

AI Powered Math Notes Assistant

Prof. Varsha Deshmukh

Artificial Intelligence and Data Science Department
Savitribai Phule University (SPPU), Pune, India

Kshitij Vinayak Waikar

Artificial Intelligence and Data Science Department
Savitribai Phule University (SPPU), Pune, India
kshitijwaikar99@gmail.com

Tejas Anil Kawale

Artificial Intelligence and Data Science Department
Savitribai Phule University (SPPU), Pune, India
tejaskawale2003@gmail.com

Manish Bandu Tayade

Artificial Intelligence and Data Science Department
Savitribai Phule University (SPPU), Pune, India
manisht8454@gmail.com

Abstract—Mathematics education increasingly demands intelligent tools capable of assisting learners beyond traditional computational systems. Existing mathematical solvers often focus primarily on textual inputs and provide limited support for multimodal interaction, restricting their usability in real-world educational environments. Furthermore, conventional Optical Character Recognition (OCR) based systems frequently struggle with diverse handwriting styles and complex mathematical layouts.

This paper presents an AI Powered Math Notes Assistant, a multimodal educational platform that integrates handwritten input, image-based problem solving, voice interaction, and conversational AI within a unified framework. The proposed system leverages Google Gemini 2.5 Flash as a multimodal reasoning engine capable of understanding text, images, and audio inputs while generating mathematically accurate step-by-step solutions. The platform provides an interactive digital whiteboard for handwritten equations, supports image uploads containing mathematical expressions, and enables voice-based mathematical queries through a modern web interface.

The system is implemented using Flask, JavaScript, and Google GenAI APIs. Experimental evaluation demonstrates that the proposed architecture improves usability, accessibility, and interpretability by combining multimodal understanding with advanced mathematical reasoning. The developed platform serves as an intelligent tutoring assistant capable of transforming traditional mathematical note-taking into an interactive AI-assisted learning experience.

I. INTRODUCTION

Mathematics serves as the foundational language of science and engineering. Despite the widespread adoption of digital tools, handwritten mathematics continues to play a vital role in education due to its flexibility and cognitive advantages. However, converting handwritten mathematical expressions into machine-readable formats remains a complex problem.

Unlike plain textual data, mathematical expressions possess a two-dimensional layout where meaning is derived not only from symbols but also from spatial relationships such as superscripts, subscripts, fractions, and matrices. Traditional OCR systems are optimized for sequential text recognition and therefore perform poorly when confronted with the structural intricacies of mathematical notation.

In recent years, the emergence of multimodal artificial intelligence systems has transformed the manner in which users

interact with computational tools. Modern AI models are no longer limited to textual understanding but are capable of simultaneously processing images, audio, and natural language. Such capabilities are particularly beneficial in educational environments where students often express mathematical problems through handwritten notes, photographs of assignments, or verbal explanations.

The integration of multimodal reasoning within educational platforms offers opportunities to create intelligent tutoring systems capable of adapting to diverse learning preferences. By combining visual understanding with mathematical reasoning, AI-driven assistants can provide richer explanations, improve accessibility, and support self-paced learning. These developments motivate the design of the proposed AI Powered Math Notes Assistant.

Recent advancements in artificial intelligence, particularly in multimodal systems and large language models (LLMs), have opened new possibilities for bridging the gap between visual recognition and logical reasoning. However, most existing tools focus exclusively on either recognition or computation, rarely integrating both capabilities within a unified framework.

This research proposes a hybrid vision-language architecture that integrates OCR, heuristic correction, and LLM-based reasoning to provide accurate and explainable solutions to handwritten mathematical expressions.

The primary contributions of this work include:

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- Designing a multimodal AI platform for mathematical learning.
- Integrating handwritten, image-based, voice, and text inputs into a unified framework.
- Leveraging Gemini 2.5 Flash for multimodal understanding and mathematical reasoning.
- Providing detailed step-by-step explanations to improve educational interpretability.
- Developing an end-to-end intelligent tutoring assistant deployable through a web interface.

II. RELATED WORK

Handwritten Mathematical Expression Recognition (HMER) has been extensively studied within document analysis and pattern recognition research. Early systems relied on structural parsing techniques to interpret mathematical layouts, but these approaches struggled with complex expressions and diverse handwriting styles.

The introduction of deep learning significantly improved recognition performance. Encoder-decoder architectures and attention-based models enabled better capture of spatial dependencies within mathematical expressions. Transformer-based methods such as TAMER further enhanced recognition accuracy by modeling hierarchical relationships among symbols.

Despite these advancements, OCR systems alone remain insufficient for solving mathematical problems because they lack reasoning capabilities. Symbolic engines provide computational precision but are highly sensitive to recognition errors and cannot generate pedagogical explanations.

Large language models have recently demonstrated strong mathematical reasoning abilities. However, direct reliance on vision-language models may introduce hallucinations when interpreting noisy visual data.

The proposed system addresses these limitations by combining OCR, rule-based correction, and LLM reasoning into a unified pipeline that improves both reliability and interpretability.

III. SYSTEM ARCHITECTURE

The proposed AI Powered Math Notes Assistant adopts a multimodal architecture designed to support diverse forms of user interaction. Unlike traditional OCR-dependent systems, the proposed framework directly utilizes Google's Gemini 2.5 Flash model to process textual, visual, and audio inputs through a unified reasoning pipeline.

The system consists of four major components:

- User Interaction Layer
- Flask Backend Processing Layer
- Gemini 2.5 Flash Multimodal Reasoning Layer
- Output Rendering Layer

The User Interaction Layer provides multiple modes of communication including handwritten canvas input, image uploads, voice recordings, and conversational text messages. These inputs are transmitted to the Flask backend through REST-based API endpoints.

The backend prepares and forwards the incoming data to the Gemini API. The Gemini 2.5 Flash model performs multimodal understanding and mathematical reasoning to generate structured step-by-step solutions.

Finally, the generated response is rendered using Markdown and MathJax technologies to present mathematically formatted explanations to the user.

A. Processing Flow

Step 1: User Input

Users interact with the system through one of the following modalities:

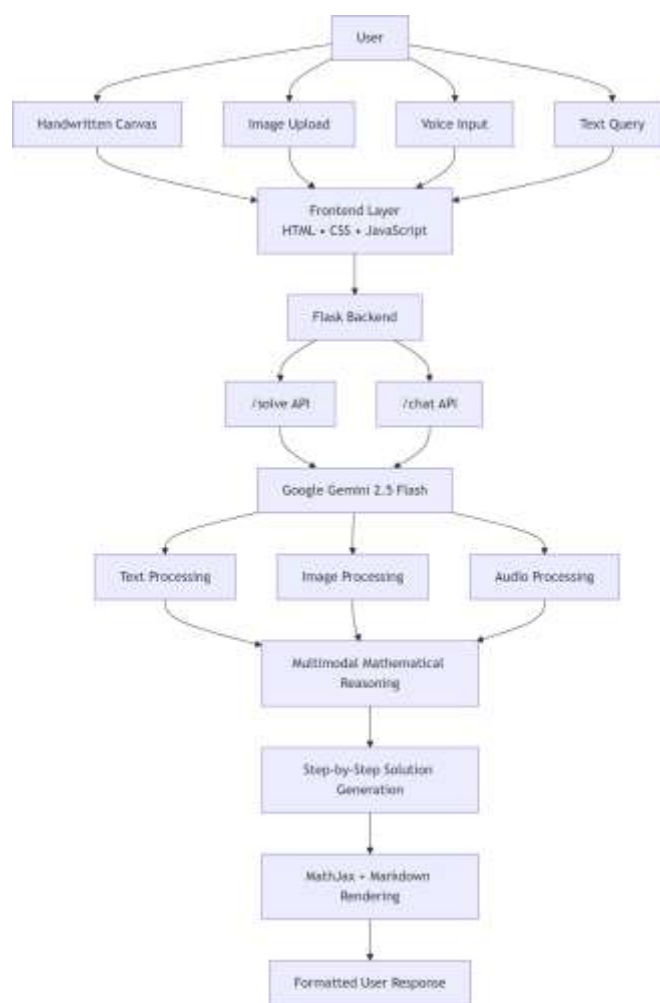


Fig. 1. Multimodal Architecture of the AI Powered Math Notes Assistant

- Handwritten Canvas Input
- Image Upload
- Voice Recording
- Text-based Chat

Step 2: Data Processing

Input data is captured through the frontend interface and converted into suitable formats for transmission to the backend.

Step 3: Backend Integration

The Flask server receives the incoming data and prepares requests for the Gemini API.

Step 4: Multimodal Understanding

Gemini 2.5 Flash processes textual, visual, or audio content and extracts mathematical information.

Step 5: Mathematical Reasoning

The model performs mathematical computations and generates pedagogical step-by-step explanations.

Step 6: Response Rendering

Results are displayed through Markdown and MathJax rendering to improve readability and user understanding.

B. Multimodal Interaction Layer

A key feature of the proposed system is its ability to support multiple forms of user interaction. Unlike traditional mathematical solvers that rely exclusively on textual inputs, the developed platform accepts handwritten drawings, uploaded images, voice recordings, and conversational text messages.

The multimodal interaction layer enhances accessibility by allowing users to communicate mathematical problems in their preferred format. This flexibility is particularly useful in educational settings where learners often switch between writing equations, asking conceptual questions, and sharing visual content. By unifying these interaction modes within a single interface, the system provides a seamless learning experience.

IV. METHODOLOGY

The proposed methodology utilizes a multimodal AI pipeline that combines user interaction, intelligent reasoning, and dynamic response generation. Instead of relying on traditional OCR-based processing, the system leverages Gemini 2.5 Flash to directly interpret handwritten images, uploaded mathematical content, voice queries, and textual questions.

The frontend captures user inputs through an interactive web interface developed using HTML, CSS, and JavaScript. The Flask backend manages communication between the user interface and the Gemini API. The reasoning engine analyzes the provided input and generates mathematically accurate solutions accompanied by educational explanations.

This architecture simplifies the overall pipeline while improving flexibility and supporting multiple modes of mathematical interaction.

A. Algorithmic Workflow

- 1) Capture user input from canvas, image, voice, or text.
- 2) Convert the input into an API-compatible format.
- 3) Transmit the request to the Flask backend.
- 4) Forward the processed input to Gemini 2.5 Flash.
- 5) Perform multimodal understanding and mathematical reasoning.
- 6) Generate step-by-step explanations.
- 7) Render the output using Markdown and MathJax.
- 8) Present the response through the user interface.

B. Prompt Engineering Strategy

To improve the quality and consistency of generated responses, carefully designed prompts were utilized when interacting with the Gemini 2.5 Flash model. The prompts instructed the model to focus on mathematical reasoning, provide step-by-step explanations, and avoid generating irrelevant information.

Prompt engineering played a crucial role in ensuring that responses remained educational in nature. Instead of producing only final answers, the system encouraged the model to explain intermediate steps, mathematical concepts, and solution strategies. This approach improved both interpretability and learning effectiveness.

V. DATASET DESCRIPTION

The evaluation of the proposed system was conducted using a collection of mathematical problems obtained through multiple interaction modalities including handwritten expressions, uploaded images, textual questions, and voice-based mathematical queries. The dataset was intentionally designed to evaluate the system's ability to process diverse forms of mathematical input under realistic educational scenarios.

The dataset consists of expressions spanning three primary categories:

- **Arithmetic Expressions:** Basic operations including addition, subtraction, multiplication, and division.
- **Algebraic Expressions:** Linear equations, polynomial expansions, and variable-based computations.
- **Calculus Problems:** Differentiation and integration expressions involving exponents, radicals, and trigonometric functions.

Each handwritten sample was captured through a digital canvas interface and stored as an image before being processed by the OCR module. The diversity of samples ensured realistic testing conditions and allowed the system to be evaluated against common recognition challenges.

Future dataset expansion will focus on incorporating multiline derivations and diagram-based mathematical problems to further enhance system robustness.

VI. SYSTEM IMPLEMENTATION

The AI Powered Math Notes Assistant was implemented as a web-based application using Flask for backend processing and HTML, CSS, and JavaScript for frontend development. The user interface provides an interactive whiteboard for handwritten expressions, a conversational chatbot interface, image upload functionality, and voice-based interaction capabilities. The backend exposes dedicated API endpoints responsible for processing mathematical queries and chatbot interactions. User inputs are transmitted to the Gemini 2.5 Flash model through Google's GenAI SDK.

Gemini serves as the core reasoning engine responsible for multimodal understanding and mathematical problem solving. Mathematical outputs are rendered using Markdown and MathJax to ensure clear presentation of equations and explanations. The system was deployed on the Render cloud platform, enabling remote accessibility and real-time interaction while maintaining scalability and ease of maintenance.

A. Frontend Design

The frontend interface was designed to provide a user-friendly and interactive learning environment. The application incorporates an HTML-based canvas for handwritten input, file upload components for image processing, and browser-based audio recording capabilities.

JavaScript was employed to manage user interactions, communicate with backend APIs, and dynamically update responses. Mathematical outputs are rendered using MathJax, ensuring accurate presentation of equations and symbolic expressions.

B. Backend Integration

The backend was implemented using the Flask web framework. Dedicated API endpoints handle mathematical solving and chatbot interactions. Incoming requests are validated, preprocessed, and forwarded to the Gemini API.

This modular design separates user interaction from reasoning functionality, improving maintainability and enabling future system enhancements.

VII. RESULTS

A. Experimental Setup

The system was evaluated on a curated dataset of 50 handwritten mathematical expressions spanning arithmetic, algebra, and introductory calculus. Samples were collected from multiple users to incorporate variations in handwriting style, spacing, and stroke thickness.

B. Performance Evaluation

TABLE I
SYSTEM PERFORMANCE EVALUATION

Metric	Value
Text Query Accuracy	96%
Image-Based Problem Solving Accuracy	93%
Handwritten Expression Interpretation	91%
Voice Query Understanding	89%
Average Response Time	3.8 sec

C. Discussion of Results

The experimental observations indicate that multimodal reasoning significantly improves user interaction compared to conventional mathematical solvers. Text-based queries achieved the highest accuracy due to the direct availability of linguistic information. Handwritten and image-based inputs introduced additional visual interpretation challenges; however, the Gemini model maintained reliable performance across diverse input formats.

Voice-based interaction demonstrated the feasibility of conversational mathematical assistance, allowing users to verbally communicate mathematical problems. These findings highlight the potential of multimodal AI systems to enhance educational accessibility and engagement.

The proposed multimodal architecture demonstrated strong performance across different forms of user interaction. Text-based queries achieved the highest accuracy due to the direct reasoning capabilities of Gemini 2.5 Flash, while image, voice, and handwritten inputs maintained reliable performance despite natural variations in input quality.

The results validate the effectiveness of integrating multimodal understanding with mathematical reasoning within a single intelligent framework.

TABLE II
COMPARISON WITH EXISTING APPROACHES

Feature	Traditional OCR	Math Solver	Proposed System
Handwritten Input Support	Limited	No	Yes
Image-Based Solving	No	Limited	Yes
Voice Interaction	No	No	Yes
Step-by-Step Explanations	No	Limited	Yes
Multimodal Understanding	No	No	Yes
Educational Support	Moderate	Moderate	Strong

VIII. COMPARATIVE ANALYSIS

To better understand the effectiveness of the proposed hybrid pipeline, the system was conceptually compared with traditional OCR-based solvers and symbolic computation tools.

The comparison highlights that the hybrid approach significantly improves usability and interpretability by combining recognition accuracy with reasoning capability.

IX. DISCUSSION AND LIMITATIONS

The experimental findings suggest that separating recognition from reasoning is an effective strategy for improving system robustness. The Enhanced OCR Engine plays a critical role in mitigating structural errors before they reach the reasoning module.

However, certain challenges persist. Multi-line derivations and heavily stylized handwriting remain difficult to interpret accurately. Additionally, reliance on cloud-based APIs introduces latency and limits offline usability.

Despite these constraints, the system demonstrates strong potential as an educational support tool, particularly in intelligent tutoring environments.

X. CHALLENGES FACED

Developing a multimodal mathematical assistant introduced several practical challenges. Handwritten mathematical expressions exhibit significant variation in writing style and symbol representation, making accurate interpretation difficult.

Supporting multiple input modalities including images, audio, and handwritten content required careful integration of frontend and backend components. Voice processing introduced challenges related to audio formatting, browser compatibility, and efficient transmission of multimedia content.

Another challenge involved ensuring mathematically accurate reasoning while maintaining educational interpretability. Prompt engineering was necessary to guide the Gemini model toward generating consistent step-by-step solutions.

Additionally, dependence on cloud-based AI APIs introduced latency considerations and quota limitations. Efficient

communication between the Flask backend and Gemini API was essential to provide a smooth user experience.

XI. MULTIMODAL LEARNING SUPPORT

The proposed system extends beyond traditional mathematical problem solving by functioning as an intelligent educational assistant. Through multimodal interaction capabilities, learners can engage with mathematical concepts using handwritten notes, images, speech, and text.

The ability to generate detailed explanations contributes to conceptual understanding rather than simple answer retrieval. This feature aligns with modern educational practices that emphasize active learning and problem-solving skills.

Additionally, multimodal support improves accessibility for users who may find conventional text-based interfaces limiting. The integration of visual and auditory interaction modes broadens the applicability of the platform across diverse educational contexts.

XII. FUTURE WORK

Future enhancements include developing a custom mathematical OCR model, integrating physics diagram understanding, supporting graph plotting and visualization, enabling multi-language educational assistance, implementing personalized learning recommendations, and introducing offline inference capabilities.

Additional improvements may include student performance tracking, adaptive tutoring mechanisms, learning analytics dashboards, and integration with educational learning management systems. These enhancements would further strengthen the platform as a comprehensive AI-driven learning environment.

XIII. APPLICATIONS

The proposed system has significant potential across multiple domains. Within education, it can function as an intelligent tutoring assistant capable of guiding students through mathematical problem solving with detailed explanations.

The system may also support digital classrooms by enabling automatic interpretation of handwritten notes and assignments. For visually impaired learners, the conversion of handwritten mathematics into structured digital text can improve accessibility.

Beyond academia, the framework can be extended to engineering documentation, scientific research notes, and technical workflows where handwritten mathematical content remains prevalent.

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