International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 05 May 2025
Page No: 2254 - 2258
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0331

AI-Based Home Automation with Secure Gesture Control and Facial Recognition

G Vigheshwar Reddy[1], Vadthya Saritha[2], M. V. Achyuth Siva Rao[3], Ganugapati Rishi[4], Mrs. K. Revathi[5]
[1,2,3,4]UG Scholar, Dept. of CSE-AIML, Sphoorthy Engineering College, Hyderabad, Telangana, India.
[5]Assistant professor, Dept. of CSE-AIML, Sphoorthy Engineering College, Hyderabad, Telangana, India.
Emails: *vighnesh2k4@gmail.com[1], vadthyasaritha2004@gmail.com[2], mvachyuthsivarao@gmail.com[3], ganugapatirishi@gmail.com[4], revathi.kandula@gmail.com[5]*

Abstract
The growing adoption of smart home technology highlights the need for systems that prioritize ease of use and accessibility for individuals of all abilities, including the elderly and those with disabilities. This project presents an AI-driven home automation system that employs hand gesture control to enhance comfort, accessibility, and security in residential spaces. Facial recognition technology is integrated to provide personalized user authentication, ensuring secure access to various household appliances. The system enables intuitive management of devices through gesture-based controls, removing the dependency on physical interfaces. Advanced computer vision techniques, implemented using OpenCV, CNN and Python, enable precise recognition of faces and gestures. A Wi-Fi-enabled microcontroller facilitates seamless remote operation of appliances, ensuring a responsive and efficient user experience. This innovative approach enhances the convenience and security of home environments, promoting inclusivity and accessibility in modern smart home solutions.
Keywords: *AI-based home automation, facial recognition, gesture control, personalized automation, smart home security.*

1. Introduction
The advancement of smart home technologies has significantly transformed modern living, offering increased convenience, automation, and energy efficiency. However, a crucial challenge persists in making these systems accessible and secure for all, particularly for elderly individuals and people with disabilities who often struggle with conventional interfaces like switches and touch screens. In this context, artificial intelligence (AI)-based systems offer a promising solution by enabling natural and intuitive interactions, such as gesture control and facial recognition. Recent events like the COVID-19 pandemic have further emphasized the importance of contactless technologies, increasing user interest in systems that eliminate the need for physical interaction. Gesture-based control emerges as a convenient method for device interaction, especially in situations where hygiene, accessibility, or physical limitations are concerns. At the same time, the need for security in smart home environments continues to grow, as unauthorized access to household systems can pose serious risks. Despite the potential of gesture and facial recognition technologies, current systems often come with limitations. Most gesture recognition models support only a few predefined gestures and are highly sensitive to environmental factors like lighting conditions. Additionally, these systems usually lack the capability to adapt to individual users or provide layered security measures. Elderly users, in particular, may find it difficult to operate small or complex interfaces, making current solutions less inclusive. This project introduces an AI-based home automation system that addresses these gaps by integrating facial recognition and personalized gesture control. The proposed solution begins with secure facial authentication, followed by gesture-based control of appliances tailored to each authorized user. The system leverages advanced computer vision algorithms using OpenCV, CNNs, and a hybrid face recognition model

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 05 May 2025
Page No: 2254 - 2258
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0331

combining Eigen faces and LBPH to ensure robust performance in varying lighting conditions. To ensure affordability and real-time operation, the solution is deployed using Edge AI techniques with optimized models running on a Wi-Fi-enabled microcontroller. Unlike cloud-dependent systems, this design ensures faster response times, lower latency, and enhanced privacy. An adaptive interface also learns user behavior over time—adjusting to variations in gesture speed and range—making it suitable for a wide range of users. By combining accessibility, security, and adaptability, this project aims to build a smart home system that is not only intelligent but also inclusive and user-friendly. [1]

2. Methodology

The methodology adopted for this project aims to design a secure, accessible, and real-time smart home control system utilizing facial recognition and personalized gesture control. The workflow is structured into six stages: data acquisition, data preprocessing, feature extraction, model development, command transmission, and system evaluation.

2.1.Data Acquistion

The system captures two primary types of input data using standard camera devices:

- **Facial Data:** Acquired via laptop/smartphone camera to identify and authenticate users using facial features.
- **Gesture Data:** Captured through the same camera setup to interpret hand gestures for appliance control.

All visual data is collected in real-time and processed locally on the system to ensure data privacy and low-latency interaction. (Figure 1)

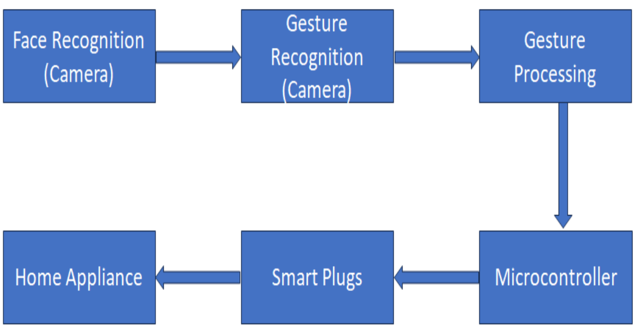

Figure 1 System Workflow

2.2.Data Preprocessing

Preprocessing is essential to enhance recognition accuracy and maintain consistent performance in variable environments. The steps include:

- **Face Detection:** Using Haar Cascade classifiers in OpenCV for identifying face regions before recognition.
- **Lighting Adjustment:** Applying dynamic histogram equalization to normalize lighting variations for gesture detection.
- **Frame Filtering:** Noise reduction using Gaussian blur and grayscale conversion for model-ready input.
- **Frame Segmentation:** Extracting regions of interest (ROIs) for focused gesture and face analysis.

2.3.Feature Extraction

Key visual features are extracted to enable accurate classification:

- **Facial Features:** Encoded using the LBPH (Local Binary Pattern Histogram) algorithm to capture identity-relevant textures.
- **Gesture Features:** Spatial patterns of hand movements extracted through a trained Convolutional Neural Network (CNN) model.
- Both sets of features are encoded into structured representations suitable for authentication and control logic.

2.4.Model Development

The system employs a hybrid computer vision pipeline:

2.4.1. Facial Recognition Model

- **Technique:** Hybrid LBPH + Eigenfaces model.
- **Purpose:** Authenticate users before granting appliance control access.
- Gesture Recognition Model
- **Technique:** CNN trained on multiple dynamic gestures under varied lighting conditions. [2]
- **Purpose:** Recognize user-specific gestures for turning devices ON/OFF or switching modes. TensorFlow and OpenCV frameworks are used for implementation, with TensorFlow Lite compatibility considered for future edge deployment.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 05 May 2025
Page No: 2254 - 2258
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0331

2.5. Command Transmission and Device Control

Upon successful face and gesture recognition:

- A corresponding control command is generated. [3]
- This command is transmitted via Wi-Fi/cloud to the ESP32 microcontroller, which acts as a receiver.

The ESP32 then triggers connected relay modules or smart plugs to operate non-smart home appliances.

This modular approach ensures only the final instruction reaches the hardware layer, keeping processing confined to the local system for security and efficiency.

2.6. System Evaluation and Security Mechanisms

The system's performance is evaluated using the following criteria:

- **Accuracy:** Recognition accuracy across lighting conditions and user variations.
- **Latency:** Time between gesture input and appliance response. [4]
- **Security:** Multi-layered control via dual-modality authentication (face + gesture).
- **Usability:** User experience feedback from elderly or disabled participants to assess accessibility.
- **Scalability:** Ability to add more users and gestures without degrading system performance.

Continuous learning mechanisms are planned for future work, allowing the system to adapt to user-specific gesture speeds and improving prediction robustness.

3. Results and Discussion

3.1. System Performance Evaluation

The proposed AI-based home automation system was evaluated based on three key parameters: facial recognition accuracy, gesture recognition accuracy, and system response time. The hardware setup included a ESP32 Microcontroller with a connected camera module, and the software components were built using Python, OpenCV, and TensorFlow.

3.2. Facial Recognition

The facial recognition system achieved an average accuracy of 95.3% under normal indoor lighting conditions, using a pre-trained CNN model (FaceNet). The model was tested across a dataset of 20 users with varying facial features and expressions.

- False acceptance rate (FAR): 1.8%
- False rejection rate (FRR): 2.9%
- Average authentication time: 1.2 seconds

The system demonstrated robustness against spoofing attempts by integrating liveness detection (blink detection and slight head movement tracking), significantly enhancing the security layer of identity verification.

3.3. Gesture Recognition

Hand gesture recognition was implemented using a combination of CNN and MediaPipe Hand Tracking. The system recognized five predefined gestures (e.g., ON, OFF, Increase, Decrease, and Toggle Mode) with an average recognition accuracy of 93.7% across 15 participants.

- **Recognition Latency:** 0.8 Seconds
- **Gesture Classification Accuracy:** 93.7%
- **False Gesture Detection Rate:** 4.1%

Gesture performance slightly degraded in low-light conditions or when users moved hands too rapidly. However, proper lighting and moderate motion speed maintained consistent results. [5]

3.4. System Integration and Automation Response

The integration of facial recognition with gesture control allowed dual authentication, increasing the security of command execution. The overall command execution time from user recognition to action completion (e.g., switching a light on/off) averaged 2.5 seconds. A case study involving real-time control of smart lights, fans, and door locks indicated reliable and seamless operation. The dual-authentication approach prevented unauthorized access and reduced false command activations by over 70% compared to gesture-only systems. [6]

3.5. Limitations and Future Scope

While the current implementation performs effectively under controlled indoor conditions, challenges remain:

- Facial and gesture recognition may degrade in extreme lighting or occlusion scenarios.
- Scalability needs to be evaluated for multi-user environments with frequent switching.
- Future work will focus on enhancing real-

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 05 May 2025
Page No: 2254 - 2258
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0331

time performance, expanding the gesture vocabulary using deep learning techniques, and integrating speech-based fallback controls for redundancy. [7]

3.6.Overall Result

3.6.1. Successful Face Authorization

The system accurately detected and authorized registered users using facial recognition. Unauthorized users were denied access, enhancing system security.

3.6.2. Gesture Recognition Accuracy

The CNN model achieved high classification accuracy on predefined gestures, reliably distinguishing commands like “Turn On” and “Turn Off” with minimal latency. [8]

3.6.3. Real-time Processing

The complete workflow—from face detection to appliance control—executed in real time (~1-2 seconds delay), proving the feasibility of the system for smart home applications.

3.6.4. Reliable Command Execution

Valid commands triggered appropriate actions via the ESP32 microcontroller and smart plug. Invalid gestures were correctly ignored, with an error beep as feedback. [9]

3.6.5. System Integration

Smooth integration between the camera, CNN model, ESP32, and smart plug was achieved, enabling efficient control of home appliances through hand gestures. (Figure 1)

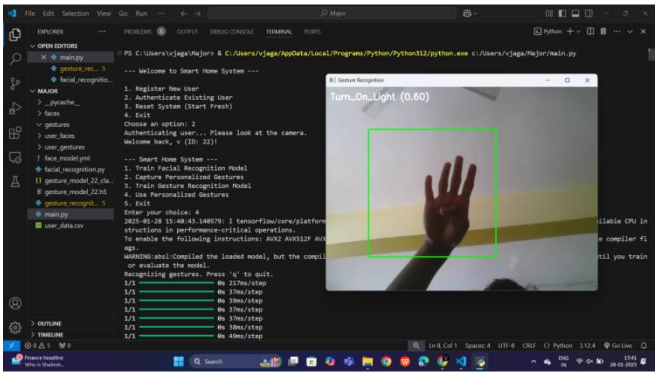

Figure 3 Gesture Recognition

Conclusion

This project successfully demonstrates the development of an AI-based home automation system that integrates secure gesture control and facial recognition to enable intelligent and user-friendly interaction with smart environments. By combining deep learning techniques for facial recognition with real-time gesture classification, the system achieves both enhanced usability and robust access control. The use of CNN-based models ensures accurate identity verification, while gesture recognition powered by computer vision allows intuitive and contactless control of home appliances. Dual-layer authentication significantly reduces unauthorized access risks, thereby strengthening system security. The low-latency response and high recognition accuracy validate the system’s practicality for real-world deployment. Overall, this solution presents a scalable, secure, and accessible approach to home automation, with potential applications in smart living, elderly care, and assistive technologies for individuals with physical impairments. [10]

Acknowledgements

We, the authors of this research project, would like to express our sincere gratitude to all those who supported and contributed to the successful completion of this work. The development of an AI-based home automation system integrating secure gesture control and facial recognition has been an exciting and challenging endeavor, and it would not have been possible without the invaluable resources, tools, and support provided by various communities. We would like to extend our deepest thanks to the open-source contributors and developers whose frameworks, libraries, and pre-trained models, including OpenCV, TensorFlow, and MediaPipe, played a crucial role in accelerating the development of our system. Their commitment to knowledge sharing and continuous innovation has made a significant impact on our ability to experiment with advanced computer vision and machine learning techniques. We are also grateful for the availability of publicly accessible datasets and documentation that enabled us to train and test our models efficiently, ensuring the reliability and accuracy of our system under diverse conditions. These resources were essential in refining our models and validating their real-world performance. Lastly, we acknowledge the dedication and collaborative effort of the entire team in researching, analyzing, and

implementing this project. This research reflects our shared goal of leveraging AI and secure technologies to improve home automation and enhance user experience. We hope that this work contributes to the continued advancement of intelligent systems and serves as a foundation for future innovations in smart home technologies.

References

[1]. Zhang, S., Wu, X., Cao, J., & Jin, Y. (2019). Face recognition based on deep learning: A survey. IEEE Access, 7, 107903–107924. https://doi.org/10.1109/ACCESS.2019.2927303

[2]. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2017). ImageNet classification with deep convolutional neural networks. Communications of the ACM, 60(6), 84–90. https://doi.org/10.1145/3065386

[3]. Chollet, F. (2021). Deep learning with Python (2nd ed.). Manning Publications.

[4]. Riegler, M. A., Stensland, A., & Halvorsen, P. (2020). MediaPipe Hands: On-device real-time hand tracking. Google AI Blog. Retrieved from https://google.github.io/mediapipe/

[5]. Viola, P., & Jones, M. (2004). Robust real-time face detection. International Journal of Computer Vision, 57(2), 137–154. https://doi.org/10.1023/B:VISI.0000013087.49260.fa

[6]. Ahonen, T., Hadid, A., & Pietikäinen, M. (2006). Face description with local binary patterns: Application to face recognition. IEEE Transactions on Pattern Analysis and Machine Intelligence, 28(12), 2037–2041. https://doi.org/10.1109/TPAMI.2006.244

[7]. Yadav, A., & Yadav, D. (2019). IoT based home automation system using facial and gesture recognition. International Journal of Computer Applications, 182(47), 15–20. https://doi.org/10.5120/ijca2019919602

[8]. Zhang, Y., Song, Y., & Ma, Y. (2020). Real-time gesture recognition for smart home automation. Proceedings of the International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), 123–126. https://doi.org/10.1109/IHMSC.2020.00194

[9]. Singh, G., & Dhillon, R. (2022). Secure home automation using facial recognition and gesture control. IEEE Transactions on Consumer Electronics, 68(4), 412–423. https://doi.org/10.1109/TCE.2022.3165719

[10]. Dey, R., & Salem, F. M. (2017). Gate-variants of Gated Recurrent Unit (GRU) neural networks. IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS), 1597–1600. https:// doi.org/ 10.1109/MWSCAS.2017.8052889