHT11, MQ-08, and water-level sensors. The model utilises machine learning for decision-making and includes facial recognition-based access control. Their work highlights the integration of AI for smart actions beyond manual operation. While effective in sensing and automation, scalability is limited, and occupancy-aware appliance optimisation is not fully explored.

Rathour N. et al. (2023) presented *Sigma Home*, an IoT-based automation platform using NodeMCU for Wi-Fi-enabled environmental monitoring. The system measures temperature, humidity, and lighting intensity in real time while allowing mobile-based appliance control. Their implementation strengthens connectivity and monitoring accuracy, yet appliance responses depend on user decisions rather than autonomous machine-learning-based adjustments.

Ghai M. & Gupta R. (2023) proposed an Arduino-based home security automation system employing PIR and vibration sensors for intrusion detection. The system improves safety through real-time alerts and motion-based monitoring. Their solution demonstrates reliability in surveillance applications, yet focuses primarily on security and not energy-efficient home automation. Automated smart control of appliances is also absent, leaving space for integration with AI-based decision systems.

III. EXISTING SYSTEM:

Current home automation systems largely depend on manual control methods, Bluetooth-based communication, or basic Internet of Things (IoT) frameworks. In traditional setups, users operate household appliances such as lights, fans, and air conditioners manually through physical switches or remote controls, which limits convenience and energy efficiency.
Bluetooth-based systems, typically built using modules like the HC-05 with Arduino, offer short-range wireless control via mobile applications. These systems allow users to operate appliances within a limited range (generally less than 10 meters) but lack internet connectivity and real-time adaptability.
On the other hand, IoT-based systems provide remote access and control over appliances through smartphone applications and cloud platforms. While these systems improve flexibility and accessibility, they often rely on static, rule-based automation where users predefine actions based on fixed schedules or conditions, such as turning on a light at a specific time.
Some recent advancements have incorporated voice-activated assistants like Amazon Alexa or Google Assistant to enhance user interaction, particularly benefiting individuals with disabilities.
However, even these systems are primarily reactive and require explicit user commands to function. Most existing systems lack intelligent decision-making, and do not adapt to changes in occupancy or environmental conditions. Consequently, they fall short in delivering fully automated and responsive smart home experiences, which highlights the need for more intelligent and adaptive solutions.

IV. PROPOSED SYSTEM AND WORKING METHODOLOGY:

The proposed smart home automation system is built to intelligently regulate household appliances by continuously analyzing environmental conditions and real-time occupancy. Raspberry Pi 5 functions as the primary controller, collecting temperature, humidity, and illumination values using DHT11 and LDR sensors while a camera module running a YOLO/CNN model identifies human presence accurately. Instead of using predefined static rules, the system follows a machine learning–based automation approach where historical environmental patterns and occupancy behavior are learned to make predictive decisions. The trained Random Forest model evaluates temperature, humidity, light intensity, time of day and occupancy information to determine whether lights or fans should be turned ON/OFF. If no person is detected in the room, the system overrides the prediction and switches OFF appliances, leading to significant energy savings. This methodology ensures automation that is responsive, adaptive, self-regulated and capable of reducing human intervention in daily appliance control.

A) DATA ACQUISITION

Sensor readings form the foundation of the proposed automation. DHT11 provides continuous temperature and humidity values, while the LDR measures brightness intensity to differentiate daylight and darkness levels. A USB/Pi camera collects live video frames which are passed through a YOLO-based CNN model for occupancy detection. These data streams, along with time-based features extracted from the internal clock, form the real-time input to the intelligent automation engine. The data is updated every few seconds, ensuring immediate dynamic response.

B) DATA PRE-PROCESSING AND FEATURE FORMATION

Raw sensor readings undergo normalization to ensure uniform scaling before being supplied to the machine learning model. Combined feature vectors are created using environmental parameters (temperature, humidity, light intensity), occupancy state (detected/not detected), and temporal context (hour of the day, day/night classification). This structured feature representation improves prediction consistency and increases system adaptability to varying conditions.

C) MACHINE LEARNING TRAINING MODEL

The automation model is developed using supervised learning. Historical datasets containing sensor patterns and corresponding appliance states are used to train models such as Random Forest, Decision Tree and Logistic Regression. Among them, Random Forest achieved better performance due to its capability to handle nonlinear patterns and multi-dimensional environmental variations effectively. The final trained model is exported using joblib and deployed on Raspberry Pi for real-time inference.

D) DECISION EXECUTION THROUGH ACTUATION

The GPIO pins of Raspberry Pi interface with relay modules and motor drivers to operate appliances based on model output. Lights, fans and AC are switched ON/OFF automatically depending on the predicted result. In addition, PWM control adjusts fan speed according to temperature and number of people detected in the room. Even during prediction errors, the system ensures safety by overriding decisions whenever the room is unoccupied.

E) BLOCK DIAGRAM

The block diagram of the proposed system clearly represents the end-to-end data flow from sensing → processing → prediction → appliance actuation. The Raspberry Pi 5 is the central control module which receives continuous input from DHT11, LDR and camera. Temperature and humidity parameters are captured through the DHT11 sensor, while illumination is measured using the LDR to differentiate day–night brightness conditions. Simultaneously, the Pi-camera streams real-time frames for YOLO/CNN-based occupancy detection. These inputs are collectively processed using the trained machine learning model embedded within the Raspberry Pi, which then predicts the most suitable operational state for lights and fans.

Once the decision is generated, control signals are sent to the relay module for lighting and to the motor driver for fan regulation. A 5V 5A power supply ensures stable operation of the system, while an HDMI-based interface displays real-time sensor readings, occupancy status, and appliance activity. The block diagram thus represents the overall architecture, showing how input data is processed by the Raspberry Pi and translated into autonomous appliance control.

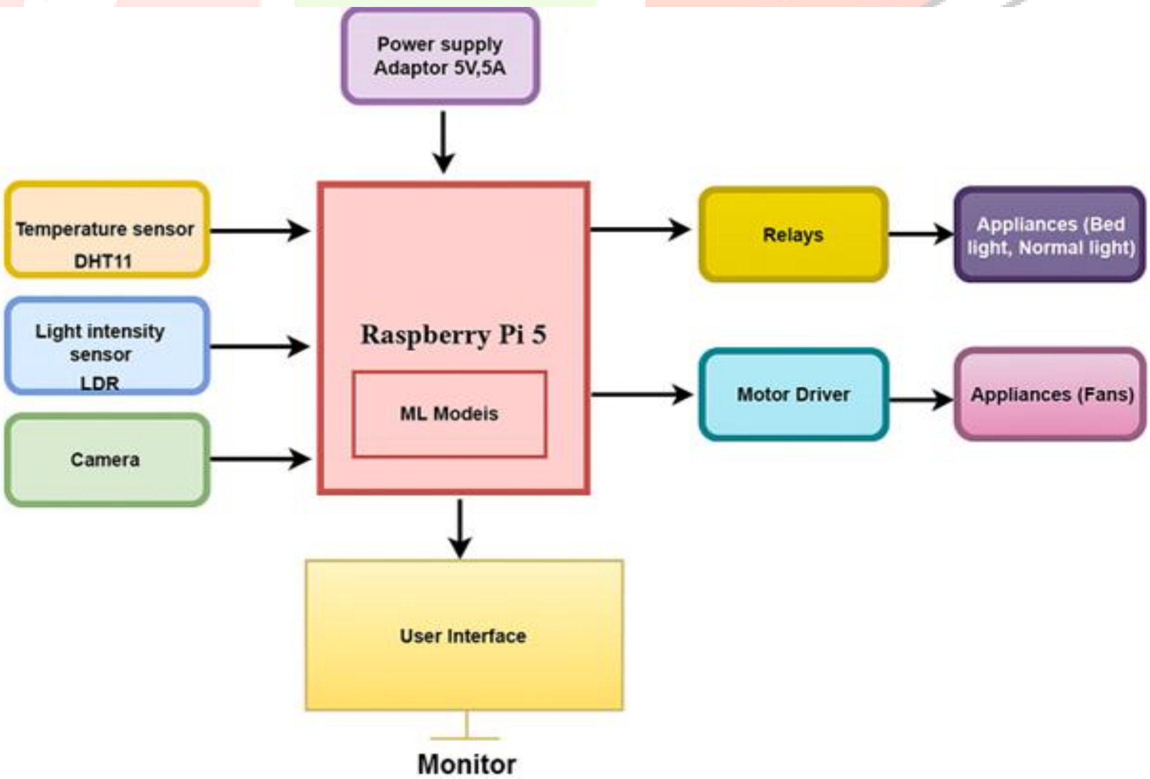

Fig. 1. Block Diagram of Proposed Smart Home Automation System

F) WORKFLOW DIAGRAM

The workflow diagram illustrates the sequential execution of the proposed system, beginning with system initialization followed by continuous monitoring of environmental and occupancy conditions. The process starts once the Raspberry Pi is powered ON. The sensors are initialized and begin capturing temperature, humidity and illumination values, while the camera simultaneously detects human presence within the room. All acquired parameters are fed into the machine learning inference module, where they are evaluated in real time to decide whether appliances need to be activated or turned OFF.

If the model predicts that light intensity is low or temperature is high when occupancy is detected, appropriate switching signals are sent to the relay or motor driver. The lights are switched ON through relay activation and fans are operated via PWM control for variable speed. In contrast, if the room remains vacant, the system cuts power to all appliances to prevent unnecessary electricity usage. After each execution cycle, the user interface is updated dynamically with live values and system state indicators, ensuring high transparency and real-time visibility. This workflow repeats continuously throughout system operation, enabling a self-regulated and energy-efficient smart home environment.

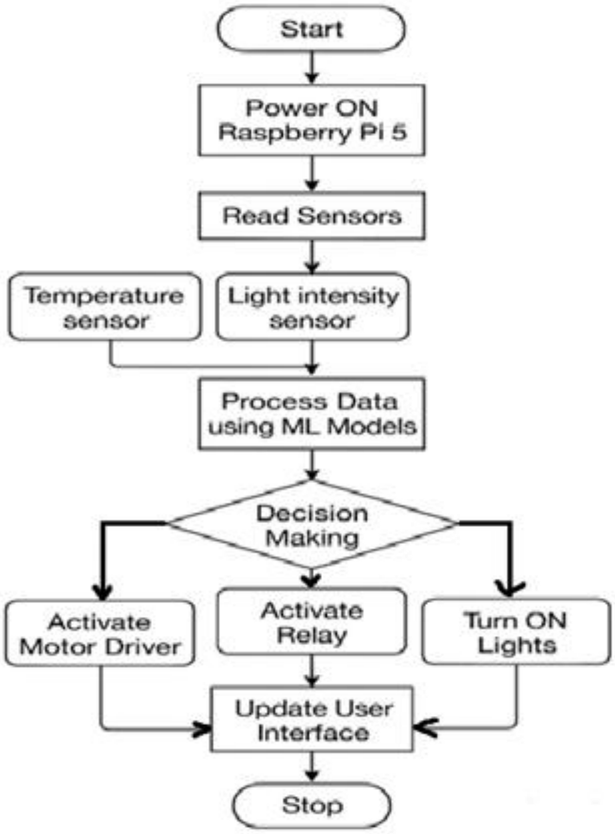

Fig. 2. Workflow Diagram of Smart Home Automation System

V. RESULT:

The developed smart home automation prototype was tested under various real-time environmental conditions to evaluate its decision-making performance. The Raspberry Pi 5 successfully processed sensor readings, detected occupancy using camera input, and controlled appliances autonomously through relay and motor driver modules. The system responded dynamically to temperature, light intensity, and human presence, ensuring efficient energy use with minimal manual intervention.

A) HARDWARE RESULT – PROTOTYPE IMPLEMENTATION

The complete working setup is shown below. The Raspberry Pi is interfaced with DHT11 (temperature–humidity), LDR (light sensor), USB camera, relay board and motor driver for dual-fan control.

Smooth wiring, stable board mounting and visible power indicators confirm reliable hardware integration.

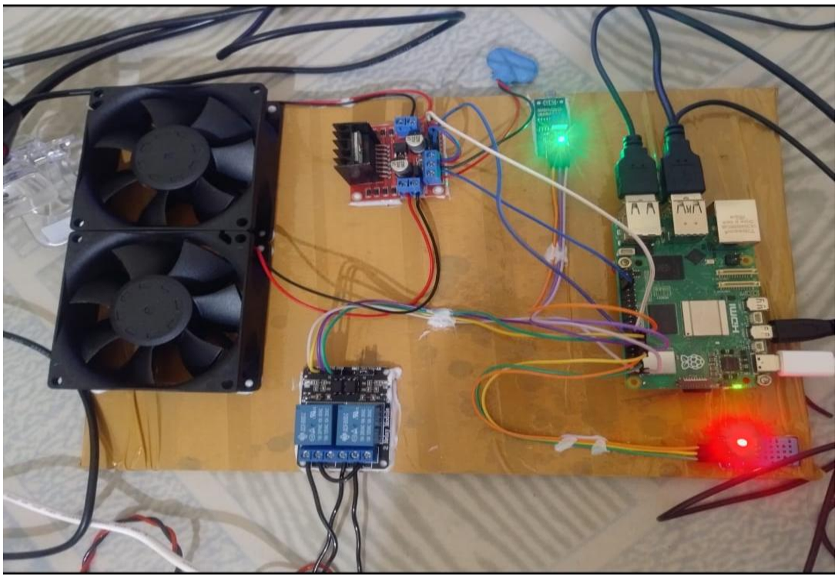

Fig. 3. Prototype setup with Raspberry Pi, sensors, relay module and dual fans.

B) PRACTICAL WORKING OUTPUT – LIVE APPLIANCE CONTROL

The system was tested with real appliances such as LED lights, bed lamp and fan. When the environment became dark and occupancy was detected, the light turned ON automatically. Similarly, under high temperature the fan was activated using PWM control for variable speed.

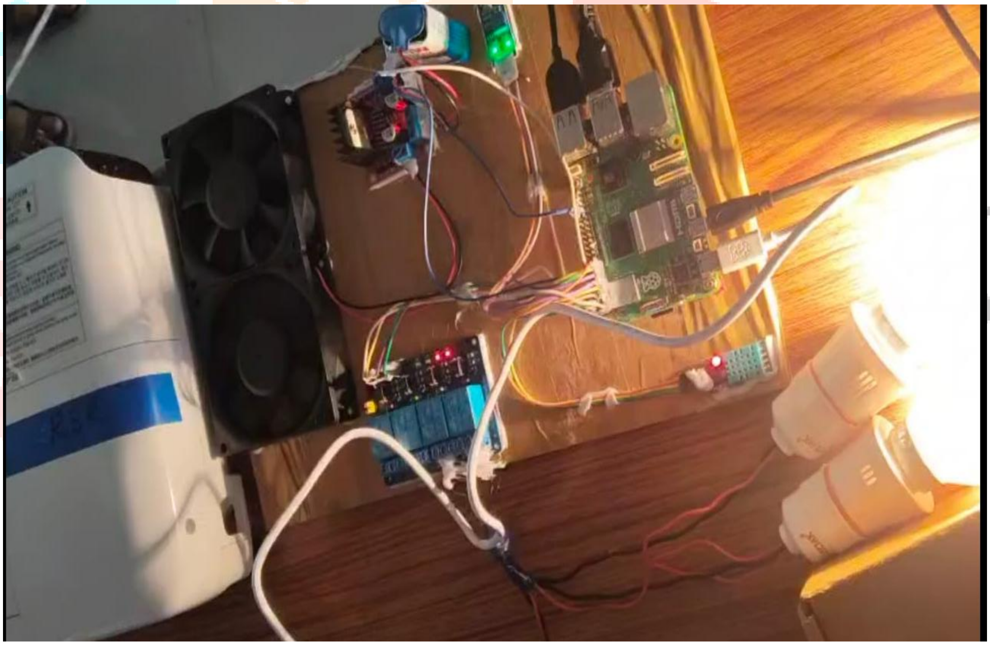

Fig. 4. System controlling real loads (light bulbs + fans) in live testing environment.

C) REAL-TIME PREDICTION SCREEN

The GUI displayed live values of temperature, light intensity, time, and detected people count, with corresponding ON/OFF decisions for appliances. When no person was detected, the model correctly switched everything OFF, saving energy.

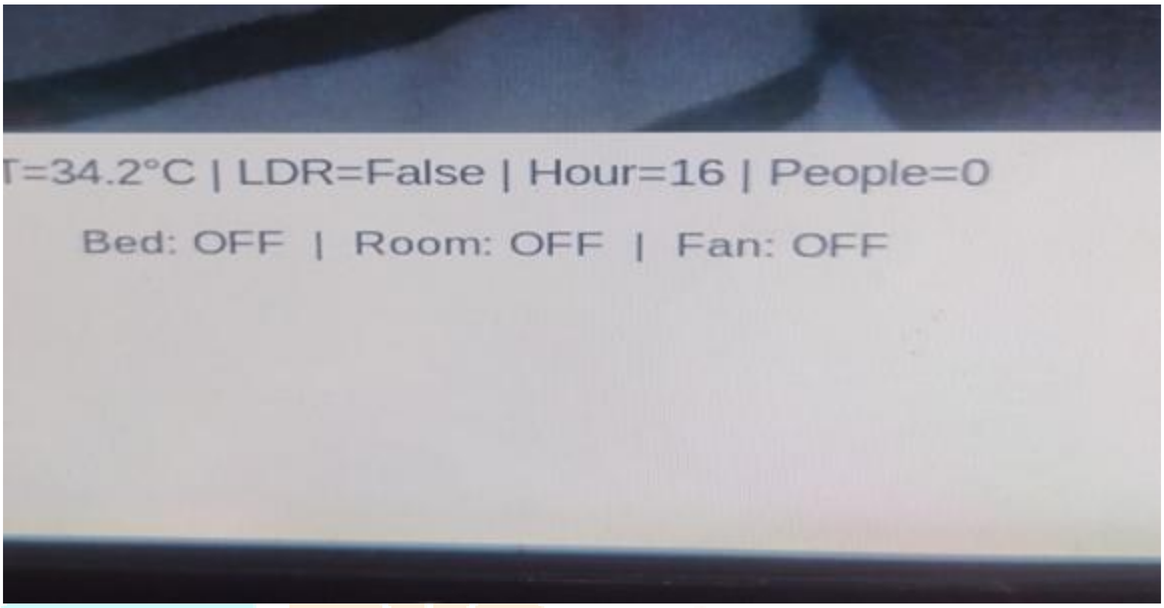

Fig. 5. UI output — No occupancy detected → Bed OFF | Room OFF | Fan OFF.

D) MODEL DECISION LOG OUTPUT

The Python console showed real-time model predictions. When temperature was high at night and one person was detected, **Bed Light ON → Fan ON** while **Room Light remained OFF**, proving contextual rule handling.

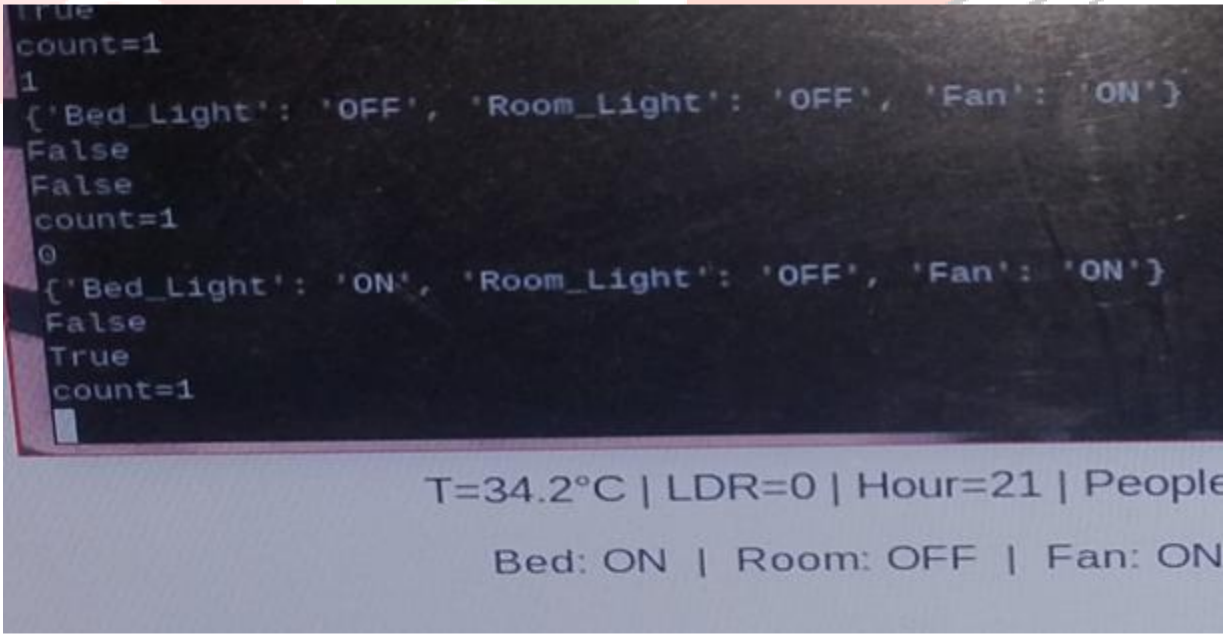

Fig. 6. Console-based prediction result displaying smart appliance decisions.

E) NIGHT-TIME AUTOMATION RESULT

During low light conditions and confirmed human presence, the system turned **Bed Light ON automatically**. This validates accurate low-light detection and occupancy-based control.

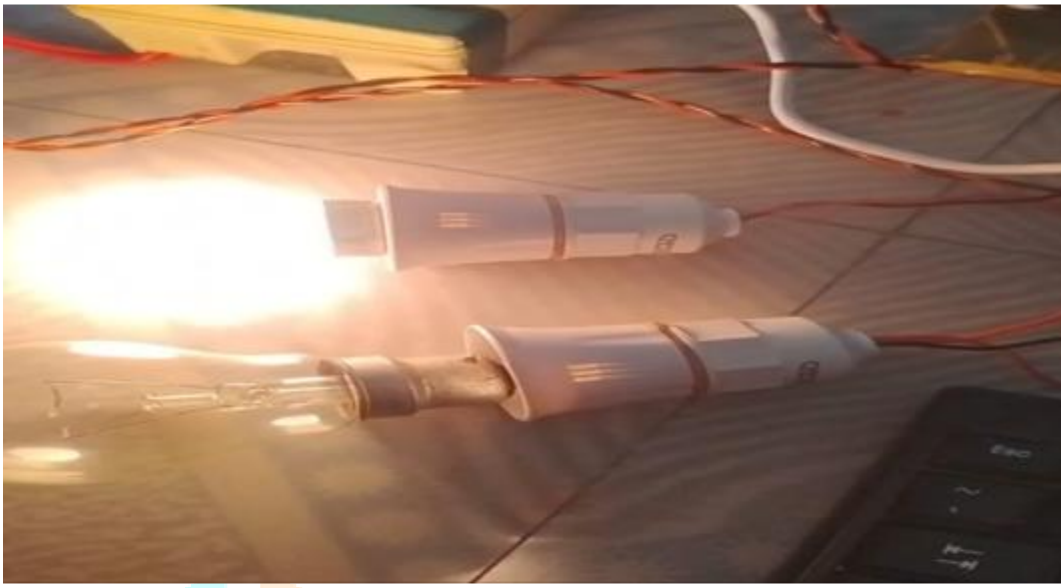

Fig. 7. Bed lamp glowing ON during night — triggered autonomously by model.

F) HIGH TEMPERATURE RESPONSE — FAN ACTIVATION

When room temperature crossed threshold and occupancy was detected, the system activated the fan instantly. Variable fan speed was controlled using PWM signals from Raspberry Pi.

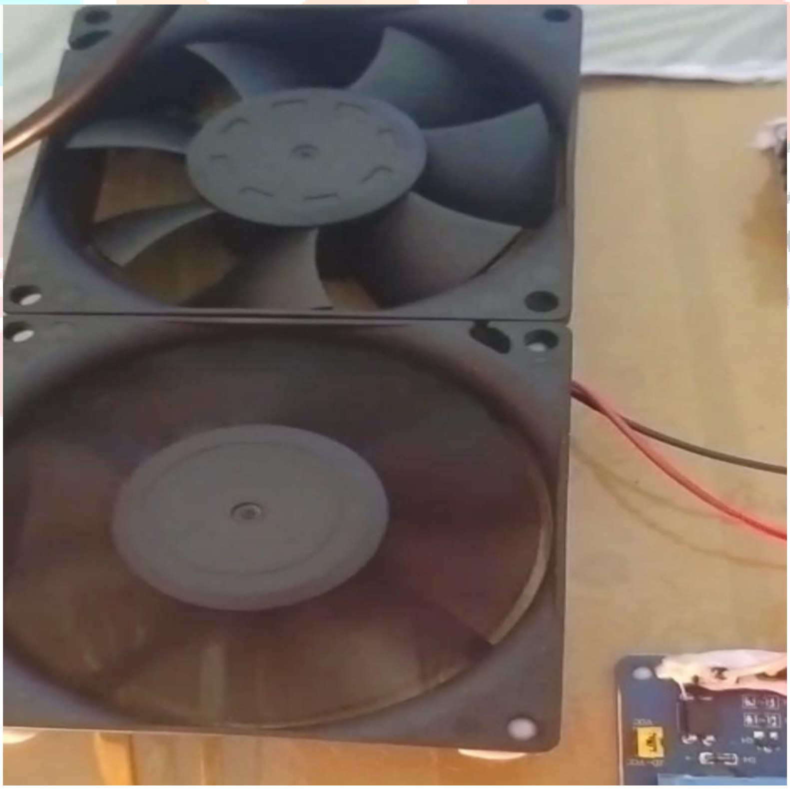

Fig. 8. Fan ON state — triggered automatically due to high temperature and presence.

SUMMARY OF RESULTS

- System controlled lights & fan without manual input
- Bed light/Fan ON only when needed → energy efficiency achieved
- Camera-based YOLO occupancy detection reduced false activation
- Continuous real-time monitoring through UI
- System successfully adapts to environment + user presence

VII. CONCLUSION:

The AI-driven smart home automation system developed in this project demonstrates the effective integration of environmental sensing, camera-based occupancy detection, and machine learning–powered decision-making to achieve dynamic and intelligent appliance control. Using the Raspberry Pi 5 as the central controller, the system collects real-time data from temperature and humidity sensors, light intensity sensors, and a camera module capable of detecting human presence. This data is processed through trained machine learning models to make context-aware predictions, which are executed through relay modules and motor drivers to control appliances such as bed light, room light, and cooling fans.

By continuously analysing environmental conditions, occupancy status, and temporal features such as the hour of the day, the system ensures that appliances operate only when necessary, thereby improving energy efficiency and reducing unnecessary power consumption. The camera-based occupancy detection significantly enhances accuracy compared to traditional PIR sensors, leading to more reliable automation and preventing false activations. Additionally, the HDMI-based user interface allows users to visualize real-time readings and appliance states, enabling intuitive monitoring and manual override options when required.

The modular and scalable design of the system allows easy integration of additional sensors, appliances, and advanced AI features, making it adaptive to evolving smart home requirements. Overall, this work demonstrates the potential of AI-driven automation to enhance comfort, safety, and energy efficiency in modern residential environments, while providing a flexible foundation for future expansion and advanced smart home applications.

Overall, the system proved to be reliable, power-efficient, and capable of making autonomous decisions without human intervention. The successful performance of the prototype under real-time conditions highlights its readiness for practical deployment in residential environments and its ability to enhance comfort, safety, and energy utilization. These results validate the relevance of AI-driven automation in modern smart lifestyle applications.

VIII. FUTURE SCOPE:

In future, the smart home automation system can be further enhanced to improve intelligence, usability, and operational efficiency. The integration of voice-based control and natural language processing can allow users to operate appliances through spoken commands, increasing accessibility and convenience. Cloud connectivity and IoT integration may enable remote monitoring and control through smartphones or web applications, while also supporting data logging for predictive maintenance and energy analysis.

The system can additionally be upgraded with advanced environmental sensors such as motion detectors,air-quality monitors, and smart energy meters, allowing deeper insight into indoor conditions. Machine learning models may evolve to reinforcement or predictive learning methods to anticipate user patterns and automate decision-making without input.

Energy management can be strengthened by integrating renewable sources like solar power, enabling sustainable and cost-efficient operation. Finally, expanding support for multi-room deployment, more appliances, and compatibility with commercial smart devices will transform the system into a fully scalable, intelligent, and interconnected smart-home ecosystem.

IX. REFERENCES:

[1] J. Han, J. Yun, J. Jang, and K.-R. Park, "User-friendly home automation based on 3D virtual world," IEEE Transactions on Consumer Electronics, vol. 56, no. 3, pp. 1843–1847, Aug. 2010.

[2] Vamsikrishna, P., Kumar, S.D., Hussain, S.R. and Naidu, K.R., 2015, March. Raspberry PI controlled SMS-update-notification (Sun) system. In 2015 IEEE international conference on electrical, computer and communication technologies (ICECCT) (pp. 1-4). IEEE.

[3] Larhgotra, A., Grover, Y., Kour, S., Dadarwal, K., Singh, M. and Bahuguna, R., AI Driven Smart Home Automation.

[4] Severance, C., 2013. Eben upton: Raspberry pi. Computer, 46(10), pp.14-16.

[5] Kulshreshtha, K., Gautam, J., Alabdeli, H., Abdullaev, J., Rani, R. and Kharayat, P.S., 2024, September. AI in Home Automation Systems. In 2024 International Conference on Communication, Computing and Energy Efficient Technologies (I3CEET) (pp. 1082-1087). IEEE.

[6] Khan, I.R., Jha, A.K., Ahmad, N. and Rawat, H., 2024. Home Automation and Security Systems Using AI and IoT. In The Next Generation Innovation in IoT and Cloud Computing with Applications (pp. 157-173). CRC Press.

[7]Soji,E.S., Gnanamalar, S., Arumugam, N., Priscila, S.S., Selvam, N. and Rajest, S.S., 2024. AI driven computer vision for intelligent home automation and surveillance systems. In Explainable AI Applications for Human Behavior Analysis (pp. 242-257). IGI Global.

[8] Elkhalik, W.A., 2023. AI-Driven Smart Homes: Challenges and Opportunities. Journal of Intelligent Systems & Internet of Things, 8(2).

[9] Alam, M.R., Reaz, M.B.I. and Ali, M.A.M., 2012. A review of smart homes—Past, present, and future. IEEE transactions on systems, man, and cybernetics, part C (applications and reviews), 42(6), pp.1190-1203.

[10] Pavithra, D. and Balakrishnan, R., 2015, April. IoT based monitoring and control system for home automation. In *2015* global conference on communication technologies (GCCT) (pp. 169-173). IEEE.

[11] N. Sriskanthan, F. Tan, and A. Karande, "Bluetooth based home automation system," Microprocessors and Microsystems, vol. 26, no. 6, pp. 281–289, 2002.

[12] A. Alaa, A. A. Zaidan, B. B. Zaidan, et al., "A review of smart home applications based on IoT: A systematic survey," Journal of Network and Computer Applications, vol. 97, pp. 48–65, 2017.

[13] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, real-time object detection," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779–788.

[14] Khan, M., Seo, J. and Kim, D., 2020. Towards energy efficient home automation: a deep learning approach. Sensors, 20(24), p.7187.

[15] P. Suresh, J. V. Prakash, V. V. Kumar, and A. A. Kumar, "A low-cost smart home automation system using Raspberry Pi," in Proc. IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), 2016, pp. 1864–1867.

[16] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of Things for Smart Cities," IEEE Internet of Things Journal, vol. 1, no. 1, pp. 22–32, Feb. 2014.

[17] Syamala, M., Komala, C.R., Pramila, P.V., Dash, S., Meenakshi, S. and Boopathi, S., 2023. Machine learning-integrated IoT-based smart home energy management system. In Handbook of research on deep learning techniques for cloud-based industrial IoT (pp. 219-235). IGI Global.

[18] Shafi, M.K.I., Sultan, M.R., Rahman, S.M.M. and Hoque, M.M., 2021, December. IoT based smart home: a machine learning approach. In 2021 24th International Conference on Computer and Information Technology (ICCIT) (pp. 1-6). IEEE.

[19] Raj, N., Sinha, A., Bharddwaj, S. and Yadav, A.L., 2024, May. AI-powered energy consumption optimization for smart homes using IoT. In 2024 International Conference on Computational Intelligence and Computing Applications (ICCICA*)* (Vol. 1, pp. 231-236). IEEE.

[20] https://www.raspberrypi.com/documentation/computers/raspberry-pi.html

[21] https://learn.adafruit.com/dht/overview.

[22] https://www.raspberrypi.org/products/raspberry-pi-3-model-b/

[23] https://docs.opencv.org/master/

[24] https://www.researchgate.net/publication/357041423_AI-Based_Smart_Home_Automation