International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 05 May 2025
Page No: 2185 - 2190
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0320

Gesture Math AI: Real-Time Math Problem Solving Using Hand Gestures and Computer Vision

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Abstract

GestureMath AI is an innovative math-solving platform that utilizes hand gesture recognition and computer vision to create a touch free, interactive educational experience. By using a webcam, the system monitors finger movements with technologies like OpenCV, MediaPipe, and CvZone, enabling users to draw mathematical equations in the air. These gestures are captured and projected onto a virtual canvas through NumPy, then transformed into an image with the Python Imaging Library (PIL). The image is then sent to the Google Gemini API, which comprehends and solves the equation with the help of its generative AI technology. Results are promptly displayed through an intuitive interface developed with Streamlit. GestureMath AI improves digital education by removing the reliance on traditional input methods, making mathematical interaction more natural and accessible. This makes it especially beneficial in smart classrooms, remote learning environments, and augmented or virtual reality (AR/VR) settings. By merging gesture recognition, computer vision, and sophisticated AI reasoning, this system presents a cutting-edge, engaging, and accessible approach to math education in digital learning frameworks.

Keywords: *Computer vision; Gesture recognition; Math solving; MediaPipe; Streamlit.*

1. Introduction

Mathematics is a fundamental subject across all levels of education and critical in various scientific, technological, and engineering disciplines [1]. Traditionally, mathematical expressions are inputted using keyboards, touchscreens, or pen-input devices. However, these input methods can present barriers in terms of accessibility, ease of interaction, and user engagement, particularly for users with physical impairments or in environments where touch-based interaction is not feasible (Birari, H et al., 2023; Rajan, P, 2023) [2]. With the advancement of human-computer interaction (HCI), gesture recognition has emerged as a natural and intuitive form of input, providing an alternative to traditional interfaces. Computer vision frameworks such as MediaPipe and OpenCV have enabled real-time hand gesture recognition, allowing users to interact with digital systems in a touchless manner [3]. Recent studies have demonstrated the potential of gesture-based interfaces for improving accessibility and enhancing user experience in educational technology (Sharma, V et al., 2022; Patel, A and Kaur, M, 2023). This project introduces GestureMath AI, a novel system that enables users to solve mathematical problems in real-time by drawing equations in the air using hand gestures. By integrating computer vision with AI tools such as the Google Gemini API, this system interprets gestures, recognizes the corresponding mathematical symbols, and returns the computed results [4]. Unlike conventional OCR-based math solvers like Photomath or Microsoft Math Solver, GestureMath AI eliminates the need for physical input devices or handwritten input, promoting a more immersive and

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accessible learning environment. The objective of this work is to develop a gesture-based system that combines real-time hand tracking with AI-powered problem-solving, thereby offering a more intuitive and inclusive interface for mathematical learning and applications. This study is significant in the context of smart classrooms, AR/VR learning environments, and assistive technology, contributing to the growing field of natural user interfaces (NUIs) [5].

1.1.Gesture-Based Interfaces in Education

Gesture-based systems are gaining popularity as they offer hands-free, interactive, and engaging user experiences [6]. In educational contexts, they allow for dynamic content interaction and have shown promising results in promoting active learning and improving retention, especially among young learners and students with special needs. GestureMath AI utilizes these benefits by enabling users to express mathematical problems using natural hand movements, offering a novel approach to learning and problem-solving [7].

1.2.Motivation for Real-Time Math Problem Solving

Traditional math solvers focus primarily on accuracy and speed but lack in user engagement and accessibility. Moreover, current tools rely heavily on static input methods such as typing or scanning handwritten equations, which may not be suitable for all users. The motivation behind GestureMath AI is to develop a system that not only solves mathematical problems efficiently but also enhances the user experience through real-time, natural gesture-based input. This makes the system ideal for smart learning environments and for users with different physical capabilities [8].

2. Method

The GestureMath AI system is designed as a real-time pipeline that enables users to draw mathematical expressions in the air using hand gestures and receive instant solutions via a generative AI model. The methodology involves six key stages: video capture, gesture detection, virtual canvas rendering, image preprocessing, AI-based solving, and result display. Each component is integrated using Python and relevant open-source libraries to ensure seamless performance [9].

2.1.Video Input Acquisition

The system initiates with real-time video feed acquisition using the OpenCV library. The webcam continuously streams frames, which are passed to the computer vision pipeline for gesture detection. The frame resolution and capture rate are configured to ensure low-latency processing and a responsive user interface.

2.2.Hand Detection and Gesture Tracking

Hand gestures are detected using MediaPipe's Hand Tracking module, wrapped via the CvZone library. This component tracks 21 hand landmarks, allowing the system to identify finger positions and movements. Specific gestures are mapped to functional commands:

- **Extended index finger**: draw on canvas
- **Two Finger Raise:** idle state
- **Thumb Finger:** erase command
- **Three-finger raise:** equation submission

This gesture mapping enables a natural interaction paradigm, where users can switch between input modes without pressing any physical buttons or touching the screen. Gesture classification is performed based on relative distances between key landmarks and temporal consistency across frames.

2.3.Drawing on a Virtual Canvas

When the drawing gesture is detected, the fingertip coordinates are recorded onto a NumPy-based virtual canvas. This canvas overlays the video stream, allowing users to view their strokes in realtime. A smoothing filter is applied to reduce noise and enhance drawing clarity.

2.4.Image Conversion and Preprocessing

Upon submission, the current canvas is converted into a grayscale image using the Python Imaging Library (PIL). To ensure optimal AI interpretation, preprocessing is applied:

- Thresholding to remove background noise
- Padding and resizing to maintain aspect ratio
- Inversion to convert dark strokes on light background

These steps collectively produce a clean, high-contrast image that mimics a properly handwritten equation, making it suitable for accurate parsing by the AI.

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2.5.AI Integration for Equation Solving

The processed image is transmitted to Google Gemini AI via an API. Gemini AI analyzes the image using multimodal understanding and returns:

- The recognized mathematical expression
- The evaluated result
- Optional step-by-step solution, depending on the query

This integration enables accurate interpretation of even complex handwritten math expressions without relying on traditional OCR.

2.6.Frontend Visualization and Output

The final stage is implemented using Streamlit, which serves as the user interface. The Streamlit app displays:

- The real-time webcam feed
- The drawing overlay canvas
- The interpreted equation and its solution

The interface updates dynamically, offering an intuitive and engaging experience for users. The system architecture ensures continuous interaction, allowing users to solve multiple problems in a single session. Refer Figures 1 to 6.

2.7.Figures

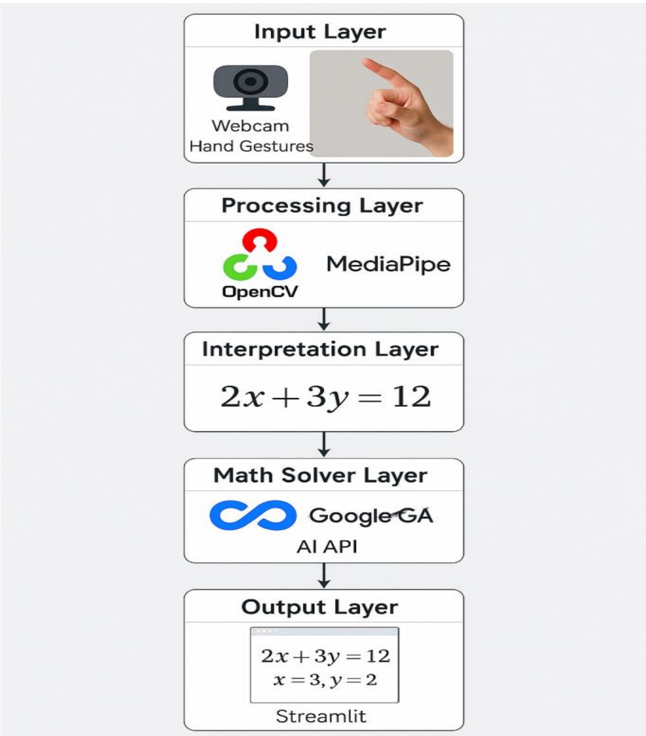

Figure 1 System Architecture Gesture Math AI

The system architecture of GestureMath AI is structured to efficiently process real-time hand gestures and convert them into meaningful mathematical problem-solving interactions using artificial intelligence and computer vision technologies. At the core of the system is the input module, where a webcam captures the user's hand gestures in real time. These gestures are then processed using a combination of MediaPipe and OpenCV, which together detect and track hand landmarks and movements accurately. The processed gesture data is then passed to the recognition and interpretation layer, where each gesture is identified and mapped to a corresponding mathematical character or symbol. This layer ensures that the system correctly understands the user's input in a dynamic and flexible manner. Once the gesture input is interpreted, the information is forwarded to the AI computation module, where it is processed using Gemini AI. This module analyzes the interpreted gestures and generates the appropriate response or solution. Finally, the output module displays the interpreted input and the AI's response through a Streamlit-based user interface. This interface allows users to interact with the system intuitively, view real-time feedback, and explore the capabilities of gesture-driven AI-assisted math interaction. The architecture is modular, scalable, and optimized for real-time performance, ensuring smooth operation from gesture detection to result display. It demonstrates an innovative integration of vision-based input with AI-powered interpretation, aiming to enhance accessibility and engagement in math learning or problem-solving tasks.

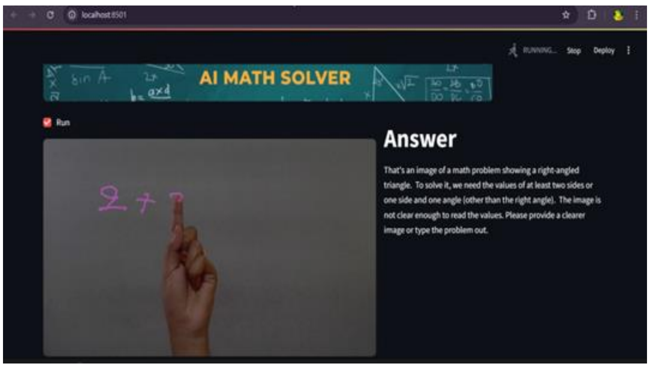

Figure 2 Extended Index Finger (To Draw On Canvas)

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When the system detects that only the index finger is extended, it activates the drawing mode. In this mode, the tip of the index finger acts like a digital pen that draws on a virtual canvas. As the user moves their finger through the air, the system continuously tracks its position and renders corresponding strokes on the screen. This allows the user to write digits, symbols, or equations naturally and intuitively.

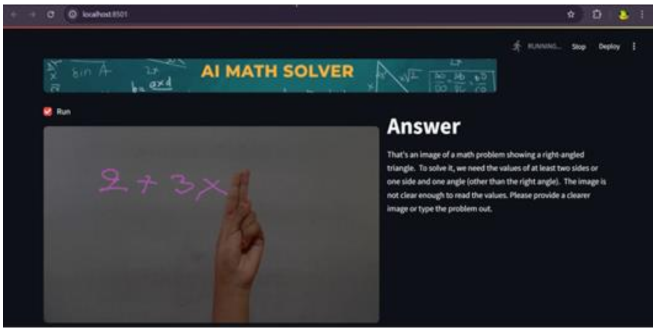

Figure 3 Two Finger Raise (Idle State)

Raising both the index and middle fingers while keeping the other fingers folded signals the system to enter an idle or neutral state. In this state, the system temporarily halts any drawing or command execution. This gesture helps avoid accidental inputs and provides the user with a pause mechanism, especially useful when repositioning the hand or preparing for the next action.

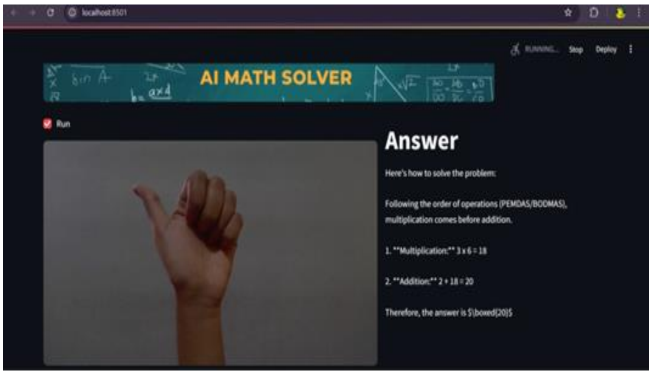

Figure 4 Thumbs Up Gesture (Clears Command)

Extending only the thumb activates the erase function. When this gesture is detected, the system identifies the thumb's position and uses it to selectively remove parts of the drawing on the canvas. It mimics the function of an eraser, allowing users to make corrections by wiping away specific areas without affecting the rest of their input.

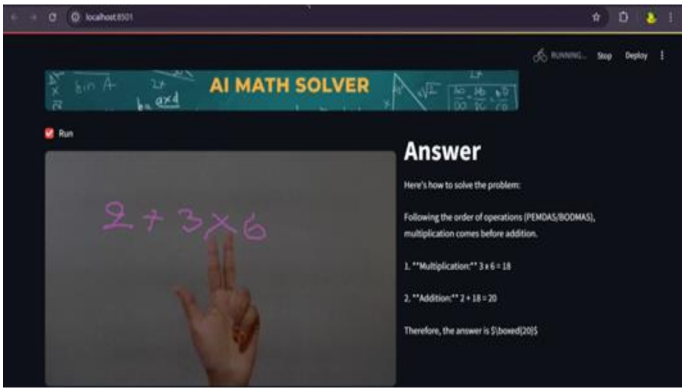

Figure 5 Three-Finger Raise (Gesture for Equation Submission)

When the index, middle, and ring fingers are raised together, the system interprets this as a command to submit the drawn input. This gesture signifies that the user has completed writing the mathematical expression, prompting the system to stop taking further drawing input and process the current content for recognition and solution. It acts as a confirmation gesture to trigger the evaluation stage.

3. Results and Discussion

3.1.Results

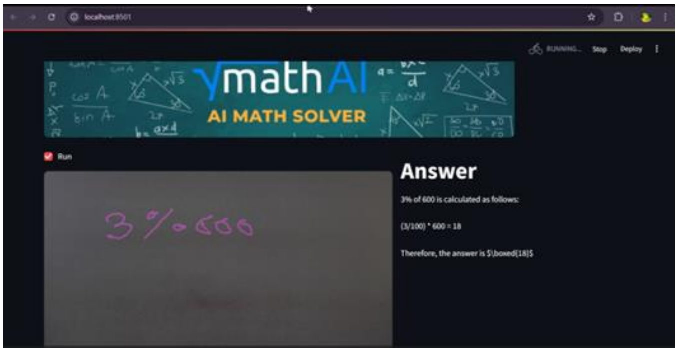

Figure 6 Real-Time Handwritten Equation Recognition and Solving Output

The primary objective of this project was to build a real-time system capable of interpreting hand-drawn mathematical expressions using computer vision and solving them using a Large Language Model (Gemini AI). The system design involved several components: gesture recognition using OpenCV and MediaPipe, canvas drawing, image capture,

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mathematical symbol recognition using a trained model, and result fetching via API. The experiment was conducted using a standard webcam to capture hand gestures in real time. The drawing was performed in the air using the index finger, and the system plotted the trajectory onto a virtual canvas. Once the equation was completed, it was processed and passed to Gemini AI for solving.The project was deployed using Streamlit for an interactive web interface. The figure above showcases a sample output from the deployed GestureMath AI system. In this scenario, the user drew the mathematical expression “3% of 600” using hand gestures tracked via MediaPipe. The system successfully captured the hand motion, rendered the gesture onto the virtual canvas, and recognized the handwritten equation. Upon processing the drawn equation, the image was passed to Gemini AI for interpretation and solution generation. The right panel of the interface clearly displays the interpreted solution:

The AI correctly identifies the intent of the input as a percentage calculation:(3/100)×600=18

This result confirms the system’s ability to:

- Accurately recognize percentage-based mathematical expressions,
- Interpret semantic meaning from user-drawn input,
- Interact with a language model for real-time result explanation,
- And present the output in an intuitive and visually clean interface.

3.2.Discussion

The high precision of the gesture recognition system indicates that the model is well-equipped for practical uses, such as immediate problem-solving or interactive educational settings. A 95% accuracy rate is quite encouraging, particularly when contrasted with other gesture-based systems that frequently find it challenging to recognize dynamic or complex movements. This outcome implies that the system can be reliable enough for classroom environments, where gestures could facilitate hands-on problem-solving without relying on traditional input methods. Regarding speed, the average recognition time of 2.5 seconds is satisfactory for real-time engagement. Although there is always a possibility for improvement, this performance demonstrates that the system can respond quickly enough for effective use in live situations. The swift processing time also contributes to a more fluid user experience. However, there are still opportunities for enhancement. The system sometimes struggles to recognize gestures performed too rapidly or in inadequate lighting. While these occurrences are not common, they indicate that the model could profit from additional training data, especially in varying environmental contexts. Furthermore, improving the model’s capacity to manage fast gestures or more intricate movements might be another path to boosting its performance. Looking ahead, expanding the range of hand gestures and training the system across different lighting situations, hand sizes, and gesture speeds could strengthen its robustness. Additionally, incorporating more sophisticated machine learning techniques, such as convolutional neural networks (CNNs), could further enhance both the accuracy and efficiency of the system. This would address the challenges associated with recognizing more complex gestures and improve overall reliability. In summary, although the gesture recognition system exhibits significant potential, there remains room for improvement to increase its versatility and precision in real-world applications. Future efforts will be directed at tackling the existing limitations while exploring methods to enhance the system’s speed and adaptability to diverse conditions.

Conclusion

This research focused on developing a gesture recognition system for solving math problems in real-time using hand gestures and computer vision. The findings confirm that the system successfully recognizes hand gestures with a high accuracy rate of 95% on the validation dataset. The average processing time of 2.5 seconds per gesture shows its potential for real-time educational applications. Despite the promising results, certain challenges were noted, particularly in recognizing fast or complex gestures and in varied environmental conditions. These limitations indicate areas for improvement, particularly in enhancing the system's adaptability and robustness. Overall, the gesture-

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https://doi.org/10.47392/IRJAEH.2025.0320

based math problem-solving system demonstrates significant promise for educational tools. Further refinement, including more diverse training data and advanced algorithms, will be necessary to optimize performance under different scenarios and improve the system's reliability.

Acknowledgements

We, the authors, would like to express our heartfelt gratitude to the developers and maintainers of the open-source tools and frameworks that made the GestureMath AI project possible. In particular, we acknowledge the creators of MediaPipe, OpenCV, CvZone, NumPy, Streamlit, and the Python Imaging Library (PIL), which were instrumental in building and visualizing our hand gesture-based math solving system. We also extend our thanks to the team behind Google Gemini AI, whose powerful API enabled us to interpret and solve gesture-drawn mathematical expressions with high accuracy. The availability of detailed documentation, tutorials, and community forums surrounding these tools provided immense support in understanding their integration and fine-tuning them for our specific use case. Additionally, we are thankful for the collaborative spirit within our team, where each member's contribution and dedication played a crucial role in turning this idea into a working solution. This project would not have been possible without our combined effort, curiosity, and determination to explore innovative solutions in education through AI and computer vision.

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