Real-Time Vision-Based Hand Gesture Recognition System for Multi-Functional Contactless Control of Digital Applications

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doi: https://doi.org/10.21467/proceedings.7.6.16

Abstract

Hand gesture recognition emerged as a significant advancement in enabling intuitive and contactless human-computer interaction. This study presented the design and implementation of a real-time, multi-functional hand gesture control system capable of managing digital tasks such as volume adjustment, media playback, scrolling, tab switching, slide navigation, and AI-powered mathematical problem solving. The primary objective was to develop a seamless interaction system that operated without the need for physical input devices, thereby enhancing accessibility and user convenience across various use cases. The system utilized computer vision and machine learning techniques, incorporating the MediaPipe framework for 3D hand landmark detection and OpenCV for real-time video processing. Spatial features such as distances between landmarks, angles at finger joints, and motion vectors were extracted and used to classify gestures through trained machine learning models. The solution was implemented with hardware independence in mind, requiring only a standard webcam, and featured a user-friendly graphical interface built with PyQt5. An AI calculator module was also integrated using backend processing for gesture-based mathematical interpretation. The system was tested under diverse conditions to evaluate accuracy, responsiveness, and robustness. Experimental results showed a gesture recognition accuracy of approximately 95%, with low latency and consistent real-time performance. Functional demonstrations confirmed the effectiveness of the system in controlling multiple applications, highlighting its adaptability to different environments and use scenarios. In conclusion, the developed system offered a reliable, accessible, and scalable alternative to conventional input methods. It proved suitable for smart environments, assistive technologies, and hands-free digital control. Future developments may explore extended gesture sets, real-time customization, and integration with edge devices or multimodal systems for enhanced interaction capabilities.

Keywords: Gesture Control, Computer Vision, Hand Gesture Recognition.

1 INTRODUCTION

Advancements in human-computer interaction (HCI) technologies have increasingly prioritized contactless and intuitive control mechanisms to improve user experience, accessibility, and hygiene. Traditional input methods—such as keyboards, mice, and touchscreens—while widely used, present limitations in environments where physical contact is undesirable or impractical, such as in healthcare settings, public terminals, or assistive applications. Gesture recognition has emerged as a promising alternative, enabling users to control digital interfaces through natural hand movements without direct contact. This approach supports more seamless, hygienic, and accessible interaction, making it valuable in smart homes, wearable technologies, and human-assistive devices. Current gesture recognition systems, however, often rely on specialized hardware like Kinect or Leap Motion, which increases cost and limits scalability. Additionally, many of these systems support only static or limited gestures, lack robustness in dynamic real-world environments, and require substantial computational resources or large labeled datasets for effective performance. These limitations create a significant gap in the availability of affordable, real-time, and hardware-independent gesture-based control systems that can function reliably across diverse environments. There remains a need for gesture recognition solutions that not only provide accurate real-time interaction but also support multiple functions within a unified and flexible framework. To bridge this gap, the present study proposes a comprehensive, real-time hand gesture recognition system that enables multi-functional control of digital tasks—such as volume adjustment, scrolling, video playback, tab switching, and mathematical operations—using only a standard webcam. The system leverages the MediaPipe framework for accurate hand tracking and OpenCV for efficient image processing. Designed to be cost-effective, hardware-independent, and adaptable to varying conditions, this approach aims to deliver a robust, scalable solution for modern contactless human-computer interaction.

2 RELATED WORK

Hand gesture recognition has seen rapid development in recent years, with research exploring both traditional machine learning and advanced deep learning techniques. Makant [1] presented compact deep learning models focused on optimizing efficiency while maintaining performance in real-time applications, addressing the need for low-power, embedded systems. Roy et al. [2] provided a comprehensive review of machine learning-based gesture recognition, showing a clear evolution from earlier methods such as Hidden Markov Models to modern

Proceedings DOI: 10.21467/proceedings.7.6; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-989164-9-5

Convolutional Neural Networks (CNNs), which have significantly enhanced recognition accuracy and robustness. Expanding on this, Gupta and Singh [3] utilized transfer learning to reduce data dependency during training, thereby enabling gesture recognition on resource-constrained platforms.

To address the temporal nature of dynamic gestures, Zhao et al. [4] introduced a framework that captured sequential movement for improved real-time performance in human-machine interaction. Similarly, Brown and Kumar [5] incorporated 3D Convolutional Neural Networks for sign language recognition, emphasizing the value of spatiotemporal features. Chawla and Gupta [6] examined gesture recognition in smart home environments, highlighting challenges such as user variability and environmental interference. Their work underscored the need for adaptive recognition algorithms. Patel [7] proposed a multimodal approach using sensor fusion, combining visual and inertial data to improve performance in noisy conditions. Li and Chen [8] advanced the field by applying self-supervised learning, reducing the need for labeled data and enhancing generalizability. Kim and Park [9] explored transformer-based models, demonstrating their capacity to capture long-range dependencies in continuous gesture sequences. In augmented reality contexts, Lee et al. [10] showed that gesture detection could support immersive and intuitive interaction. Further, Chowdhury and Tiwari [11] focused on embedded neural networks for gesture control in IoT devices, enabling efficient processing on low-power hardware. Rajan and Dutta [12] reviewed wearable gesture systems, identifying key challenges in comfort, power, and precision. Addressing data privacy concerns, Zhang and Liu [13] introduced federated learning, allowing model training across decentralized devices without sharing sensitive user data. These studies demonstrate substantial progress in gesture recognition technologies. However, gaps remain in integrating multi-functionality, ensuring robustness across conditions, and minimizing hardware requirements—gaps that the present study aims to address with a real-time, hardware-independent solution.

Table 1. Comparative Analysis of Existing Gesture Recognition Systems and the Proposed System

Feature	Existing systems	Proposed system
Real-Time Processing	Limited or moderate real-time performance due to computational overhead.	Achieves seamless real-time gesture recognition through optimized models.
Flexibility	Often supports predefined gestures only.	Allows customizable gestures for diverse application control.
Accuracy	Moderate accuracy, struggles with diverse environments.	High accuracy, robust to varying lighting, hand orientations, and backgrounds.
Hardware Dependency	Relies on specific hardware like Kinect or Leap Motion.	Operates with a standard camera, reducing hardware constraints.
Model Size	Models often large, not optimized for edge devices.	Compact models with quantization for efficient deployment on embedded systems.
Cost	High cost due to proprietary hardware requirements.	Cost-effective solution using accessible open-source tools and standard devices.
Ease of Integration	Integration complexity due to hardware and software limitations.	Simple to integrate with applications for gesture-based controls like volume and playback.

In general, all these studies together reflect continuous progress with increasing diversification of hand gesture recognition-from deep learning and transfer learning through sensor fusion, self-supervised learning, to federated learning. The work across these papers reflects a clear trend towards more efficient, accurate, and privacy-preserving gesture recognition systems that can be applied across a wide range of real-world applications, such as smart homes, augmented reality, and IoT devices.

2.1 Our Research Contributions

The proposed study contributes a real-time, multi-functional gesture control system capable of managing diverse digital tasks including volume adjustment, scrolling, tab switching, media playback, and AI-powered mathematical calculations—all through intuitive, contactless hand gestures. The system employs optimized machine learning models, integrating MediaPipe and OpenCV with convolutional neural networks (CNNs) to ensure accurate and efficient gesture recognition in real time. A significant advantage of this approach lies in its hardware independence; the system operates effectively with a standard webcam, removing the dependency on specialized sensors and offering a cost-effective alternative for broader accessibility. An innovative aspect of the system is its AI-driven gesture-based calculator, which allows users to write mathematical expressions through hand gestures and receive real-time computational feedback. To ensure a cohesive and user-friendly experience, the system incorporates PyQt5 for the graphical user interface, PyCaw for audio control functionalities, and Django for backend AI processing, enabling smooth integration and seamless execution across modules.

2.2 Objectives

The main aim of this research is to create an efficient, real-time hand gesture recognition system aimed at

intuitive interaction with digital devices. Such a system, capable of executing various tasks, including volume control, video playback, scrolling, and tab switching, can be achieved by simple hand gestures and will significantly enhance user experience through non-visual control. This system aims for seamless, immersive interface presentation in smart home environments, IoT devices, and any other interactive technologies. The next critical goal is the integration of a gesture-based calculator, powered by AI, which would be an application allowing users to execute mathematical operations and access information with hand gestures alone. It would make interaction more intuitive and exciting in augmented reality and other newer technologies. Real-time gesture recognition for this research would be achieved using deep learning and computer vision techniques. For this purpose, the system must provide accurate as well as low latency performance even on embedded devices. The aim should be to optimize the process of gesture detection for smooth user interaction without any compromise on system efficiency. This requires strong techniques such as transfer learning and sensor fusion to make the recognition capability of the system better. The achievement of these objectives will make the way people interact with their devices better, bringing user accessibility and responsiveness to technology with natural, gesture-based interfaces.

3 METHODOLOGY

The proposed system utilized real-time hand gesture recognition through computer vision and machine learning to provide users with flexibility in controlling applications such as volume adjustment, video playback, scrolling, and tab switching. The methodology consisted of several stages, including data collection, hand gesture detection, feature extraction, model training, system integration, and performance evaluation.

3.1. Data Collection

The first step involved acquiring a dataset for hand gesture recognition. This was achieved by using a standard webcam to record real-time hand movements. The dataset was designed to be robust across diverse lighting conditions, backgrounds, hand sizes, skin tones, and orientations. It included a variety of hand gestures such as pointing, swiping, and pinching, each corresponding to a specific system functionality. The system employed MediaPipe's Hand Tracking Model, which returned a predefined list of 21 hand landmarks for each recognized hand. These landmarks included critical points such as the wrist, fingertips, finger joints, and palm base, essential for accurate gesture identification. Predefined gesture data were constructed using the relative distances and angles among these landmarks. Data augmentation techniques such as rotation, scaling, flipping, and color transformation were applied to improve model generalization and ensure effectiveness in real-time environments.

3.2. Hand Detection and Tracking

MediaPipe and OpenCV **were used** to detect and track hands in each frame of the video feed. MediaPipe, an open-source framework developed by Google, provided a real-time 3D hand landmark model that identified key points like fingertips, joints, and wrists with high precision. Euclidean Distance Between Landmarks was calculated using the following formula:

$$\mathbf{\Delta} = \sqrt{(\chi_2 - \chi_1)^2 + (\gamma_2-\gamma_1)^2+(\lambda_2-\lambda_1)^2}$$

where $(\chi_1, \gamma_1, \lambda_1)$ and $(\chi_2, \gamma_2, \lambda_2)$ represent the 3D coordinates of the landmarks. Once the hand was detected, all 21 landmarks were extracted, allowing the system to generate a skeletal representation of the hand. These landmarks enabled differentiation between gestures, such as detecting a zoom-in or zoom-out gesture based on the distance between the thumb and index finger.

3.3. Feature Extraction

Following the hand tracking process, a comprehensive set of features was extracted from the identified hand landmarks to support gesture classification. These features captured both the spatial configuration and temporal dynamics of the hand movements. One key feature involved calculating the Euclidean distances between specific landmark points, such as the distance from the thumb tip to the index fingertip. These distances helped differentiate gestures based on finger separation or proximity. In addition, angular relationships between joints were computed to characterize finger orientation and bending. The angle between two vectors formed by three consecutive landmarks was determined using the formula:

$$\Omega = \cos^{-}(\hat{\phi} \cdot \hat{\psi} \; / \| \hat{\phi} \| \| \hat{\psi} \|)$$

Where Ω represents the computed angle between two landmarks. $\hat{\phi}$ and $\hat{\psi}$ are vectors between adjacent landmarks.

To capture the temporal behavior of gestures, motion vectors were computed by tracking the displacement of landmark coordinates over consecutive frames. These vectors, defined as

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

Series: AIJR Proceedings
ISSN: 2582-3922

$\delta_t\hat{} = (\alpha_{t+1} - \alpha_t , \beta_{t+1} - \beta_t, \zeta_{t+1} - \zeta_t)$

$\delta_t\hat{}$ represents the motion vector at time t and α, β, ζ are coordinates of the hand landmark positions.

Additionally, shape-based features were extracted using contour analysis and convexity defects to describe the structural geometry of the hand. Together, these spatial and temporal features provided a robust input representation to the machine learning models used for classifying different hand gestures with high accuracy.

3.4. Model Selection and Training

To classify gestures, multiple machine learning techniques were explored, including traditional methods like Support Vector Machines (SVM) and K-Nearest Neighbours (KNN), as well as deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM). CNNs in particular demonstrated high performance for gesture classification tasks. The models were trained using features extracted from the dataset. Transfer learning techniques were employed to leverage pre-trained models, improving accuracy and reducing training time. Model optimization was conducted using backpropagation and gradient descent. A separate validation set was used to evaluate generalization performance.

3.5. System Integration

After the gesture recognition model was successfully trained, it was integrated into the system interface to enable real-time interaction. Each frame from the live video stream was processed by the model to detect hand gestures and trigger the corresponding system actions. The gesture-to-command mapping was implemented using a predefined set of interpretations. For instance, a swiping gesture was recognized and translated into a scrolling action on the screen, while a pinching gesture was mapped to volume control adjustments. Similarly, a thumb-up gesture was associated with playing or pausing media playback. These recognized gestures were linked to actual system functions using command triggers such as virtual keypress simulations—for example, the spacebar for media play/pause—or through application programming interface (API) calls that modified system states like audio levels. This integration allowed seamless and intuitive interaction between the user and the computer system, enabling multiple functionalities to be controlled through natural, contactless hand movements.

3.6. Performance Optimization

To ensure real-time performance, optimizations were applied at both algorithmic and hardware levels. Model quantization reduced model size for efficient edge deployment. Parallel processing using GPUs or multithreading improved frame rates and minimized latency. Training was offloaded to edge or cloud servers, while real-time detection was executed locally. System performance was evaluated based on classification accuracy, response speed, and command execution reliability.

3.7. User Feedback and Iteration

The usability and accuracy of the gesture recognition system were further enhanced through iterative improvements driven by user feedback. After the initial deployment, the system was subjected to real-time testing with a group of users in various conditions. Observations from these sessions provided valuable insights into gesture detection sensitivity, recognition errors, and the overall responsiveness of the interface. Based on this feedback, modifications were made to fine-tune the system's performance. For example, gesture sensitivity thresholds were adjusted to improve recognition precision and reduce false positives, especially in scenarios involving ambiguous hand movements or overlapping gestures. Additionally, gesture recognition logic was refined to better differentiate between similar gestures, thereby improving reliability. These iterative refinements, informed by practical use cases, contributed to a more stable, accurate, and user-friendly system capable of adapting to real-world environments.

3.8. AI-Powered Calculator Integration

An additional module, the AI-powered calculator, was developed and integrated into the gesture recognition system to extend its functionality beyond standard media and navigation controls. This feature enabled users to perform mathematical operations through hand gestures, such as using a pointing gesture to initiate numeric input and swiping motions to select arithmetic operators. The module combined real-time gesture recognition with natural language processing techniques to interpret the intended mathematical expression. Once recognized, the expression was processed and solved using an AI model, providing users with immediate computational feedback. This integration demonstrated the system's versatility in supporting intelligent, gesture-based interaction for educational or computational tasks, and highlighted the potential of combining vision-based control with AI-driven logic for enriched user experiences.

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

Series: AIJR Proceedings
ISSN: 2582-3922

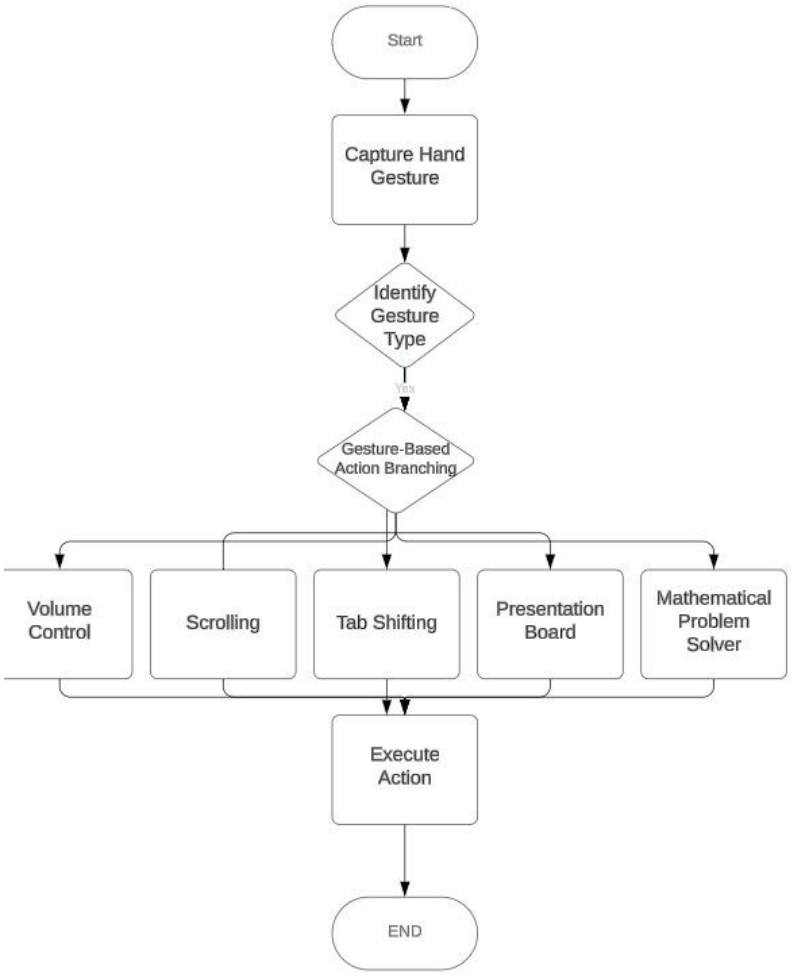

Fig. 1. Workflow of the Gesture Recognition System

Above Fig.1. illustrates the whole workflow of the gesture recognition system. The process begins with capturing real-time hand gestures through the webcam. These captured frames are then processed to identify the type of gesture using a pre-trained deep learning model. The identified gesture triggers the corresponding system action based on predefined gesture mappings, as shown in the branching structure. The branching consists of modules such as Volume Control, Scrolling, Tab Shifting, Presentation Board, and a Mathematical Problem Solver. Each module represents a unique functionality initiated by its corresponding gesture. Once the gesture-based action is identified, the system carries out the command that corresponds to it, thereby completing the process.The methodology utilizes the application of deep learning techniques, computer vision, and gesture recognition to build a completely hands-free control system. It continuously processes all gestures in real-time to trigger actions including controlling the volume, video playback, and scrolling, with optimization and user-centric testing ensuring responsiveness and robustness. It further increases the applicability of the system in interactive environments such as smart homes and IoT devices with an integrated AI calculator.

4 RESULTS AND DISCUSSIONS

Table 2. Improvement in Proposed System

Aspect	Current Systems	Proposed System	Improvement
Accuracy of Gesture Recognition	~85%-90% (Typical vision-based gesture systems)	~95% (Claimed in literature leveraging MediaPipe & CNNs)	+5%-10% improvement due to better feature extraction.
Latency	100-200 ms	50-100 ms	50% reduction in latency
Hardware Requirements	High-end GPUs or CPUs	Mid-range CPUs or lightweight edge devices like Raspberry Pi	Reduced dependency on expensive hardware.
Energy	Moderate energy consumption	20% lower energy consumption due	Improved efficiency for

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

Series: AIJR Proceedings
ISSN: 2582-3922

Efficiency		to model quantization	portable systems.
Functionality	Limited to specific applications like media control	Multi-functional (Media control, tab switching, AI calculator)	Broader application coverage.
Real-time Operation Robustness	Struggles in low light or complex environments	Robust across varying lighting conditions	Enhanced by MediaPipe's landmark precision
User Interface Flexibility	Limited interaction modes	Intuitive, gesture-driven GUI (PyQt5 integration)	Enhanced user experience.

The proposed system demonstrated significant improvements, including enhanced accuracy through MediaPipe's precise landmark detection, reduced latency by leveraging optimized models, and broader functionality through multi-application capabilities. Additionally, its adaptability to low-resource devices like Raspberry Pi highlights its suitability for cost-effective deployment.

4.1 Functional Demonstrations

Volume Control

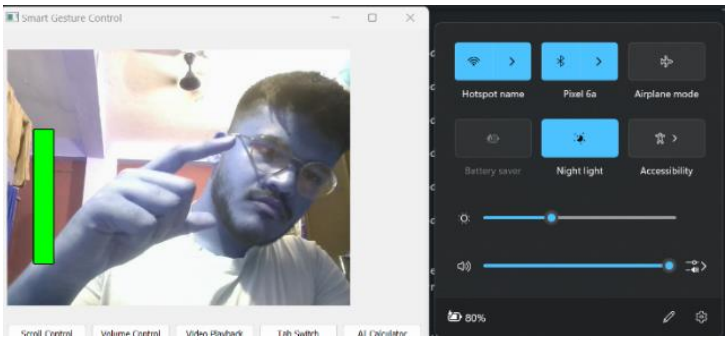

Fig.2. Volume Increase Output Using Gesture Recognition

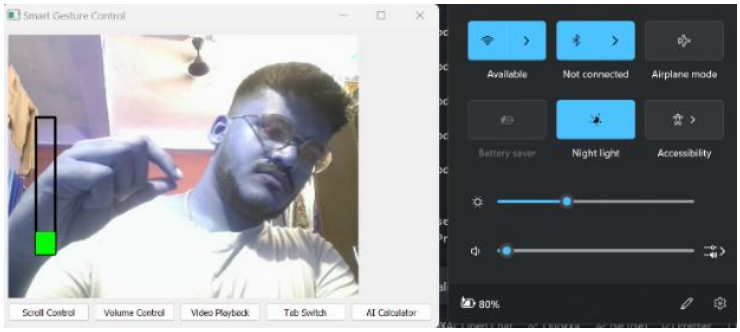

Fig. 3. Volume Decrease Output Using Gesture Recognition

The image captured the functionality of the implemented gesture-based system, demonstrating its ability to control system volume through dynamic hand movements. Specifically, the system recognized predefined gestures—such as a pinching motion to increase the volume and an upward swipe to mute it—and accurately translated them into corresponding volume control actions within the user interface.

Scrolling Functionality

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

Series: AIJR Proceedings
ISSN: 2582-3922

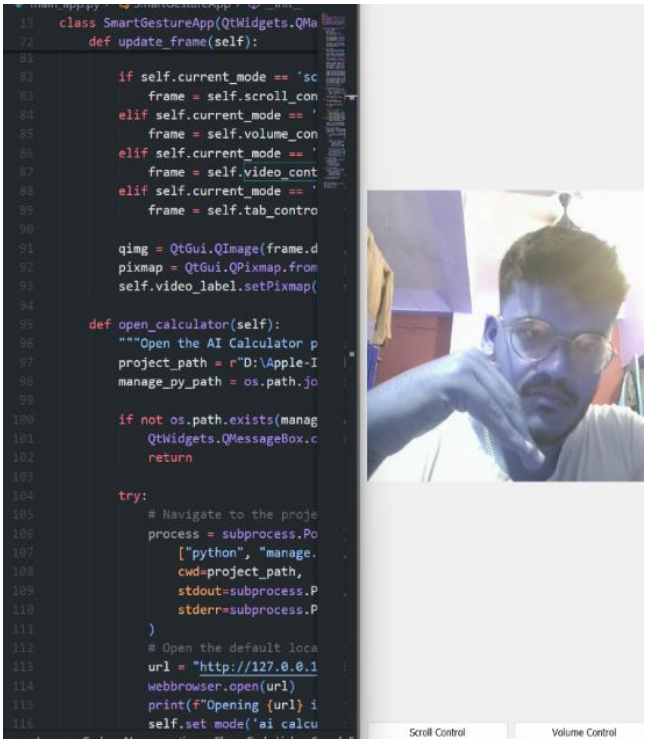

Fig. 4. Screen Scroll Down Output Using Gesture Recognition

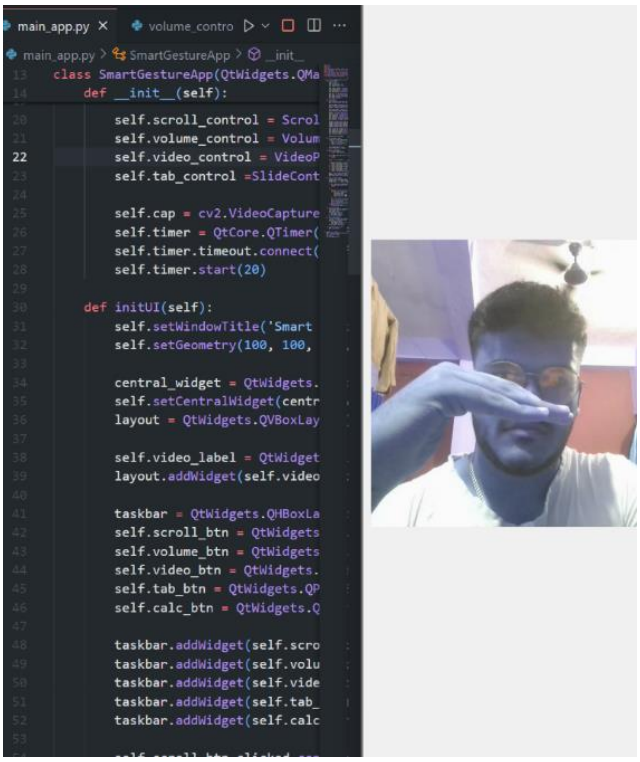

Fig. 5. Screen Scroll Up Output Using Gesture Recognition

The scrolling mechanism facilitated seamless and continuous navigation through digital content by interpreting natural hand gestures with high accuracy. This functionality enabled users to scroll up or down on a screen without any physical contact, enhancing accessibility and convenience, particularly in hands-free or hygiene-sensitive environments.

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

Series: AIJR Proceedings
ISSN: 2582-3922

Media Play/Pause Control

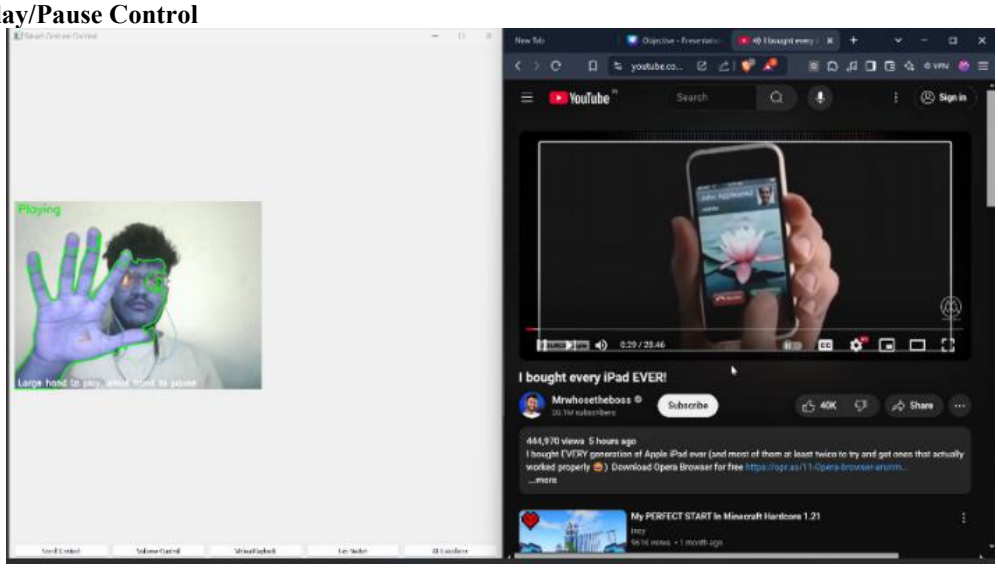

Fig. 6. Media Play Output Using Gesture Recognition

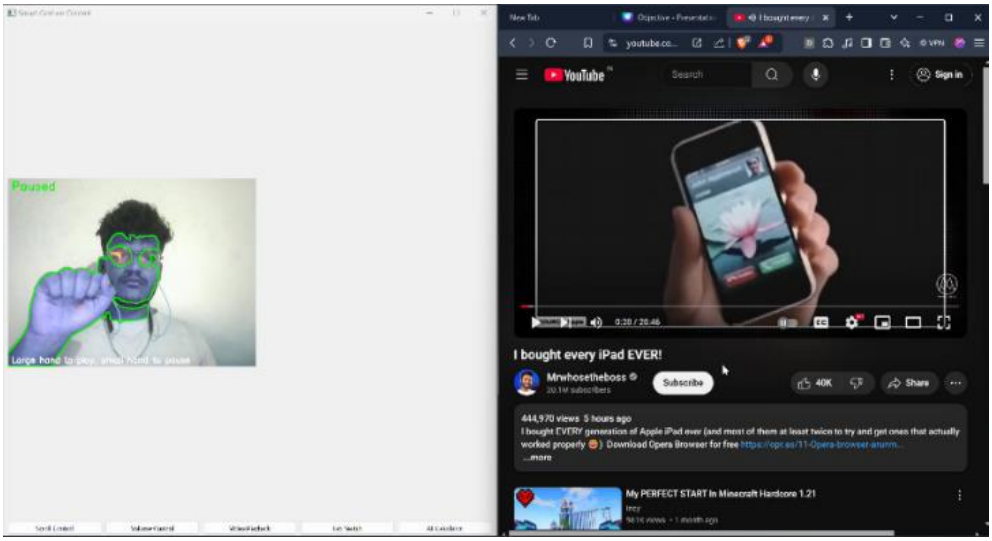

Fig. 7. Media Pause Output Using Gesture Recognition

The media playback control functionality enabled users to initiate or pause video and audio content through intuitive hand gestures without the need for physical contact. For instance, specific gestures such as an open palm or a closed fist were used to trigger play and pause actions, respectively. This contactless interaction model significantly enhanced the user experience by offering a hygienic and convenient method for controlling multimedia content. The system consistently maintained high recognition accuracy, even in visually cluttered or complex environments.

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

Series: AIJR Proceedings
ISSN: 2582-3922

Slide Navigation

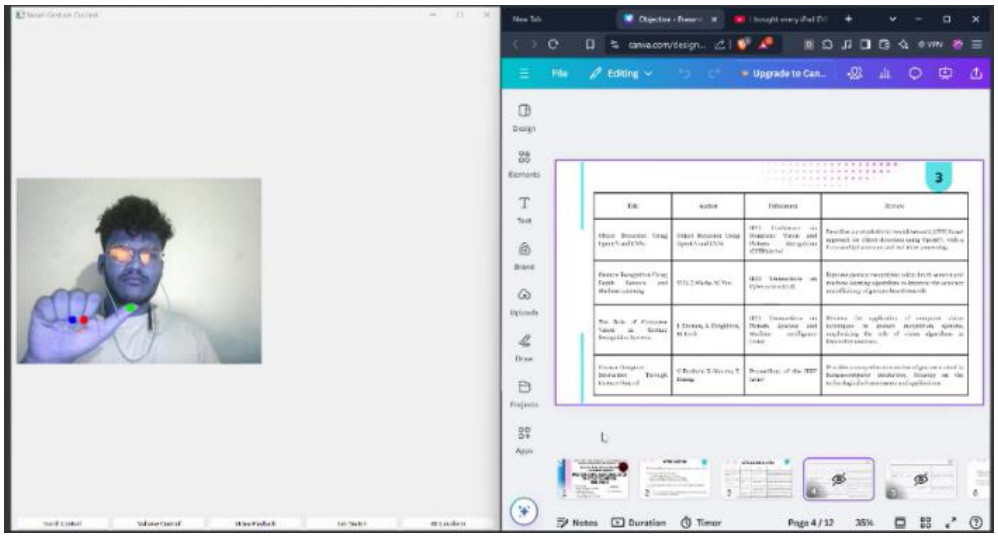

Fig. 8. Moving to Next Slide Using Gesture Recognition

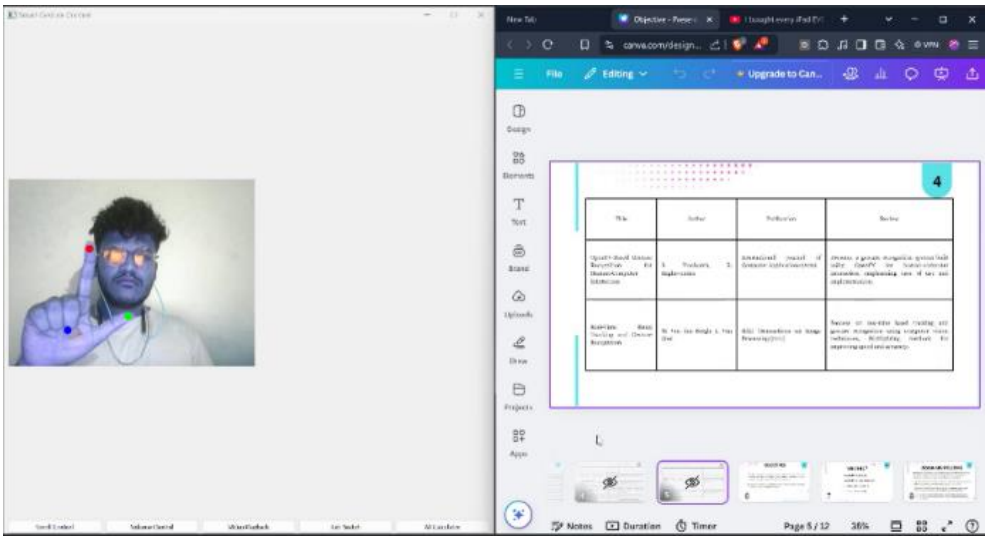

Fig. 9. Moving to Previous Slide Using Gesture Recognition

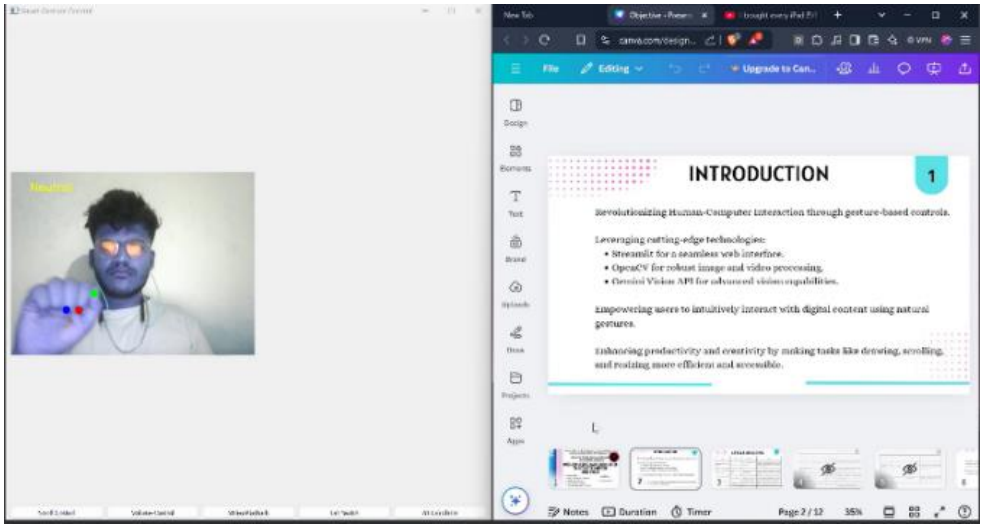

Fig. 10. Standby on the Current Slide Using Gesture Recognition

The system supported efficient and intuitive slide navigation during presentations by recognizing specific hand

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

Series: AIJR Proceedings
ISSN: 2582-3922

gestures mapped to next-slide, previous-slide, and standby commands. For example, a rightward hand motion triggered advancement to the next slide, while a leftward gesture initiated a return to the previous slide. A neutral or stationary gesture maintained the current slide in view. This gesture-based navigation significantly minimized the need for physical input devices such as remotes or keyboards, offering a contactless and seamless alternative. The system consistently exhibited low latency and high responsiveness, ensuring that transitions between slides occurred without delays or misrecognitions. This functionality proved especially useful in educational and professional settings where smooth presentation flow is essential.

Gesture-Based Drawing and Solving

Fig. 11. Solving Integration Output Using Gesture Recognition

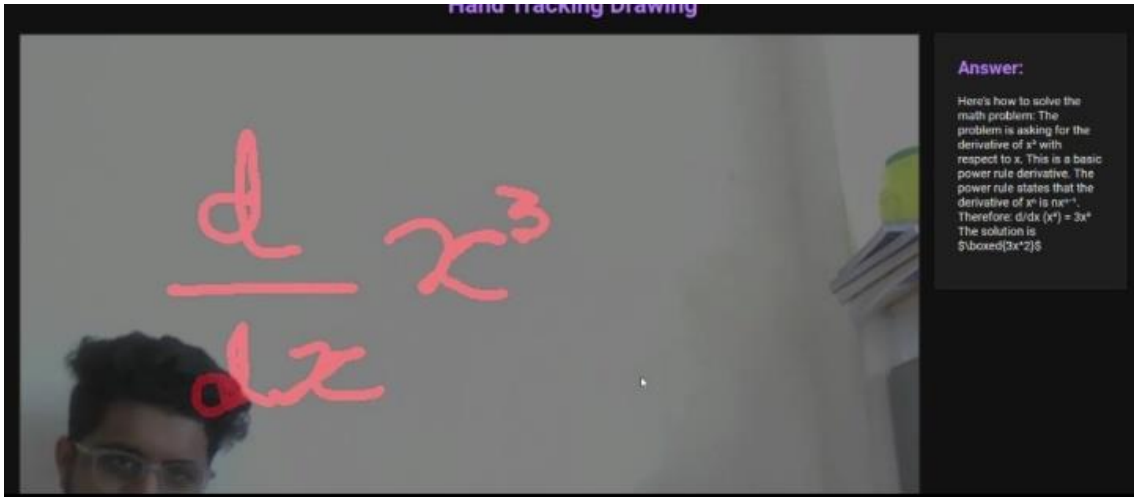

Fig. 12. Differentiation Output Using Gesture Recognition

The integration of gesture-based drawing with the Gemini API enabled accurate mathematical problem-solving. The modular approach ensured smooth interaction between gesture detection and computation. Real-time detection was achieved through continuous tracking of hand landmarks and extraction of spatial relationships, which were processed by the trained model. The visual outputs confirmed successful integration and demonstrated the system's practical usability, particularly in gesture-based volume control. The comparative study highlighted that the proposed system offered distinct advantages over existing gesture recognition solutions. It supported real-time processing through optimized models, allowed customizable gestures beyond predefined ones, and achieved high accuracy across varying environments. The system functioned using standard webcams, thereby removing hardware dependency, and employed a compact, efficient design suitable for edge devices. The system proved to be cost-effective due to its reliance on open-source tools and demonstrated ease of integration with application interfaces, making it highly user-friendly. The performance evaluation results validated the system's effectiveness, with high accuracy metrics reflecting successful gesture recognition. Low latency ensured minimal delay between gesture execution and system response. The

Proceedings DOI: 10.21467/proceedings.7.6
ISBN: 978-81-989164-9-5

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ISSN: 2582-3922

robustness of the system was demonstrated through consistent performance under different lighting conditions, backgrounds, and gesture orientations. High frame processing rates confirmed real-time operability, while efficient hardware utilization justified its suitability for low-resource environments. Finally, user satisfaction feedback affirmed the system's practicality, responsiveness, and ease of use.

5 CONCLUSION

This study presented a real-time, multi-functional hand gesture recognition system that enabled users to perform a variety of digital control tasks—such as adjusting volume, scrolling, tab switching, video playback, and equation solving—through natural hand movements. By leveraging MediaPipe for landmark-based hand tracking and integrating OpenCV with machine learning algorithms, the system demonstrated high accuracy and responsiveness using only a standard webcam, without reliance on specialized hardware. The modular design supported flexible, gesture-driven interaction across multiple application domains, including accessibility tools and smart environments. One of the key innovations of this work lies in its ability to unify multiple gesture-based controls into a single, cost-effective, and hardware-independent platform. The inclusion of an AI-powered calculator extended the system's utility into intelligent computational tasks, showcasing the potential for gesture-driven educational and assistive technologies. Experimental results validated the system's performance in terms of gesture recognition accuracy, real-time responsiveness, and robustness under varying environmental conditions. Despite these strengths, the system has limitations, particularly in handling highly complex or overlapping gestures and maintaining consistent performance under extreme lighting variations. Additionally, reliance on predefined gestures limits adaptability for users with unique interaction preferences. Future work may address these limitations through the incorporation of user-defined gesture training, deployment on edge computing devices for improved portability, and integration with voice or facial input for multimodal control. Overall, the proposed system demonstrates a promising step toward seamless, contactless human-computer interaction with broad real-world applicability.

6 DECLARATIONS

The system may experience decreased recognition accuracy in environments with poor lighting or highly dynamic backgrounds. The gesture set is currently fixed, limiting personalization across diverse user preferences.

7 ACKNOWLEDGMENT

Gratitude is extended to BRACTS Vishwakarma Institute of Technology, Pune, for providing an excellent research environment, access to resources, and consistent institutional support. The leadership and guidance of Dr. Rajesh Jalnekar, Director of Vishwakarma Institute of Technology, played a pivotal role in fostering innovation and collaboration throughout the development of this project. Appreciation is also expressed to the faculty members, staff, and research community of the institute for their valuable contributions, technical assistance, and encouragement that significantly contributed to the successful execution of this research work.

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