Gesture-Controlled Home Automation: AI-Driven Interaction for Smart Living

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Abstract. Smart home automation technology has been greatly advanced to provide users with convenient and smart control of home appliances. Touchless (e.g., gesture-based) home automation applications can deliver seamless user experiences allowing hands-off control, for when interacting directly with switches is inconvenient, or voice commands cannot be used. This paper demonstrates AI based gesture control automation using computer vision, machine learning and IOTs, to give convenient usage of the home devices to the user using hand gestures. A Python-based camera driven gesture recognition system that recognizes different hand gestures and sends corresponding commands to an Arduino Uno, which is connected to other smart devices like a multi-color LED lights, fan, etc. The system is intended to be used as an online gesture recognition system with low delay and high rate of recognition. By hand tracking with Media Pipe, gesture classification with deep learning models, and serial communication protocols for fractioning the device in tools, we make very easy the integration of the device in tools and giving users the possibility to be adapted to these systems. Evaluation was conducted with different lighting and gesture complexities, to assess the reliability and robustness. It has security concerns: Gesture-based password can help preclude unauthorized access to control of smart home etc. Experimental results demonstrate high accuracy, responsiveness, and ease of use, making this approach suitable for real-world applications, including assisted living for elderly and disabled individuals**.** Gesture-based automation offers a hygienic and intuitive alternative to traditional switch-based and voice-controlled systems. Future improvements will focus on multimodal interaction**,** incorporating voice commands and adaptive AI models for enhanced recognition across diverse environments. Advancing human-computer interaction, this paper contributes to the growing field of smart home technology with AI-powered gesture recognition.

Keywords: Smart Home Automation, Gesture Recognition, Computer Vision, IoT, Machine Learning, Arduino, MediaPipe, Deep Learning, Touchless Control.

1 Introduction

The rapid advancement of smart home automation has transformed modern living by enhancing comfort, energy efficiency, and security. Over the years, traditional home automation systems have relied on physical switches, remote controls, and, more recently, voice assistants to facilitate user interaction with household devices. While these methods have provided convenience, they still have inherent limitations in accessibility, hygiene, and adaptability. With the emergence of Artificial Intelligence (AI) and the Internet of Things (IoT), smart home ecosystems are evolving toward touchless control systems, allowing users

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to interact with appliances through natural gestures, making automation more intuitive and inclusive.

Over the past few years, the interest in gesture-controlled home automation has increased due to the requirement of more hygienic, contact less and accessible interface for the physically impaired as well as for the people living in high traffic induced surroundings. Conventional interfaces, such as switches and remote-control input devices, require a physical intervention, which is inconvenient if hands are busy or users are mobility-impaired. Voice assistants are widely available, but they can have limitations in terms of noisy environment, language dependence, and privacy, making them not robust enough for universal use [2]. Another alternative is the creation of a non-verbal communication system between humans and devices, enabled by computer vision and AI recognition.

Although there are still some remaining problems such as accuracy, gesture recognition and latency and environment adaptability, in smart home automation for gesture recognition. All-lighting condition, hand-pose and depth maps recognition can be restricted by relatively slow and un-efficient recognition accuracy which misunderstandings often occurs. And then, with home automation you also need near-instant responsiveness (not doing anything on the commands will easily frustrate the people using the under system). Trade-off between environmental variability and precision is a key technical challenge [3]**.**

This paper describes the development of home automation by considering different gesture for control the home devices in real-time using computer vision and IoT based deep learning. "Utilizing the real-time processing and text extraction is suitable and system operation is restricted to use with advanced recognition models such as Media Pipe, OpenCV, and CNN-based models. Moreover, the security and privacy concerns for gesture - based systems are addressed with the utilization of gesture-based authentication for unauthorized users to access and control smart home devices [4]. One of the notable work enhancements of the next generation automation system using computer vision and IoT by utilizing the merits from the both domains. The architecture offers the empirical assessment of the performance of recognition models, which has been developed with numerous AI-driven models for real-time home automation.

The work also adds to growing concerns around security in smart home ecosystems, and privacy implications of the trend, with gestures as those that could be used for unauthorized access and privacy [5]. By integrating gesture recognition with the Internet of things, automation, it seeks to deliver a generation new at home automation which is more flexible, secure and easy to use. The practical application of the proposed method enhances the convenience more efficiently, and promotes the overall efficiency and reliability of smart home significantly, so it has potentiality of replacing the existing controller. Other Automation and enhanced multimodal interaction, edge AI processing, and adaptive learning will further refine the gesture-based automation experience and create a smarter, friendlier living environment.

2 Literature Review

The perfect balance between AI, IoT and computer Vision is that now gesture based home automation is not farfetched anymore, rather it’s a hands-free interaction natural not so long ago. It was discussed the role of AI-powered gesture recognition in realizing accessibility, in particular for those with disabilities. Recognition methods are usually divided to camera's perception sensor-based recognition including RGB and depth camera, and the second category is sensor-based recognition. While camera-based solutions might be vulnerable to light effects and background complexity, sensor-based methods require hand-worn devices, which are usually cumbersome. Varriale, L et.al examines how these technologies can be utilized to enhance the quality of life for individuals with disabilities, considering both the organizational structures that support them and the human factors that influence the adoption and effectiveness of such technologies. The authors discuss various aspects, including accessibility, usability, and the socio-technical challenges that arise when implementing home automation solutions for people with disabilities [15].

Models like CNNs, YOLO, Media Pipe and others have significantly improved recognition accuracy. Suryawanshi, P et al., emphasized that the behavior of MediaPipe is also tested in a simple computer application [9], Oudah et al., [5] stressed the better accuracy of CNNs (at the cost of more computation). Relate Work YOLO, famous for its real-time object detection, is appropriate to achieve automation at mobile phone side. However, accurate recognition in various lighting conditions, hand positions, and background noise is still a difficult problem. The IoT integration has made it possible for uniform automation, combining cloud and edge-based AI processing. Popalzai [6] indicated that cloud-based approaches alleviate hardware dependency and incur latency due to network overhead. On the other hand, [4] Kerosi and Moywaywa demonstrated that edge AI, implemented on devices like Raspberry Pi and Jetson Nano, enhances responsiveness by processing gestures locally. Communication protocols such as Wi-Fi, Zigbee, and MQTT facilitate connectivity, with Zigbee and MQTT offering energy-efficient solutions.

Mid-air gesture interaction, supported by depth-sensing technologies like Kinect and RealSense, enables touchless control. [10] Vogiatzidakis and Koutsabasis explored how spatial augmented reality enhances usability by providing visual feedback. However, usability challenges persist, including gesture memorization and processing requirements. Hybrid systems that combine gestures with voice or haptic feedback improve adaptability and user experience [3]. Security remains a major concern in gesture-based automation. [7] Rustam et al., identified risks such as gesture replication and spoofing, while [1] Fatima et al. proposed multi-factor authentication, integrating gestures with facial recognition or RFID for enhanced security. [5] Oudah et al. proposed a motion-based verification to alleviate spoofing risks. Dealing with these security issues is crucial in guaranteeing secure and reliable intelligent gesture-based homes.

3 Methodology

The project uses an MQTT protocol for communication and employs a computer vision (CV)-based gesture recognition system. This system includes object detection, face detection, and gesture control algorithms to process and respond to user input [6].

3.1 System Architecture

Based on a modular hardware architecture, the system integrates various parts to produce an online gesture recognition. The camera module records the movement of the hand, based on which Python programs with computer vision algorithms are conducted [11]. The processed hand gestures are passed to the Arduino Uno and it automatically compiles them to operate the home automation devices. Fan and Switch Output devices are connected with system via Relay Ckt to drive LED color lights and Fan [7]. The devices perform local processing using technologies like the ARM-based Raspberry Pi, Jetson Nano, or Arduino. This enables real-time gesture recognition and reduces latency by processing the data directly on the device, rather than relying on cloud-based servers. It is important to monitor traffic from IoT devices (such as bulbs, fans, and security systems) to your network in the context of smart home automation. Understanding this traffic ensures efficient system performance and helps manage network resources [8]. The system utilizes an AI stack that includes models like CNN, YOLO, and MediaPipe. These models are integrated to optimize gesture recognition efficiency, enabling real-time processing with minimal computational cost. The system uses communication protocols such as MQTT, HTTPS API, and Bluetooth, ensuring seamless device integration within a larger ecosystem [9]. Edge computing also facilitates locational processing of gesture data directly to the moves locally in the edge device without having to submit requests and wait for responses from cloud servers, helping in further reducing latency and increasing processing speed.

System Flow Diagram

The image below illustrates the complete flow of the gesture-controlled home automation system: Fig 1 shows the System Architecture of the Gesture-Controlled Home Automation System.

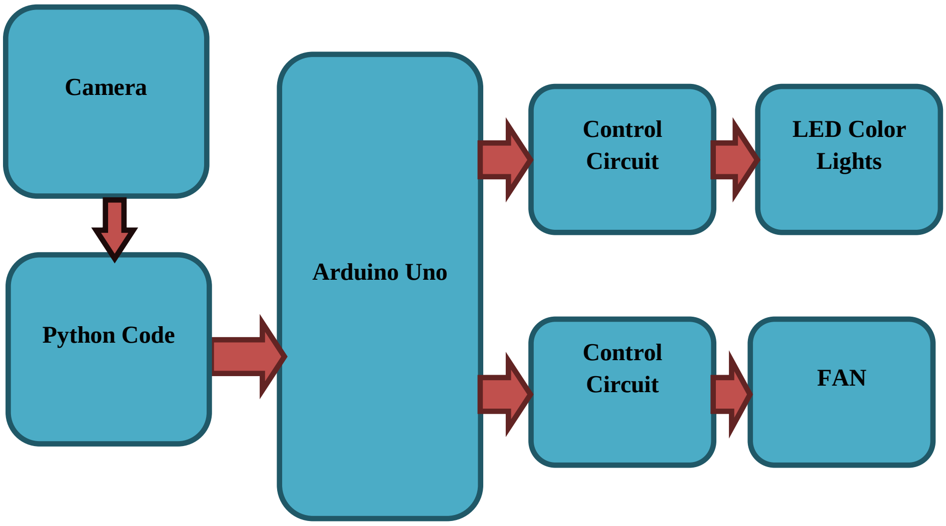

Fig. 1. System Architecture of the Gesture-Controlled Home Automation System.

The camera module captures real-time hand gestures, which are processed using Python-based AI models. The processed commands are transmitted to the Arduino Uno, which acts as the central controller. The Arduino then triggers the control circuits, which activate specific appliances, such as LED color lights or a fan, based on the recognized gesture. Fig 2 shows the Hand gesture recognition process for home automation.

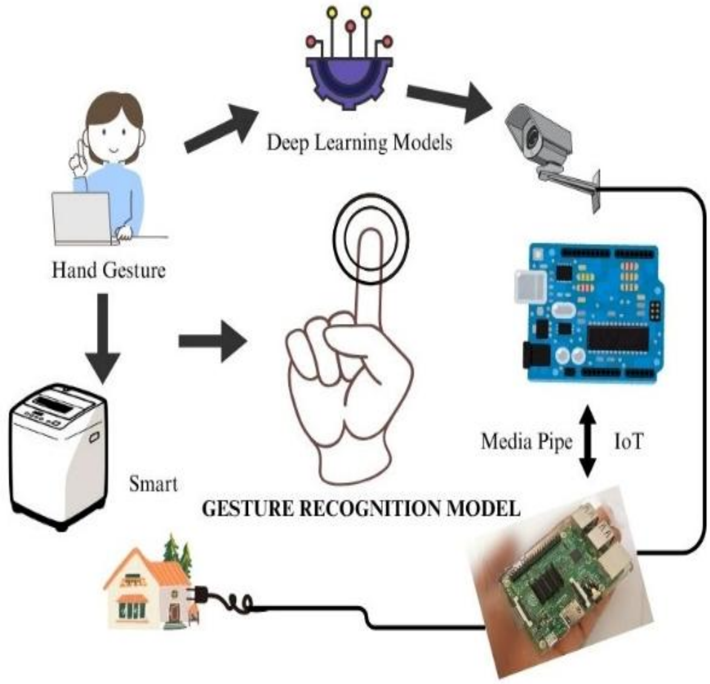

Fig. 2. Hand gesture recognition process for home automation.

3.2 Gesture Recognition Pipeline

The camera module records live hand gestures and the resulting action is carried out by AI models with Python. Arduino Uno (central controller): The preprocessed commands are sent to Arduino Uno. It triggers through the control circuits, so that some appliances (like LED color lights or fan) are turned on based on the recognized gesture. The gesture recognition pipeline includes a series of stages such as data acquisition, preprocessing and classification to achieve high accuracy and robustness. Data acquisition consists of recording a custom dataset of hand gestures in varying lighting conditions and backgrounds to increase the generalization capability of the model [13].

C: Similar performance is achieved when tested on virtue of other pre-collected datasets, in which the diverse ability for gesture recognition is guaranteed as is the case even with the ASL (American Sign Language) and Ego Hands datasets. The captured images are preprocessed before being inputted to the AI model. This also occurs in image segmentation with OpenCV, where the background noise is unwanted. Deep feature extractions with CNN and MobileNet are effective at capturing distinctive gesture features, while being computationally efficient.

For the classification, it also benchmarks MediaPipe, YOLO, and CNNs to observe the accuracy, speed, and performance. MediaPipe tends to lightweight real-time tracking, and YOLO performs faster object detection [12]. In order to improve the recognition of sequence gestures, we propose a hybrid model that combines with LSTM (Long Short-Term Memory) that is capable of recognizing the dynamic palm and accomplishing more responsive to the dynamic hand movement [10].

Gestures can be identified based on extracted features. The extracted features are represented as:

$$F = \sum_{x,y} w(x,y) I(x,y) \tag{1}$$

where:
- $I(x,y)$ is the intensity of the image at pixel (x,y).
- $w(x,y)$ is the weight assigned to each pixel by the feature extraction algorithm (e.g., CNN filters)?

When discussing CNN-based classification, add the convolution operation equation:

$$o(i,j) = \sum_m \sum_n I(i+m, j+n) K(m,n) \tag{2}$$

where:
- $O(i,j)$ is the output feature map?
- $I(i+m, j+n)$ is the input image matrix?
- $K(m,n)$ is the kernel filter.

CNN classification assigns a probability score P for each gesture g using softmax:

$$P(g) = \frac{e^{z_g}}{\sum_{i=1}^{N} e^{z_i}} \tag{3}$$

where:
- z_g is the output of the last fully connected layer for gesture g.
- N is the total number of gesture classes?

3.3 Home Automation Framework

- With the hand gesture detected the system converts it to IoT control commands on the fly. The AI handles the gesture input and outputs the proper control signal that is transmitted to the Arduino Uno. The relay circuit switches the appliances ON/OFF or it sets the fan speed and the intensity of the light [3] and [4].

- The system includes a user-friendly interface (UI) that allows users to easily program and customize gestures for controlling appliances via a web or mobile application. Users can assign specific gestures to different appliances and modify these settings at any time, providing a flexible and personalized experience.

- With this dashboard you can get real-time feedback and you can add, remove, or change gesture commands easily, making the usage of the glove way to personalize and flexible for you. Security mechanisms are also adopted to protect it from being accessed by an unauthorized person [4]. The home devices are controlled by a gesture-based authentication mechanism for registered users. Moreover, it also uses gesture motion analysis to protect against spoof attacks where static images or previously-recorded gestures are used to invoke an automation [5]. Thanks to the integration AI-enabled recognition, IoT controlled and security improved interaction, the approach provides a robust, user-friendly, and efficient home automation. The study was focused on evaluating perceived comfort, usability, privacy and benefits of ISHS. Although initial feelings of usability and privacy led to hesitance in the use of ISHS, increased awareness of the potential benefits suggested by survey data eventually made participants more willing to adopt [14].

• Upcoming improvements will be concentrated on adaptive learning, multimodal interaction (gesture + voice), and to extend IoT connectivity to build a complete smart home ecosystem.

• When the gesture is recognized, then there is a control signal that can operate smart home appliances:

$$S = f(G, T) \tag{4}$$

where:

- G represents the recognized gesture.
- T is the threshold value for confidence score (e.g., 90% for CNN, 85% for YOLO).
- $f(G, T)$ is the function mapping the recognized gesture to appliance commands.

The communication between the AI processing unit and Arduino Uno uses Serial Communication, represented as:

$$D_{out} = \sum_{i=1}^{N} B_i \times 2^{i-1} \tag{5}$$

where:
• D_{out} is the digital output signal?
• B_i is the binary signal (1 or 0) corresponding to appliance ON/OFF states?

If gesture control extends to adjusting appliance intensity (e.g., fan speed), a PWM (Pulse Width Modulation) Signalis used:

$$D = \frac{t_{on}}{t_{on} + t_{off}} \times 100\% \tag{6}$$

where:
• D is the duty cycle percentage?
• t_{on} and t_{off} are the ON and OFF durations of the PWM signal.

4 Results & Performance Evaluation

Experiments were conducted using an RGB camera, Arduino Uno, and IoT-enabled appliances such as LED lights and a fan. Gesture recognition processing was performed on Raspberry Pi 4 and Jetson Nano, while cloud-based execution was tested using Google Cloud AI services. Tests were carried out in indoor and outdoor settings under varying lighting conditions to evaluate robustness. The system was assessed for gesture recognition accuracy, response time, user experience, and security performance.

4.1 Gesture Recognition Accuracy

Performance comparison between YOLO, MediaPipe, and CNN-based models showed that CNNs achieved the highest accuracy (97.2%), but required more processing time. YOLO (92.8%) and MediaPipe (90.5%) were slightly less accurate but performed faster in real-time tracking.

Latency analysis revealed that YOLO processed gestures in 15ms, MediaPipe in 12ms, and CNNs in 28ms, indicating a tradeoff between accuracy and speed. The confusion matrix analysis further confirmed that CNNs had the lowest misclassification rate, but real-time responsiveness was better with MediaPipe and YOLO. Fig 2 illustrates the accuracy comparison of the three AI models—YOLO, MediaPipe, and CNN—evaluated under different environmental conditions.

The results indicate that CNN provides the highest accuracy, whereas MediaPipe is the fastest in real-time execution. Fig 3 shows the: Gesture Recognition Accuracy Comparison of YOLO, Media Pipe, and CNN.

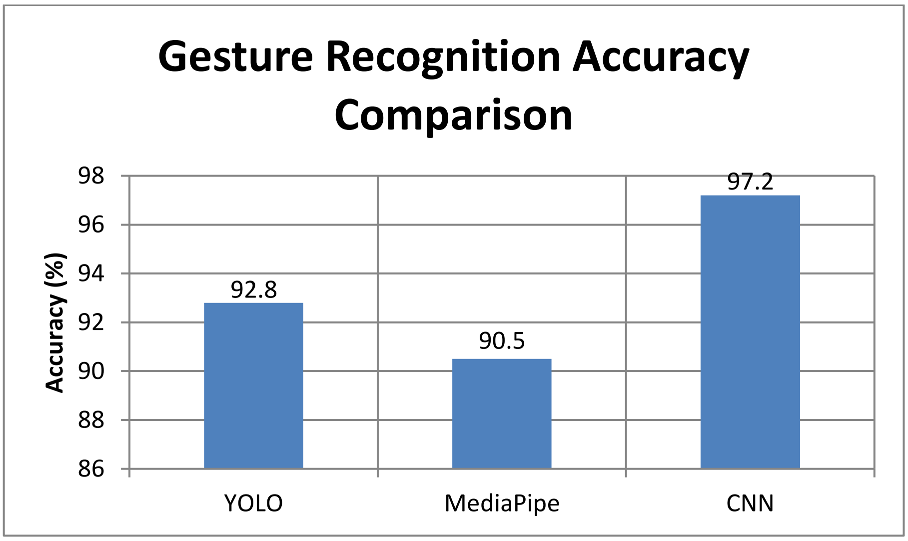

Fig. 3. Gesture Recognition Accuracy Comparison of YOLO, Media Pipe, and CNN.

To evaluate the system's performance, metrics like accuracy, precision, and recall can be mathematically expressed:

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{6}$$

where:

- TP = True Positives (correctly recognized gestures).
- TN= True Negatives (correctly rejected gestures).

- FP = False Positives (wrongly classified gestures).

- FN = False Negatives (missed gestures).

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}}, \qquad \text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \tag{7}$$

These metrics help assess model reliability and responsiveness.

4.2 Smart Home Control Response Time

Response time testing compared cloud-based and edge AI processing. Edge AI on Jetson Nano (38ms) and Raspberry Pi (45ms) significantly outperformed cloud processing (120ms) due to network latency. Real-time command execution was faster in local processing, making edge AI the preferred solution for gesture-based home automation.

Fig 3 compares the response time of Edge AI processing (Jetson Nano and Raspberry Pi) with cloud-based processing. The results show that Edge AI significantly reduces latency, making it a preferable solution for real-time smart home automation. Fig 4 shows Response Time Comparison (Edge vs. Cloud Processing).

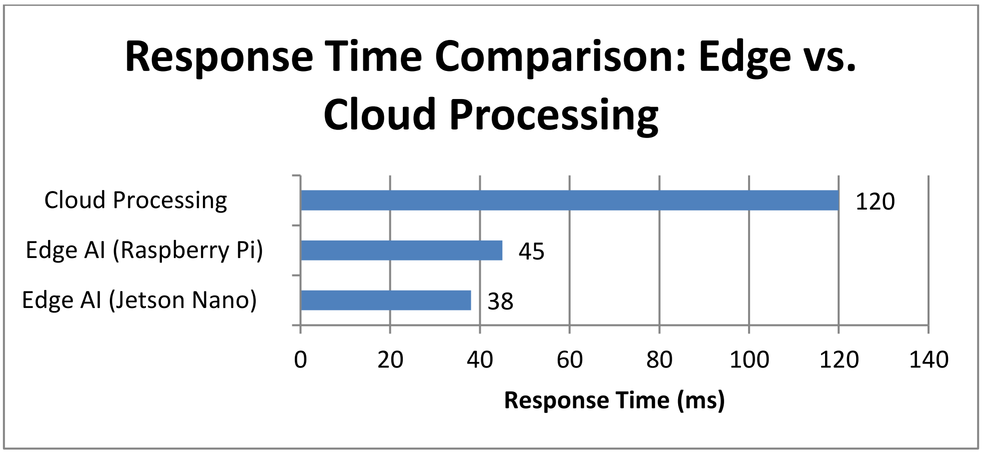

Fig. 4. Response Time Comparison (Edge vs. Cloud Processing).

The latency$L$of gesture-controlled home automation is given by:

$$L = t_c + t_p + t_d \tag{8}$$

where:

- $\boldsymbol{t_c}$ is the time for gesture capture?

- $\boldsymbol{t_p}$ is the processing time for recognition?

- $\boldsymbol{t_d}$is the delay in sending control signals to the appliances?

For Edge AI processing, where real-time execution is crucial, we compare:

$$L_{Edge} = t_c + t_p + t_d \tag{9}$$

$$L_{Cloud} = t_c + t_p + t_d + t_n \tag{10}$$

where t_n is the network delay in cloud processing? Ideally, Edge AI minimizest_n to enhance real-time execution.

4.3 User Experience and Feedback

A usability study was conducted with 20 participants to assess system accuracy, ease of use, and real-time response efficiency. Most users found the interface intuitive, but some required time to learn specific gesture patterns. MediaPipe was preferred for smooth tracking, while YOLO was appreciated for its quick execution. CNN-based recognition was the most accurate but slightly slower. The system was particularly useful for individuals with mobility impairments, making gesture-based automation an accessible alternative to traditional control methods.

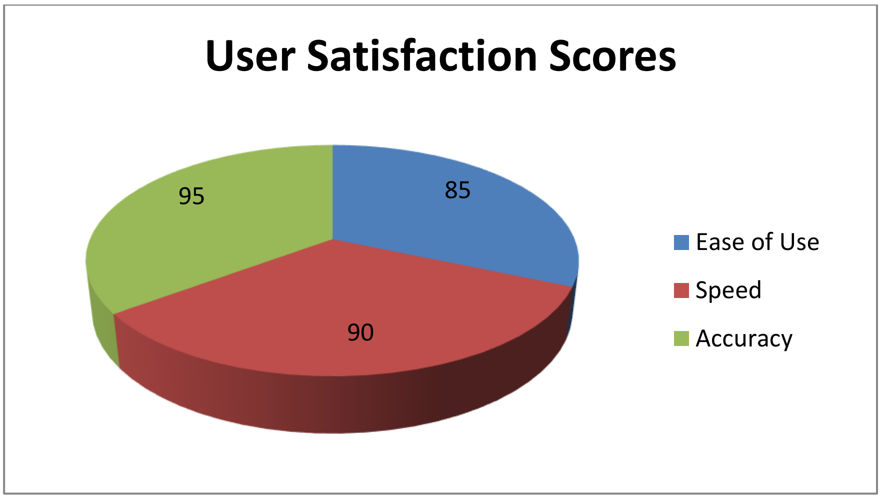

Fig. 5. User Satisfaction Scores.

A pie chart has shown participant ratings for ease of use, speed, and accuracy, illustrating overall system effectiveness. Fig 5 shows the User Satisfaction Scores.

4.4 Security & Privacy Testing

Security evaluation measured the false acceptance rate (FAR) and false rejection rate (FRR). Results showed a FAR of 2.1% and FRR of 3.4%, indicating high reliability. Spoofing tests using pre-recorded gestures and static images were 98% unsuccessful, proving that the system effectively prevents unauthorized access. Gesture motion analysis further enhanced security by distinguishing between real and fake gestures.

Fig 5 compares the system's security performance based on False Acceptance Rate (FAR) and False Rejection Rate (FRR). The findings confirm that the system maintains a low FAR, ensuring robust security against unauthorized gesture inputs. Fig 6 shows the FAR vs. FRR Comparison.

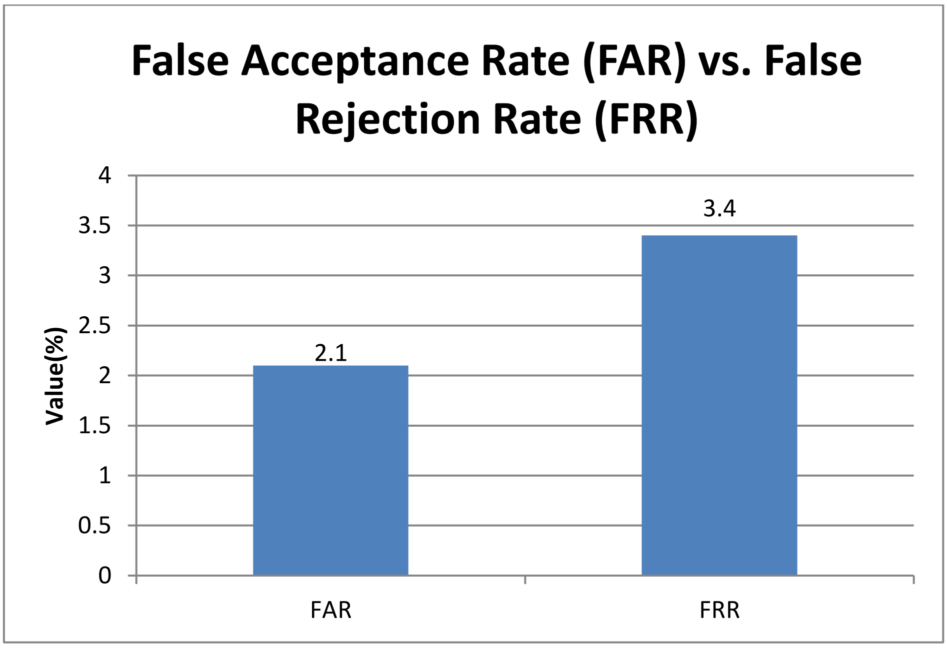

Fig. 6. FAR vs. FRR Comparison.

The system's security performance is measured using False Acceptance Rate (FAR) and False Rejection Rate (FRR)**:**

$$FAR = \frac{F_A}{F_A + T_A}, \qquad FRR = \frac{F_R}{F_R + T_R} \tag{11}$$

where:

- F_A= Number of falsely accepted gestures (unauthorized access).
- T_A = Total number of valid access attempts.
- F_R = Number of falsely rejected gestures.
- T_R = Total number of valid gestures attempted.

4.5 Summary of Findings

CNNs delivered the highest recognition accuracy, while YOLO and MediaPipe provided better real-time execution.

Edge AI processing was significantly faster than cloud-based execution, making it ideal for instant home automation commands. User testing highlighted the system's intuitive nature and accessibility, while security tests confirmed low error rates and strong resistance to spoofing attacks. Future improvements will focus on adaptive gesture learning, multimodal interaction, and expanded IoT connectivity to further enhance system efficiency and user experience.

5 Discussion

We are using advances in hand gesture recognition technology to bring to you a silent, natural and no-touch control for your home replacing the switches or voice assistants. Regardless of the background noise, varying types of speech, and language dependence, gesture recognition technique provides a more robust interaction method. Furthermore, switch-based automation is physical and not suitable for mobility-disabled users. On the other hand, gesture-based control offers a more touchless and intuitive method, making it easier for average users to interact with smart homes.

In spite of these benefits, several environmental conditions like changes in illumination, background noise and occlusions can degrade the recognition accuracy. For example, inadequate lighting can cause to camera to be inefficient in its operation and, thus result in mis-interpretation of signals. The features extraction and selection are followed by an adaptation of spatial preprocessing methods (dynamic background subtraction, histogram equalization, contrast improvement) to enhance the clarity of an image before feature calculation. Also, infrared sensors in addition to RGB cameras could be used to robustly operate in low light, so that gesture recognition works everywhere regardless of lighting conditions. Moreover, complex multi-gesture inputs need more sophisticated temporal models that can capture the sequential nature of hand movements. However, the LSTM-based hybrid models achieve improved performance on recognition of continuous gestures at the cost of computationally more expensive processing. Possible future work may investigate the lightweight deep learning networks that are best suited to deliver both the accuracy and efficiency required for real-time multi-gesture recognition within smart homes.

6 Conclusion and Future Work

The developed gesture-controlled home automation system incorporates AI-based recognition, IoT connectivity, and edge processing contributing to a real-time, contact-less and intuitive UX. Utilizing the YOLO, Media Pipe and CNN it achieves both high accuracy and low latency. Edge AI processing allows for a much faster response time and is more efficient than cloud-based execution. Security technologies such as gesture-based authentication are designed to increase the guard level against unauthorized access, making it a sound and stable system. User reviews also recommend its ease of use, convenience, and support for smart living.

In the future, we aim to improve adaptive AI models to better recognize the environment, to integrate multimodal interactions, and to investigate hybrid cloud-edge processing to better meet real-time performance with reduced computational burden. Augmented reality integration might further improve user interaction and offer visual feedback for smart home control.

References

[1] Fatima, B., Mushtaq, B., Iqbal, M. A., & Ahmed, A. (2024). IoT-based smart home automation using gesture control and machine learning for individuals with auditory challenges. *IECE Transactions on Internet of Things, 2*(4), 74–82.

[2] Harale, A. D., Bankar, A. S., & Karande, K. J. (2021). Gestures controlled home automation using deep learning: A review. *International Journal of Current Engineering and Technology, 11*(6), 617-618. https://doi.org/10.14741/ijcet/v.11.6.4

[3] Khan, S., & Ansari, N. (2024). Voice-controlled wheelchair with home automation. *International Journal of Computer Applications, 186*(23).

[4] Kerosi, J. M., & Moywaywa, B. A. (2024). Gesture-driven home automation system. *IOSR Journal of Electrical and Electronics Engineering, 19*(6), 10-15. https://www.researchgate.net/publication/386541036

[5] Oudah, M., Al-Naji, A., &Chahl, J. (2020). Hand gesture recognition based on computer vision: A review of techniques. *Journal of Imaging, 6*(8), 73. https://doi.org/10.3390/jimaging6080073

[6] Popalzai, P. K. (2024). Home automation using Internet of Things. *International Research Journal of Modernization in Engineering Technology and Science*. https://www.researchgate.net/publication/383043365

[7] Rustam, H., Muneeb, M., Alsuhibany, S., &Ghadi, Y. (2024). Home automation-based health assessment along gesture recognition via inertial sensors. *Air University Research Publication*. https://www.researchgate.net/publication/384665645

[8] Sarkar, S., & Gade, A. (2016). Smart and energy-efficient gesture-controlled home automation. *International Journal of Innovative Science, Engineering & Technology, 3*(4). https://www.ijiset.com

[9] Suryawanshi, P., Singh, Y., &Deokar, S. (2023). A Mediapipe-based hand gesture recognition home automation system. *INCOFT 2023 Conference Proceedings*. https://www.researchgate.net/publication/378420087

[10] Vogiatzidakis, P., & Koutsabasis, P. (2020). Mid-air gesture control of multiple home devices in spatial augmented reality prototype. *Multimodal Technologies and Interaction, 4*(3), 61. https://doi.org/10.3390/mti4030061

[11] Yang.L.L.,Huang.,Feng.J.,T.I.A.N.,Hong-An,W.A.N.G.,Guo-Zhong,D.A.I.(2019).Gesture interaction in virtual reality. Virtual reality & intelligent hardware,1(1),84-112.https://www.researchgate.net/publication/330282934

[12] Park, G., Chandrasegar, V.K & Koh,J (2023). Accuracy enhancement of hand gesture recognition using CNN. IEEE Access,11,26496-26501. https://www.researchgate.net/publication/369137189

[13] Sun, J.H., Ji, T.T., Zhang, S.B., Yang, J.K., & Ji, G.R. (2018, December). Research on the hand gesture recognition based on deep learning. In 2018 12th International symposium on antennas propagation and EM theory (ISAPE) (pp. 1-4). IEEE.

[14] Jo, T.H., Ma, J.H., Cha, S.H., Elderly perception on the internet of things-based integrated smart-home system. Sensors, vol.21, no.4, p.1284, Feb-2021.

[15] Varriale, L., Briganti, P., & Mele, S. (2020). Disability and home automation: insights and challenges within organizational and human challenges (pp. 47-66). Springer international publishing.