RESEARCH ARTICLE

Check for updates

IoT-based Smart Home Automation Using Gesture Control and Machine Learning for Individuals with Auditory Challenges

Baleegha Fatima[1], **Bilal Mushtaq**[1,*], **Muhammad Ammar Iqbal**[1] **and Abbas Ahmed**[1]

[1] Beaconhouse International College, Islamabad, Pakistan

Abstract

This paper reviews advancements in assistive technology for deaf and hard of hearing individuals, highlighting the Internet of Things' (IoTs) pivotal role in enhancing their daily lives. Despite progress in sign language technologies, communication barriers persist. To address these gaps, we developed a video-based American Sign Language (ASL) identification system. Our approach utilizes MediaPipe for hand tracking, OpenCV for image normalization, and Gesture Control Convolutional Neural Network (CNN) for gesture localization. Implemented in Python, the system records video streams, filters hand regions, and recognizes ASL letter gestures with high accuracy. Leveraging computer vision and machine learning, our system enhances user experience, breaks communication barriers, promotes inclusivity, and supports accessible technologies. This innovative solution empowers deaf and hard of hearing individuals to fully participate in their communities, contributing to a more inclusive and accessible environment.

Keywords: convolutional neural networks, sign language, artificial intelligence, machine learning, American sign language, image processing, internet of things, home automation.

1 Introduction

Gestures are a fundamental component of human communication, facilitating the conveyance of critical information through coordinated movements of the hands, fingers, and arms [1–4]. For individuals who rely on sign language, gesture-based interaction transcends mere communication; it embodies empowerment, accessibility, and independence [5]. As smart home technology evolves, the integration of gesture recognition has emerged as a promising approach for enhancing user-device interaction, particularly for individuals with physical disabilities or restricted mobility [9–11].

However, existing gesture recognition systems face significant challenges that limit their effectiveness, including issues with accuracy, sensitivity to lighting conditions, and inadequate representation of diverse data sets [6, 7]. Vision-based hand gesture recognition, a focus of this study, must address these challenges to achieve reliable and practical

Academic Editor:
Jinchao Chen

Submitted: 02 September 2024
Accepted: 04 November 2024
Published: 19 November 2024

Vol. 2, **No.** 4, 2024.
10.62762/TIOT.2024.723193

***Corresponding author:**
Bilal Mushtaq
bilal.mushtaq@bic.edu.pk

Citation
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.

real-world applications [8]. To this end, this research investigates the use of a Convolutional Neural Network (CNN)-based framework for recognizing American Sign Language (ASL) gestures, leveraging the integration of computer vision techniques with Arduino-UNO microcontrollers to enable robust home automation. This approach seeks to improve user-device interaction and foster inclusivity [12, 24].

Historically, the field of human-computer interaction has employed two primary methods for gesture recognition: data gloves and vision-based techniques. While data gloves offer precise tracking through embedded sensors, they come with drawbacks such as user discomfort and high costs, limiting their practical adoption [13, 14]. Vision-based methods, by contrast, provide a non-invasive, cost-effective solution by utilizing 2D cameras to capture and analyze hand movements [25]. This study harnesses advanced computer vision techniques—including hand segmentation, part detection, and motion tracking—to achieve effective gesture classification [14, 26]. The application of CNNs facilitates enhanced image processing and feature extraction, essential for maintaining recognition accuracy under variable conditions [27].

The development of smart home technology has a rich history, with noteworthy advancements like ECHO IV and the Kitchen Computer marking the first steps in this field [15–17]. The 2000s witnessed the emergence of more affordable smart home solutions, designed to optimize utility and privacy through sophisticated security mechanisms operating at specific frequencies [18, 19]. These innovations were particularly beneficial for individuals with disabilities or limited mobility [20–23]. Figure 1 illustrates the key developments in communication, gesture-based inputs, human-computer interaction systems, and smart home technology.

The history of the modern smart home concept, where integrated household appliances became central to domestic life, reflects the trends in technological advancement within 20th-century society [28]. This paper explores the latest advancements in hand gesture recognition systems for home automation, with a particular focus on integrating gesture recognition technologies with home automation solutions [29]. The system can infer the gestures being performed by employing a hand landmarks model to track key points on the hand. Our approach to real-time hand gesture recognition exemplifies the application of advanced machine learning and human-computer interaction, enabling users to intuitively control devices and systems [30]. Such a system has the potential to revolutionize domestic technology interactions, making them more accessible and user-friendly for applications including home automation, accessibility enhancement, elderly care, and emergency response [31, 32].

Furthermore, future advancements in technology are anticipated to facilitate further improvements in user experience and the development of new applications. This project aims to create a real-time hand gesture recognition system for ASL and interface it with home automation systems. The ultimate goal is to design a simple yet effective communication interface for individuals with hearing loss, improving the coordination and efficiency of home automation systems [12–16].

The paper consists of Section 2, where research contributes to global sustainability initiatives by enhancing home automation through IoT and hand gesture recognition technologies. By improving accessibility and user interaction, the system aligns with Industry, Innovation, and Infrastructure, advancing sustainable technological solutions for everyday life. In Section 3, we describe the methodology of our research, while in Section 4, we analyse our simulation results followed by our conclusions in Section 5.

2 Research Objective

The primary objective of this study is to bridge the gap between gesture-based communication and practical implementation by developing an efficient, real-time American Sign Language (ASL) recognition system, leveraging computer vision and machine learning frameworks to facilitate improved communication and inclusive technology. This research makes significant contributions to the field:

- Landmark Detection: Utilizing MediaPipe and OpenCV in Python for accurate hand landmark detection.
- Real-Time ASL Gesture Recognition: Optimized algorithms for enhanced accuracy and responsiveness.
- Hardware Implementation: Arduino-UNO microcontroller-based interface for real-life applications, aiding individuals with special needs.

- **Prehistoric Era:**
  - In early human history, communication was vital for survival, and before the development of spoken languages, people relied on non-verbal methods like gestures, facial expressions, and body movements. These non-verbal cues were essential for hunting, gathering, and social interactions (Smith, 2011).
- **Ancient Civilizations (circa 3000 BCE – 500 CE):**
  - Ancient cultures, such as those in Egypt, began using pictograms and hieroglyphs as early forms of written communication, which laid the foundation for more complex systems of expression (Johnson & Cross, 2015).
  - Additionally, in certain societies, gestures played an important role in rituals and settings where speaking was difficult or impossible (Lee, 2018).
- **Middle Ages (500 CE – 1500 CE):**
  - Monks developed silent gesture systems for communication during vows of silence (Davis, 2007).
  - Rudimentary sign systems emerged for non-verbal interaction (Harris, 2012).
- **17th-18th Century:**
  - Juan Pablo Bonet's 1620 manual alphabet for teaching speech to the deaf (Bonet, 1620).
  - John Bulwer's *Chirologia* (1644) explored hand gestures in communication (Bulwer, 1644).
- **19th Century:**
  - Emergence of formal sign languages like American Sign Language (ASL) (Lane, 1984).
  - Initial exploration into gesture-based accessibility (Murray, 1891).
- **Early 20th Century (1900s-1950s):**
  - Development of basic assistive technologies such as hearing aids (Jones, 1953).
  - Introduction of simple home automation tools (Kline, 2000).
- **1960s-1970s:**
  - *ECHO IV* (1966): Early home automation system (Sullivan, 1966).
  - *Kitchen Computer* (1969): Attempt to integrate technology into the home (McCarthy, 1970).
  - Research in gesture recognition using early computer vision (Reid, 1978).
- **1980s:**
  - Development of data gloves, such as the DataGlove, enhancing human-computer interaction (Zimmerman et al., 1987).
  - Advancements in AI supported improved gesture recognition (Nilsson, 1984).
- **1990s:**
  - Progress in gesture interfaces for virtual reality and interactive systems (Pavlovic et al., 1997).
  - Enhanced computer vision for reliable hand gesture recognition (Huang & Brady, 1999).
- **2000s:**
  - Expansion of smart home technologies, aiding people with disabilities (Harper, 2003).
  - Introduction of touchscreen technology for gesture-based device interaction (Westerman, 2007).
- **2010s:**
  - CNNs improved gesture recognition for home automation (LeCun et al., 2015).
  - Gesture control became standard in consumer electronics (Anderson, 2012).
  - IoT-based automation allowed for connected, gesture-controlled homes (Atzori et al., 2010).
- **2020s:**
  - Integration of machine learning and IoT for adaptive systems (Goodfellow et al., 2020).
  - Real-time gesture recognition with microcontrollers like Arduino-UNO (Zhang et al., 2022).
  - AI-powered assistive tools for enhanced gesture detection and automation (Chen et al., 2021).

Figure 1. Timeline of Key Developments in Communication, Gesture-Based Interaction, and Smart Home Technology.

This work enhances human-computer interaction, expands smart technology accessibility, and supports communities by providing a reliable, user-friendly communication method. Aligning with global sustainability initiatives, this research contributes to:

- Infrastructural development (SDG 9)
- Inclusive urban environments (SDG 11)

Furthermore, this paper presents a novel system for real-time recognition of hand gestures in American Sign Language (ASL), combining cutting-edge machine learning techniques with practical hardware implementation. Meanwhile, this project aims to advance human-computer interaction by developing a real-time ASL recognition system integrated with hardware that can be utilized in practical, everyday settings. By focusing on inclusivity and accessibility, this research contributes to a more equitable technological landscape, reinforcing the infrastructure needed for sustainable development and supportive communities.

3 Methodology

Gestures play an integral role in human communication and interaction, with their absence presenting significant challenges in daily life. To address this, we have developed an advanced system that recognizes hand gestures utilizing OpenCV, Python, and the MediaPipe framework. This system captures and processes images of the user's hand gestures in real-time through a camera, enabling immediate analysis. The recognized gestures are then used to control various home appliances, such as fans and lights, through an Arduino-UNO module, which acts as the system's central control unit.

Vision-based systems for hand tracking, while popular, often face limitations such as restricted movement areas and difficulty handling scenarios where hands overlap or are partially occluded. However, as illustrated in Figure 2, the proposed gesture recognition system overcomes these challenges by detecting real-time hand movements in multiple directions. By leveraging color and depth data, the system effectively segments the hand, focusing on the palm, wrist, and fingers, while excluding the arm and wrist to eliminate redundant information. The system analyzes key features—including finger positions, heights, and distances from the hand's center—to accurately extract and identify critical gesture components.

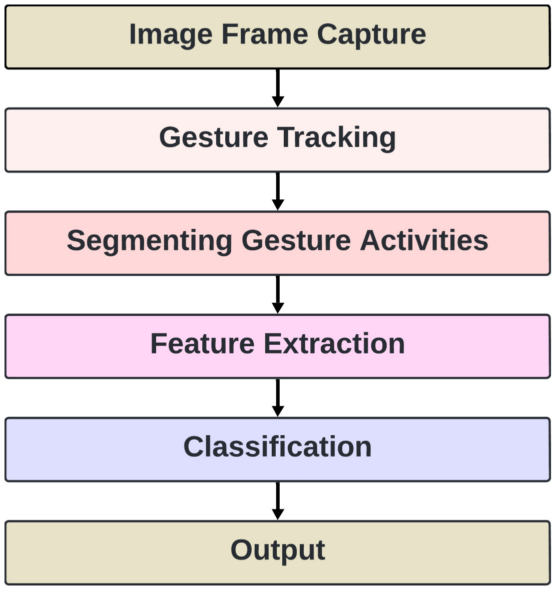

Figure 2. Frame Capture to Output Sequence.

The hand gesture recognition process, illustrated in Figure 2, commences with frame capture, where images are acquired from a video feed to provide raw input for further processing. Next, the tracking phase monitors object position and movement within each frame, enabling spatial and temporal analysis. The system then isolates hand gestures and relevant objects from the captured images, followed by feature extraction to identify key characteristics such as gesture shape, motion dynamics, and contextual relevance. These extracted features are subsequently classified into predefined categories based on established algorithms and classification rules. Finally, the recognized gestures are displayed as graphical displays, text, or control commands, completing the process.

The hand gesture recognition process initiates with hand detection within the image through camera as indicated in Step 1 of Figure 3, followed by refinement of the hand region to enhance accuracy. This process is known as pre-processing as shown in Step 2 of Figure 3. Subsequently, feature extraction and mapping are performed, correlating the identified features with a gesture dictionary for classification as indicated in Step 3 of Figure 3. This method helps to classified as Gesture leading to data extraction. Upon successful gesture identification, the extracted features are processed, and the system interfaces with the Arduino UNO board using the 'pyfirmata library'. This integration enables seamless translation of recognized gestures into control actions, as illustrated in Step 4 and Step 5 of Figure 3 respectively.

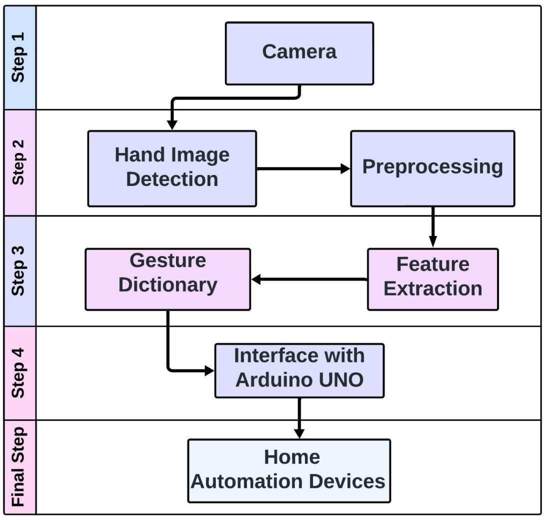

Figure 3. Gesture Recognition and Automation Execution.

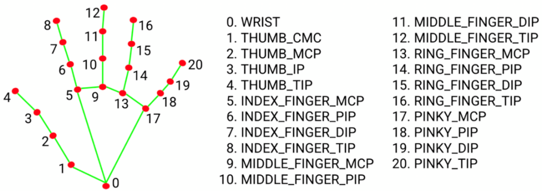

Figure 4. Hand Landmark Model.

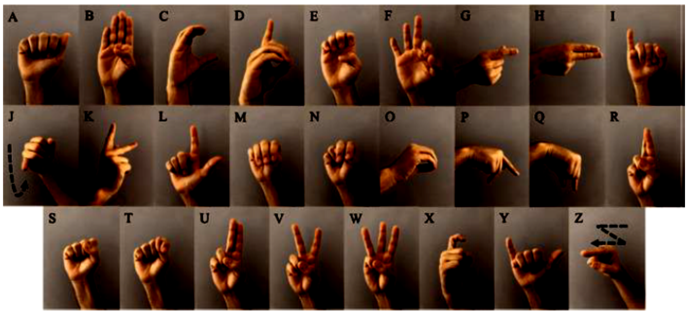

Figure 5. American Sign Language (ASL) Gestures.

The Hand Landmarks model accurately estimates 21 coordinate points corresponding to hand landmarks, including finger joints, knuckles, palm center, and wrist. These coordinates facilitate precise tracking and analysis of minor hand motions and positions, providing the foundation for image and gesture recognition as indicated in Figure 4. Moreover, in video or live streaming mode, the Hand Landmarker leverages tracked palms from previous frames, utilizing the landmarks model's bounding box to identify hands in subsequent frames. This approach optimizes performance by reducing palm detection workload. Palm detection reactivates only when the landmarks model fails to detect or recognize a hand.

To achieve real-time video compression and processing, the system utilizes MediaPipe, enabling concurrent execution of multiple tasks. MediaPipe's bounding box approach streamlines hand tracking, reducing palm detection model activations and enhancing efficiency. The processing pipeline optimizes RGB image sequence capture, focusing on temporal dynamics of hand movements rather than individual frame processing. A hierarchical neural network architecture then facilitates hand gesture recognition. Initially, a Hand Detection Neural Network (HDNN) segments the hand from the background and isolates it from the body. Next, a Convolutional Neural Network (CNN) analyzes anatomical regions, such as the palm curve, knuckles, and fingertips, extracting spatial features that define hand shape. Finally, a Feed Forward Neural Network (FFNN) classifies hand gestures based on learned representations. This multi-stage architecture enables recognition of complex gestures, enhancing real-time hand movement understanding and categorization.

4 Results

The activation of specific gestures, such as those representing 'A', 'B', and 'C', enables real-time control of system functions, as demonstrated in Figure 5. Specifically, American Sign Language (ASL) gestures for 'A', 'B', and 'C' can be mapped to customizable actions, including turning on/off a light bulb, controlling a servo motor for door mechanisms, or triggering other automated tasks. This gesture-based interface enhances accessibility and interaction with smart devices, providing an intuitive and efficient way to control various system functions.

Figure 6 showcases the hand signal 'A', which functions as a trigger for operating a standard white light. When detected by the camera, this specific gesture instantly activates the light, demonstrating the system's real-time responsiveness and intuitive gesture-based interface.

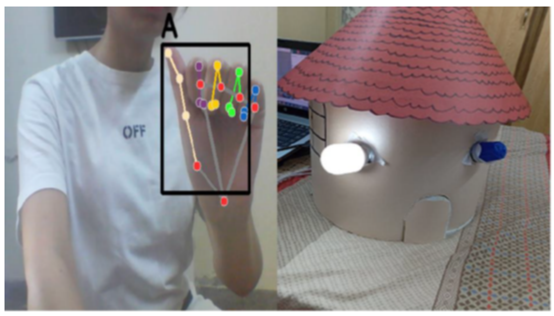

Figure 6. ASL Gesture 'A' and white bulb.

Figure 7 demonstrates the system's ability to perform multi-stage tasks using American Sign Language

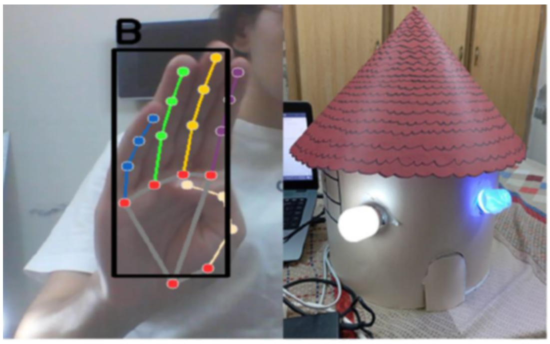

Figure 7. ASL Gesture 'B' both white and blue bulbs.

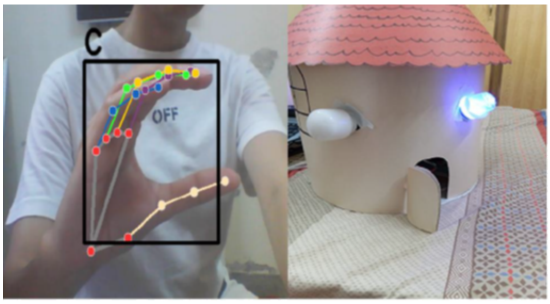

Figure 8. ASL Gesture "C" makes white bulb off.

(ASL) hand motions. Specifically, the figure illustrates the process of identifying, recognizing, and subsequently switching on the lights. To activate two lights, a distinct hand motion labeled 'B' is required. The system's integrated camera detects this gesture and responds accordingly, seamlessly controlling both white and blue lights.

Figure 8 illustrates the system's ability to execute multi-stage tasks using American Sign Language (ASL) hand gestures. Specifically, the hand gesture labeled 'C' triggers the system to turn off the lights, leveraging the integrated camera's detection of white light. This seamless interaction demonstrates the system's capability to recognize and respond to distinct ASL gestures, enabling intuitive control over lighting.

Figure 9 demonstrates the system's robustness in recognizing hand gestures under diverse lighting conditions, including low-light scenarios with varied light sources. Testing revealed excellent detection and tracking capabilities for multiple hands, regardless of direction or orientation. This

Figure 9. Dynamics Hand Gesture.

Table 1. Probability of Gesture Detection in Multiple Lighting Conditions.

Lightning Condition	Low	Medium	High
N(A)	1870	2024	2134
N(S)	2200	2200	2200
P = N(A)/N(S)	0.80	0.92	0.97

Table 2. Probability of Gesture Detection with Different Distances.

Varying Distance	1-meter	2-meter	4-meter
N(A)	2090	1958	1846
N(S)	2200	2200	2200
P = N(A)/N(S)	0.95	0.89	0.84

enables seamless interaction with multiple users and accurate interpretation of complex hand movements requiring inter-hand coordination. The evaluation also confirmed the system's versatility in recognizing hand gestures in various positions, including relaxed and raised hands, further underscoring its reliability and adaptability.

Moreover, the system produced favorable results under various lighting conditions, maintaining proper functionality even with reduced light levels. Additionally, the system's performance remained consistent despite changes in the distance between the hand and the camera. The probability of gestural detection was assessed using Tables 1 and 2 under various asymmetric lighting conditions.

The gesture control automation system seamlessly interfaces with hardware components through an Arduino UNO microcontroller connected to the laptop via COM4. The Arduino regulates a relay module and servo motor, executing commands based on recognized hand gestures. Specifically, the servo motor, connected to one of the Arduino's digital pins, adjusts its angle in response to specific gestures , as indicated in Figure 10. Additionally, a four-channel relay module manages the power supply to two low-power LED bulbs, activating them according to software commands.

The system's hardware components share a common ground (GND) and are powered by the microcontroller's 5V supply rail, ensuring reliable interaction between software and hardware. This integrated setup enables the gesture control system to provide visual indicators through the LED bulbs, lighting up in response to particular gesture movements.

Table 3. Comparison Table for Gesture Detection Efficiency.

Lightning Condition	Distance(m)	[2]	[3]	[4]	[6]	[13]	My Work
Low Light Efficiency	<1	0.84	0.88	0.93	0.80	0.91	0.93
	1<4	0.83	0.86	0.89	0.78	0.88	0.91
	4<8	0.83	0.85	0.86	0.85	0.85	0.87
	9<13	0.78	0.81	0.75	0.72	0.78	0.81
Medium Light Efficiency	<1	0.87	0.90	0.94	0.84	0.93	0.95
	1<4	0.85	0.87	0.91	0.80	0.89	0.93
	4<8	0.81	0.83	0.88	0.77	0.87	0.90
	9<13	0.74	0.80	0.87	0.74	0.85	0.86
High Light Efficiency	<1	0.87	0.91	0.94	0.87	0.94	0.98
	1<4	0.83	0.89	0.90	0.85	0.92	0.95
	4<8	0.79	0.88	0.88	0.82	0.88	0.91
	9<13	0.76	0.84	0.86	0.79	0.86	0.89

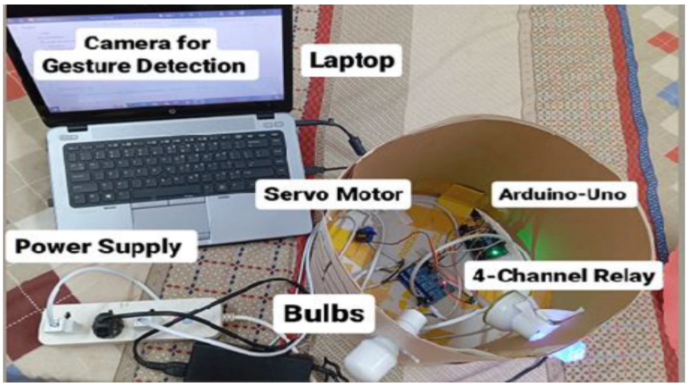

Figure 10. Hardware Design Interfacing.

Table 3 provides a comparison of our simulation results for system performance as a function of distance under varying lighting conditions. The results indicate that our designed system maintains high performance across different distances and lighting environments. Specifically, the system achieves a maximum accuracy of up to 98% in high-light conditions, while the lowest accuracy, around 81%, is observed under minimal lighting. Additionally, the system's efficiency improves with increased distance, provided the algorithm operates effectively, enabling rapid detection and optimal performance.

5 Conclusion

In this work revolutionizes home automation by converging IoT platforms with hand gesture recognition technology. Leveraging IoT protocols like MQTT or CoAP, this innovative system seamlessly integrates with mobile phones and voice assistants, enabling users to control household devices via mobile apps. At its core, the advanced gesture recognition system utilizes a hand landmarks tracking model, allowing intuitive device control through simple camera-captured gestures.

The Arduino-UNO microcontroller and relays activate gesture-controlled devices, such as lights, kitchen appliances, and door servos. This pioneering approach significantly enhances user engagement, optimizing home automation benefits. Moreover, the system's capabilities extend to enhancing accessibility for people with disabilities, supporting elderly care, and responding to emergencies.

This integration of human-computer interaction and home technology marks substantial progress, paving the way for a more inclusive, convenient, and connected living experience. By merging cutting-edge technologies, his work demonstrates the vast potential for innovation in smart home automation, transforming the way we interact with our living spaces.

Conflicts of Interest

The authors declare no conflicts of interest.

Funding

This work was supported without any funding.

References

[1] Yang, L. I., Huang, J., Feng, 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. [CrossRef]

[2] Kheratkar, N., Bhavani, S., Jarali, A., Pathak, A., & Kumbhar, S. (2020, May). Gesture controlled home automation using CNN. In *2020 4th International*

Conference on Intelligent Computing and Control Systems (ICICCS) (pp. 620-626). IEEE. [CrossRef]

[3] Tomar, D., Nauni, D., Zaidi, A. M., & Kaur, M. (2023, November). Gesture-Controlled Home Automation for the Differently Abled: Enhanced Accessibility and Independence. In *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)* (pp. 1560-1564). IEEE. [CrossRef]

[4] Okokpujie, K., Jacinth, D., James, G. A., Okokpujie, I. P., & Vincent, A. A. (2023). An IoT-based multimodal real-time home control system for the physically challenged: Design and implementation. *Inf. Dyn. Appl*, 2(2), 90-100.

[5] Kurian, B., Regi, J., John, D., Hari, P., & Mahesh, T. Y. (2023, May). Visual Gesture-Based Home Automation. In *2023 3rd International Conference on Advances in Computing, Communication, Embedded and Secure Systems (ACCESS)* (pp. 286-290). IEEE. [CrossRef]

[6] Yang, Y. (2016). *Gesture controlled user interface for elderly people* (Master's thesis, Oslo and Akershus University College of Applied Sciences).

[7] Davis, J., & Shah, M. (1994). Recognizing hand gestures. In *Computer Vision—ECCV'94: Third European Conference on Computer Vision Stockholm, Sweden, May 2–6, 1994 Proceedings, Volume I 3* (pp. 331-340). Springer Berlin Heidelberg.

[8] Wu, Y., & Huang, T. S. (2001). Hand modeling, analysis and recognition. *IEEE Signal Processing Magazine*, 18(3), 51-60. [CrossRef]

[9] Park, G., Chandrasegar, V. K., & Koh, J. (2023). Accuracy enhancement of hand gesture recognition using CNN. IEEE Access, 11, 26496-26501. [CrossRef]

[10] 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. [CrossRef]

[11] Licsár, A., & Szirányi, T. (2004, August). Dynamic training of hand gesture recognition system. In *Proceedings of the 17th International Conference on Pattern Recognition, 2004. ICPR 2004.* (Vol. 4, pp. 971-974). IEEE. [CrossRef]

[12] Hendricks, D. (2014). The history of smart homes. *IoT Evolution World*.

[13] Varriale, L., Briganti, P., & Mele, S. (2020). Disability and home automation: insights and challenges within organizational settings. In *Exploring Digital Ecosystems: Organizational and Human Challenges* (pp. 47-66). Springer International Publishing.

[14] Mushtaq, B., Rehman, M. A., Hussain, A., & Abbass, M. J. (2023, March). A highly selective dual bandpass filter using couple line resonator for modern wireless communication systems. In *2023 4th International Conference on Computing, Mathematics and Engineering Technologies (iCoMET)* (pp. 1-5). IEEE.[CrossRef]

[15] Asadullah, M., & Raza, A. (2016, November). An overview of home automation systems. In *2016 2nd international conference on robotics and artificial intelligence (ICRAI)* (pp. 27-31). IEEE. [CrossRef]

[16] Mushtaq, B., Rehman, M. A., Khalid, S., & Alhaisoni, M. (2023). Design of Tri-Band Bandpass Filter Using Modified X-Shaped Structure for IoT-Based Wireless Applications. *IEEE Embedded Systems Letters*, 16(2), 194-197. [CrossRef]

[17] Kim, Y., & Toomajian, B. (2016). Hand gesture recognition using micro-Doppler signatures with convolutional neural network. *IEEE Access*, 4, 7125-7130. [CrossRef]

[18] Abdul Rehman, M., Khalid, S., Mushtaq, B., & Idrees, M. (2022). Design of a novel compact highly selective wideband bandstop RF filter using dual path lossy resonator for next generation applications. *Plos one*, 17(10), e0273514. [CrossRef]

[19] Katre, S. R., & Rojatkar, D. V. (2017). Home automation: past, present and future. *International research journal of engineering and technology*, 4(10), 343-346.

[20] Ahmed, A., Botsinis, P., Won, S., Yang, L. L., & Hanzo, L. (2018). EXIT Chart Aided Convergence Analysis of Recursive Soft $ m $-Sequence Initial Acquisition in Nakagami-m Fading Channels. *IEEE Transactions on Vehicular Technology*, 67(5), 4655-4660. [CrossRef]

[21] Ahmed, A. (2019). *Iterative initial synchronization in wireless communications* (Doctoral dissertation, University of Southampton).

[22] Mushtaq, B., & Khalid, S. (2023). Design of miniaturized single and dual-band bandpass filters using diamond-shaped coupled line resonator for next-generation wireless systems. *International Journal of Microwave and Wireless Technologies*, 15(3), 375-383.[CrossRef]

[23] Mushtaq, B., Khalid, S., & Rehman, M. A. (2022). Design of a compact novel stub loaded pentaband bandpass filter for next generation wireless RF front ends. *IEEE Access*, 10, 109919-109924. [CrossRef]

[24] Ahmed, A., Ahmed, Q. Z., Almogren, A., Haider, S. K., & Rehman, A. U. (2021). Hybrid precoding aided fast frequency-hopping for millimeter-wave Communication. *IEEE Access*, 9, 149596-149608. [CrossRef]

[25] UN DESA. 2023. *The Sustainable Development Goals Report 2023: Special Edition*. New York, USA: UN DESA. © UN DESA. [CrossRef]

[26] Khokher, A., Mushtaq, B., Rehman, M. A., & Abbas, M. J. (2024). RF Planning And Optimization Of 5G On The City Campus (MUST) of Mirpur, Pakistan. IECE Transactions on Sensing, Communication, and Control, 1(1), 52-59.[CrossRef]

[27] Rehman, M. A., Mushtaq, B., Khalid, S., & Iqbal, J. (2023, August). Design and Analysis of Broadband Bandstop Filter using Dual Path Capacitive Coupled

Resonator for 4G and 5G Applications. In *2023 20th International Bhurban Conference on Applied Sciences and Technology (IBCAST)* (pp. 385-392). IEEE.[CrossRef]

[28] Idrees, M., Mushtaq, B., Rehman, M. A., Khalid, S., & Iqbal, J. (2023, August). Design of a Planar Four-Port Microstrip Triplexer using Stub-Loaded Coupled Line Resonator for Advanced Wireless Applications. In *2023 20th International Bhurban Conference on Applied Sciences and Technology (IBCAST)* (pp. 398-403). IEEE.[CrossRef]

[29] Rehman, M. A., Mushtaq, B., Khalid, S., & Rehman, M. U. (2024). Design of a miniaturized multi resonance resonator based highly selective dual wideband bandpass filter. *Microelectronics Journal*, 153, 106411. [CrossRef]

[30] Idrees, M., Khalid, S., Abdulrehman, M., Mushtaq, B., Najam, A. I., & Alhaisoni, M. (2023). Design of a stub-loaded coupled line diplexer for IoT-based applications. *IEEE Embedded Systems Letters*, 16(2), 186-189. [CrossRef]

[31] Abdul Rehman, M., Khalid, S., Mushtaq, B., Uddin, M., Iqbal, J., Abdelhaq, M., & Alsaqour, R. (2023). A Novel Synthesis of Quasi-Chebyshev Ultra-Wideband Bandpass Filter Using N th Order Stub Loaded Coupled-Line Resonator. *Micromachines*, 14(10), 1874. [CrossRef]

[32] Rehman, A., Rahman, M. A., Aziz, N., Mushtaq, B., Abbass, M. J., Khalid, S., & Jan, A. Z. (2022). Design of Highly Selective Dual Band Band Stop Filter using Dual-Path Step Impedance Resonator. *Pakistan Journal of Engineering and Technology*, 5(2), 146-151. [CrossRef]

Baleegha Fatima is doing BEng (Hons) in Electrical and Electronics Engineering From Beaconhouse international college, Islamabad, Pakistan. (Email:baleegha.8197@bic.edu.pk)

Bilal Mushtaq (Associate Editor, IECE) Has done his PhD in electrical engineering from Riphah Internatial university, Islamabad Pakistan. He is currently serving in the capacity of lecturer in Beaconhouse internatial College, Islamabad Pakistan. (Email: bilal.mushtaq@bic.edu.pk)

Muhammad Ammar Iqbal has received MS in Electrical Engineering from National University of Science and Technology (SEECS School of Electrical Engineering and Computer Science). He is Currently working as a Lab Engineer Electrical and Electronics Engineering Department of Beaconhouse International College. (Email: Muhammad.ammar.98330@bic.edu.pk)

Abbas Ahmedhas received a PhD. degree in Electrical and Electronic Engineering from University of Southampton, UK in 2019. He has also done two posts as a doc from the University of Huddersfield and University of Leeds, UK. He is currently working as a program head in electrical and electronics engineering department of Beaconhouse international college Islamabad. (Email: Abbas.ahmed@bic.edu.pk)