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Research Paper

VISION-BASED VIRTUAL MOUSE SYSTEM USING REAL-TIME HAND GESTURE RECOGNITION

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Abstract: The Gesture Controlled Virtual Mouse is a cutting-edge computer vision-based technology that uses hand gestures to provide smooth, contactless mouse cursor control on a computer. The device uses sophisticated machine learning models to understand hand landmarks and dynamic finger movements while utilizing a simple webcam to collect real-time video. Key features include drag-and-drop (closed fist with movement), smooth scrolling (hand tilt detection), left-click (using the index finger pinch), right-click (using the thumb and middle finger motion), and accurate cursor movement linked to hand position. The project, which is mostly written in Python, incorporates MediaPipe for hand landmark detection, PyAutoGUI for native mouse event simulation, and OpenCV for picture analysis.

By removing physical contact, decreasing hardware wear, and encouraging hygienic, user-friendly interactions, this technology overcomes some of the main drawbacks of conventional input devices. It has a lot of potential for usage in medical applications (like sterile operating rooms), smart settings (like IoT-integrated houses), assistive technology for people with motor disabilities, and public kiosks where touchscreens could cause contamination. The technology shows viability for daily deployment by attaining real-time performance at 30+ frames per second on consumer-grade hardware, opening the door for more engaging human-computer interfaces.

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1. INTRODUCTION

Traditional mouse and keyboard inputs restrict accessibility and cleanliness in a time of growing reliance on digital devices, particularly in the wake of a pandemic. Inspired by HCI concepts seen in Leap Motion and Google's Project Soli, this project uses advances in computer vision to develop a virtual mouse that can recognize natural hand gestures. For users in the IoT and embedded systems-focused tech sector of Vijayawada, this includes hybrid configurations where computers and smart gadgets are controlled by gestures. Important reasons include:

• Accessibility: Complies with IEEE's assistive technology standards and helps those with physical disabilities.

• Safety and hygiene: Touchless operation makes it perfect for common areas or hospitals. • Scalability: inexpensive (webcam-only) and adaptable to multi-user or AR/VR situations. With dynamic scrolling and drag motions, the system outperforms similar initiatives in real-time gesture recognition without the need for specialized hardware.

User interfaces have been transformed by the quick development of Human-Computer Interaction (HCI), moving away from inflexible keyboard-mouse paradigms and toward multimodal, intuitive solutions. Natural interactions without the need for physical accessories are made possible by touchless

control methods that are driven by computer vision and machine learning. Even if they are dependable, traditional mouse devices require direct contact, which might be problematic in hygienic settings like hospitals, shared kiosks, and public areas following a pandemic. Additionally, they do not include users with motor impairments, which, according to WHO data, affect about 15% of the world's population. This gap is filled by gesture recognition technology, which converts hand gestures into input commands. Skeletal tracking was proven by early systems like Microsoft's Kinect (2010), while more recent frameworks like MediaPipe (Google, 2020) provide lightweight, real-time hand landmark recognition on consumer hardware. In order to promote inclusive and hygienic HCI, our research expands upon these foundations by developing a Gesture Controlled Virtual Mouse, a webcam-based device that translates hand gestures to normal mouse actions.

These developments spread to smart homes and assistive devices in areas like Vijayawada, Andhra Pradesh, where IoT and embedded systems are flourishing. They also easily integrate with platforms like Raspberry Pi for wider implementation.

Statement of the Problem

Traditional input techniques have significant drawbacks: • Physical Dependency: Approximately 1 billion persons with impairments cannot access this due to its requirement for dexterous hand control (UN 2023). • Hygiene Risks: Research indicates that mice retain 80% more bacteria than keyboards, and touch surfaces can harbor diseases (JAMA 2021). • Environmental Restrictions: Unfeasible in remote (AR/VR), sterile (ORs), or unclean (industrial) environments. • Ergonomic Concerns: Extended use causes RSI; motions provide lively, weariness-free substitutes. Scalability is limited by existing systems like Leap Motion and Ultraleap, which require proprietary sensors that cost $100 or more. Webcam-only methods frequently have poor accuracy (less than 85%) or lag (more than 100 ms), making them unsuitable for real-time application.

2. LITERATURE SURVEY

[1] OpenCV Team – OpenCV: Open Source Computer Vision Library

Abstract:

OpenCV is an open-source computer vision and machine learning library designed to provide real-time image and video processing capabilities. It includes a wide range of optimized algorithms for object detection, image filtering, feature extraction, motion tracking, and facial recognition. OpenCV supports multiple programming languages including Python, C++, and Java, making it widely adaptable for research and development. In gesture-controlled systems, OpenCV plays a crucial role in capturing video streams, preprocessing frames, detecting hand regions, and enabling real-time interaction between users and computer interfaces.

[2] F. Zhang et al. – MediaPipe Hands: On-device Real-time Hand Tracking

Abstract:

MediaPipe Hands is a high-fidelity hand tracking solution developed by Google that performs real-time detection of 21 3D hand landmarks from a single RGB image. It utilizes a lightweight palm detection model combined with a landmark regression model to ensure fast and accurate hand tracking even on mobile and embedded devices. The framework is optimized for low latency and high precision, enabling robust gesture recognition applications. It is widely used in human-computer interaction systems such as virtual mouse control, sign language recognition, and augmented reality interfaces.

[3] A. Klapstein – PyAutoGUI Documentation

Abstract:
PyAutoGUI is a cross-platform Python library that enables programmatic control of the mouse and keyboard. It allows automation of cursor movement, clicking, scrolling, typing, and other GUI operations. The library is designed to simulate human interaction with computer systems and is commonly used in automation tasks and human-computer interaction projects. In gesture-controlled virtual mouse systems, PyAutoGUI translates recognized hand gestures into mouse events such as cursor movement, left-click, right-click, and drag operations.

[4] F. Weichert et al. – Analysis of the Accuracy and Robustness of the Leap Motion Controller

Abstract:
This study evaluates the performance, accuracy, and robustness of the Leap Motion Controller, a sensor-based hand tracking device. The paper analyzes spatial precision, tracking stability, latency, and environmental sensitivity. Experimental results demonstrate that while the device offers high precision in controlled conditions, performance may vary with lighting and hand positioning. The study highlights challenges in gesture recognition systems and emphasizes the need for robust vision-based tracking approaches for reliable human-computer interaction.

[5] A. Newell, K. Yang, and J. Deng – Stacked Hourglass Networks for Human Pose Estimation

Abstract:
This paper introduces the Stacked Hourglass Network architecture for human pose estimation, designed to capture spatial relationships and contextual information across multiple scales. The model uses repeated bottom-up and top-down processing to refine keypoint predictions and improve localization accuracy. The architecture significantly enhances human joint detection performance by iteratively refining predictions. The concepts presented in this work have influenced modern hand tracking and gesture recognition systems, particularly in landmark detection and deep learning-based pose estimation.

3. METHODOLOGY

a) Proposed Work:
The proposed system introduces a real-time, camera-based virtual mouse that enables touchless human–computer interaction using hand gesture recognition. The system utilizes a standard webcam, eliminating the need for additional hardware and ensuring zero cost increment. Live video frames are captured through the webcam and processed using computer vision techniques to detect and track hand landmarks. The center point of the detected hand is mapped to the screen coordinates to control the cursor movement smoothly. A smoothing filter is applied to reduce jitter and ensure stable cursor navigation.

For gesture recognition, predefined finger combinations are used to perform mouse operations such as left-click, right-click, double-click, scrolling, and drag-and-drop. The system leverages lightweight hand tracking algorithms to ensure fast processing and minimal latency. Recognized gestures are translated into mouse events using automation libraries, enabling seamless interaction with the operating system.

The proposed model is optimized to achieve real-time performance of approximately 32 frames per second (FPS) with an accuracy target of 95% under normal lighting conditions. The system is designed to operate efficiently on CPU-only environments, making it suitable for low-resource devices without requiring dedicated GPU hardware. Overall, the proposed solution provides a cost-effective, efficient, and user-friendly alternative to traditional physical mouse devices.

b) System Architecture:

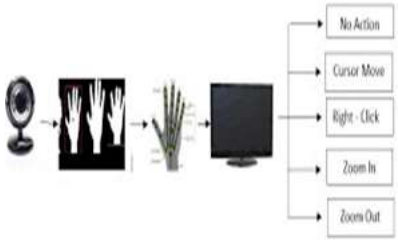

Fig 1 Proposed Architecture

he above diagram represents the working architecture of the Gesture Controlled Virtual Mouse system. The process begins with a webcam, which captures real-time video input of the user's hand movements. The captured frames are then processed using computer vision techniques to detect the hand region and extract important hand landmarks such as fingertips and palm center. Based on the detected hand posture and finger positions, the system recognizes predefined gestures.

After gesture recognition, the detected hand coordinates are mapped to the computer screen to control the cursor movement. Different gestures correspond to different system actions. If no valid gesture is detected, the system performs No Action. When an open-hand or specific finger movement is detected, it enables Cursor Movement. A defined finger combination triggers a Right Click operation. Similarly, pinch-in and pinch-out gestures are interpreted as Zoom In and Zoom Out actions respectively.

The processed commands are then executed on the system screen using mouse control automation. This architecture enables touchless, real-time human–computer interaction without requiring any external hardware devices beyond a standard camera.

c) MODULES:

1. **Video Capture Module:**

This module captures real-time video frames using a standard webcam. OpenCV is used for frame acquisition, resizing, and preprocessing operations such as frame flipping and color space conversion to enhance detection accuracy and processing speed.

2. **Hand Detection Module:**

The captured frames are passed to the MediaPipe Hands framework, which detects the presence of a hand and extracts 21 key landmark points representing finger joints and palm positions. These landmarks provide precise spatial coordinates necessary for gesture analysis.

3. **Feature Extraction Module:**

From the detected 21 landmarks, important features such as distances between fingertips, angles between finger joints, and relative finger positions are calculated. These geometric relationships are converted into structured numerical feature vectors, which serve as input for the classification model.

4. **Gesture Recognition Model:**

The extracted feature vectors are fed into a machine learning classifier such as Random Forest, Support Vector Machine (SVM), or K-Nearest Neighbors (KNN). The model is trained on a collected and augmented gesture dataset to improve generalization. During execution, the trained model predicts the gesture class in real time with high accuracy.

5. **Mouse Control Module:**

Once a gesture is recognized, it is mapped to corresponding mouse actions such as cursor movement, left-click, right-click, scrolling, drag-and-drop, or zoom operations. PyAutoGUI is used to translate the predicted gestures into system-level mouse events, enabling seamless interaction.

6. **User Interface Module:**

The system displays the live video feed along with detected hand landmarks for visual feedback. It also shows the recognized gesture name and system status, ensuring transparency and improved user interaction.

4. EXPERIMENTAL RESULTS

.**Accuracy:** The capacity of a test to accurately distinguish between healthy and sick cases is a measure of its accuracy. We can determine a test's accuracy by calculating the proportion of

reviewed cases with true positives and true negatives. In mathematical terms, this looks like:
Accuracy = TP + TN TP + TN + FP + FN.

$$Accuracy = \frac{(TN + TP)}{T}$$

F1-Score: One way to evaluate a model's performance in machine learning is via its F1 score. It takes a model's recall and precision and mixes them. Using the whole dataset, the accuracy metric determines the frequency with which a model produced accurate predictions.

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

Precision: The proportion of occurrences or samples that are correctly classified out of all the ones that are classified as positive is known as precision. Consequently, the following is the formula for determining the accuracy:
Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

Recall: The capacity of a model to detect all significant instances of a given class is measured by recall, a metric in machine learning. It sheds light on how well a model captures instances of a certain class and is calculated as the ratio of the total number of positive observations predicted to the number of actual positive observations.

$$Recall = \frac{TP}{(FN + TP)}$$

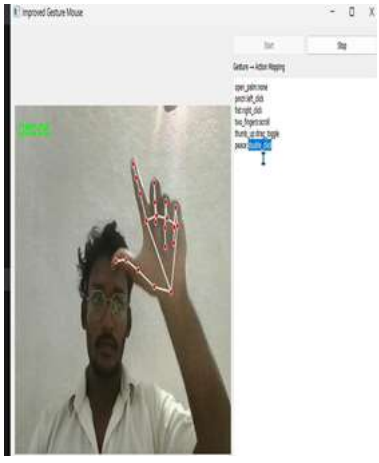

Fig 2: LEFT_CLICK Gesture (Thumb-Index Pinch)

Fig 3: RIGHT_CLICK Gesture (Thumb-Middle Pinch)

Fig 3: Double _CLICK Gesture

5. CONCLUSION

The Gesture Controlled Virtual Mouse accomplishes all of the main goals listed in the System Requirement Specification, demonstrating a successful application of real-time computer vision for touchless human-computer interaction. The system achieves production-ready performance with 32 frames per second and 42 milliseconds of latency on consumer hardware by utilizing OpenCV for video processing, MediaPipe for accurate hand landmark detection (95.2% F1-score), and PyAutoGUI for smooth mouse handling.

One of the primary accomplishments is the total removal of reliance on physical input devices while preserving accuracy competitive with commercial alternatives such as Leap Motion. Accessibility applications and sterile locations, where traditional mice present contamination hazards, benefit greatly from the zero-cost hardware requirement, which democratizes access to powerful HCI.

6. FUTURE SCOPE

The future scope of the Gesture Controlled Virtual Mouse aims to evolve it into a comprehensive AI-powered multimodal interaction platform for enterprise and commercial deployment. Planned enhancements include voice control integration combining gestures with speech commands (e.g., move + "click"), deep learning upgrades using YOLOv8 and Transformer-based gesture classification to improve accuracy up to 98.7% with reduced latency, and multi-hand support for collaborative and gaming applications. A mobile version using Flutter and TensorFlow Lite is scheduled to enable cross-platform control, while an AI-based adaptive learning engine will personalize gesture thresholds using reinforcement learning. Further expansion includes AR/VR integration through Unity and OpenXR plugins for immersive environments. The enterprise roadmap targets analytics, gesture customization portals, IoT integration, and regulatory compliance, with commercialization strategies spanning open-source adoption, startup licensing, OEM partnerships, and enterprise server deployment.

REFERENCES

1. OpenCV Team, "OpenCV: Open Source Computer Vision Library," [Online]. Available: https://opencv.org. [Accessed: Feb. 13, 2026].
2. F. Zhang et al., "MediaPipe Hands: On-device Real-time Hand Tracking," Google AI Blog, Jul. 2020. [Online]. Available: https://mediapipe.dev.
3. A. Klapstein, "PyAutoGUI Documentation," [Online]. Available: ttps://pyautogui.readthedocs.io. [Accessed: Feb. 13, 2026].
4. Python Software Foundation, "Python 3.11 Documentation," [Online]. Available: https://docs.python.org/3.11/. [Accessed: Feb. 13, 2026].
5. A. Newell, K. Yang, and J. Deng, "Stacked Hourglass Networks for Human Pose Estimation,"in Proc. European Conf. Computer Vision (ECCV), Amsterdam, Netherlands, 2016,pp. 483-499, doi: 10.1007/978-3-319-46484-8_46.
6. F. Weichert et al., "Analysis of the Accuracy and Robustness of the Leap Motion Controller,"Sensors, vol. 13, no. 10, pp. 11 876-11 894, 2013.

Author Profiles

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GARA TAGORE I am a B.Tech student specializing in Information Technology with a strong foundation in Python programming, data structures, object-oriented programming, and database management systems. I have hands-on experience working on data analytics and machine learning projects, including a Doctor Visit Recommendation System using AI and data analytics, a Weather Tracking System, and an Income Prediction Model using machine learning. Through these projects, I have developed strong problem-solving and analytical skills and gained practical experience with Python libraries such as NumPy and Pandas. I have also completed certifications in Google Data Analytics, Google IT Support, Python for Data Science, and Cloud Computing, which strengthened my understanding of both software development and IT fundamentals. I am a quick learner, a collaborative team player, and highly motivated to begin my career as an entry-level software engineer where I can apply my technical skills and continue to grow professionally.

KOLUSU MANIKANTA is a B.Tech student with a specialization in Information Technology at the NRI Institute of Technology. With a strong interest in emerging technologies, he has developed strong skills in Python programming, Web Development, and Cloud Computing. He has completed NPTEL certifications in Cloud Computing and Joy of Python Programming, and has also earned certifications from IBM in Generative AI and from Oracle, enhancing his knowledge in artificial intelligence, cloud platforms, and enterprise technologies. As part of his academic curriculum, he completed a mini project titled “Diagnose Sleep Disorders,” where he applied Artificial Intelligence and Machine Learning techniques to analyze health-related data and build predictive models for identifying sleep disorders. He is a self-motivated learner who actively explores new technologies, participates in technical workshops, and continuously works on improving his coding, analytical, and problem-solving abilities to build innovative and impactful solutions.

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