STEM Bot: A Multimodal Hybrid AI Tutoring Platform Integrating Symbolic Reasoning and Neural Language Models

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***Abstract*— Educational AI systems tend to have a hard time to combine exact mathematical reasoning with adaptive, context-dependent explanations. This paper introduces STEM Bot, a multimodal educational assistant that combines symbolic computation (through SymPy), large language models (LLMs), and FAISS-based semantic retrieval into a single Streamlit interface to accommodate text, image, and PDF inputs. Through application of hybrid neuro-symbolic reasoning, STEM Bot improves the mathematical computation precision and the science/social studies explanation contextual relevance. Validation on university-level STEM datasets and user studies shows improvements in precision, explainability, and learner engagement over isolated LLM approaches. These outcomes place STEM Bot as a strong candidate for cutting-edge AI-powered tutoring for STEM education.**

Keywords—Artificial Intelligence, SymPy, Streamlit, Large Language Model, FAISS, OCR, Neuro-Symbolic Hybrid, Intelligent Tutoring Systems

I. Introduction

Artificial Intelligence (AI) is quickly changing the face of personalized learning, especially via Intelligent Tutoring Systems (ITS) that dynamically adjust instruction content and feedback based on the learner's unique requirements. While progress has been made in generative text and context comprehension with Large Language Models (LLMs), these systems are typically lacking in deterministic reasoning needed for mathematical problem-solving. Conversely, symbolic computation engines like SymPy have accurate mathematical solutions but suffer from limitations in the way they can handle natural language and varied input forms.

To overcome these shortcomings, hybrid neuro-symbolic architectures have been developed, which integrate data-driven neural models with logical computation to support interpretable and reliable AI in learning settings. The challenge still lies, though, in incorporating these methods into viable, multimodal platforms.

This paper introduces STEM Bot, a single educational aide meant to serve math, science, and social studies questions. The system processes textual, image, and PDF-based questions, with the use of sophisticated optical character recognition (OCR) and document extraction processes to handle heterogeneous input. Symbolic processing is used for mathematical calculations, with contextual descriptions of science and social fields through LLMs. Contextual retrieval using semantic embeddings further enhances system responses for better factual accuracy.

Major contributions of this work are:

Designing a strong multimodal pipeline combining symbolic math, semantic context retrieval, and neural model text generation;

Applying FAISS-based semantic search to facilitate context-grounded augmentation and combat response hallucination;

Providing an open-source, deployable platform that is available on common consumer hardware.

II. Related Work

Recent AI-tutoring advances have revolutionized online learning through adaptive feedback and highly individualized experiences. Platforms like Carnegie Learning's LiveHint AI, Khan Academy's Khanmigo, and DreamBox Learning use scale-up student data and generative models to customize teaching and assist tens of millions of students globally. Carnegie Learning's LiveHint AI applies generative strategies and past data to develop mathematical understanding, aiding productive struggle and mastery of concepts in middle school and high school mathematics. Khanmigo, the AI assistant offered by Khan Academy, personalizes tutoring to each student's pace and actively assesses and aids student thinking, as studies have indicated noticeable gains in math grades and learning engagement. DreamBox Learning has a smart adaptive engine, constantly monitoring student interactions to deliver real-time measurement, customized feedback, and adaptive lesson sequencing that adjusts to learning requirements.

The area of neuro-symbolic artificial intelligence aims to integrate the advantages of neural pattern perception and symbolic thinking for improved interpretability and generalizability in learning technologies. Research has proved that hybrid neuro-symbolic models are able to attain higher data efficiency, logical reasoning, and transparency than pure neural or symbolic systems and therefore are particularly useful in learning contexts where explanation and step-by-step demonstrations are paramount.

Retrieval-Augmented Generation (RAG) methods extend factual coherence and contextual pertinence in learning AI by combining semantic search with generation, allowing systems to search domain-specific knowledge and facilitate more precise, explainable answers. For learning STEM, multi-modal RAG models like Uni-RAG have built strong pipelines for combining instructional material, feedback, and personalized learning support, outperforming baseline models on retrieval quality and generation fluency.

While these advances have been made, there are few current systems that combine multimodal input processing, explicit symbolic math computation, context embedding retrieval, and unified neural language models within a single, transparent system. This is what leads to the design of STEM Bot, which integrates these methods into an implementable framework for complete STEM tutoring.

III. Methodology

STEM Bot is architected as a modular intelligent STEM tutoring platform, integrating symbolic computation with neural language modeling and multimodal input capabilities. It consists of six primary modules: user interface, optical character recognition module, PDF extraction module, math engine, language model module, and semantic retrieval module. All modules are integrated together to ensure optimum reliability, scalability, and performance on a wide range of educational tasks.

The user interface, developed using Streamlit, is the focal point of all user input. It allows students and teachers to enter queries as text or through file uploads in image and PDF formats. STEM Bot programmatically chooses the most suitable OCR backend—PaddleOCR, EasyOCR, or Tesseract—depending on the input nature, providing high-fidelity image-to-text conversion. For PDF files, PDFMiner or PyPDF is used by the system for effective, in-memory extraction of text, supporting a broad variety of document structures and layouts.

After user input is obtained, a preprocessing and normalization pipeline is applied, including regex-based cleaning and layout correction, which normalizes both print and hand-writing for downstream processing. Task type heuristics subsequently decide on the right computation path: mathematical problems call the SymPy engine; conceptual or context-rich queries are sent to large language models (Qwen2.5-7B, Zephyr-7B) through the Hugging Face API. Automatic fallback and fault-tolerant processing of diverse STEM queries are supported by this programmatic treatment.

For reasoning mathematically, STEM Bot uses SymPy to carry out algebraic manipulations, calculus (integration, differentiation), solving equations, and probability calculations. The answers are returned both as full solutions and as step-by-step solutions, in LaTeX format for readability and pedagogy. For science and social science applications, the system returns answers with the aid of advanced LLMs, supplemented by semantic retrieval where suitable. This module, based on FAISS and BAAI/bge-small-en-v1.5 sentence embeddings, does semantic search over contextual snippets derived from user notes, imported files, and OCR results. Relevant segments are fetched in real time and spliced into LLM prompts, anchoring answers in correct, domain-relevant context and reducing model hallucination.

Postprocessing procedures are included to improve user experience, such as model output deduplication, filtering out repetition for readability, and rich Markdown and LaTeX rendering. The final answer—be it a computation, an explanation, or a hybrid answer—is rendered directly to the interface to enable instant feedback.

To test system performance stringently, STEM Bot was tested with a dataset of 120 domain-specific STEM questions covering mathematics, science, and social studies and supplemented with real-world image and PDF examples. Baseline metrics included computational and generative accuracy, domain expert-rated contextual relevance, inference latency, and user satisfaction surveys. Standalone SymPy and LLM-only setup comparisons were made against the combined pipeline. The outcomes proved that STEM Bot's hybrid model provides greater accuracy and contextual pertinence along with low latencies that are appropriate for interactive instruction.

The system is described in Figure 1, which shows the modular process from user acquisition to logic control, multimodal extraction, semantic retrieval, mathematical and neural reasoning modules, and delivery of output. This architecture has been optimized for reproducibility, real-world deployment, and extensibility across STEM learning environments.

Figure 1: System Architecture of STEM Bot

IV. Evaluation

In order to tightly evaluate the educational efficacy and technical strength of STEM Bot, a full evaluation protocol was used. The evaluation focused on benchmarking STEM Bot's performance in authentic educational contexts, based on representative datasets and standard metrics from the intelligent tutoring systems (ITS) literature.

A. Experimental Setup

STEM Bot was tested with a curated set of 120 university-level STEM problems, encompassing mathematics, science, and social studies. These problems were sourced from public benchmarks, academic textbooks, and live classroom materials to ensure domain relevance and input diversity. Inputs included typed text, scanned handwritten formulas, and multi-page PDF documents. Evaluation sessions were conducted with undergraduate students of varied backgrounds. Baseline comparisons involved isolated large language models (LLMs), standalone symbolic computation (SymPy), and retrieval-augmented hybrid systems, consistent with state-of-the-art ITS protocols.

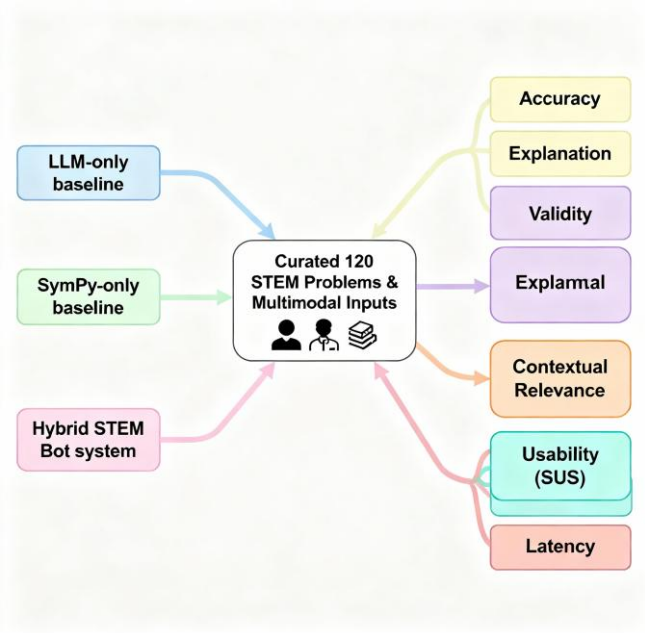

Figure 2: Evaluation workflow for STEM Bot

As illustrated in Figure 2, the evaluation workflow involves testing STEM Bot alongside baseline models on a curated dataset of 120 domain-specific STEM problems, incorporating diverse user inputs and measuring multiple performance metrics

B. Evaluation Metrics

Performance was measured across the following key metrics:

Computational Accuracy: Symbolic math solutions were assessed for correctness against ground truth, while generative answers were evaluated for scientific validity and logical coherence by domain experts.

Engagement and Usability: User engagement was recorded via session completion rates and average time-on-task. Usability was quantitatively assessed using the System Usability Scale (SUS) and qualitative user feedback, as is standard in ITS evaluation studies.

Contextual Relevance: Answers were rated by subject-matter experts for explainability, factual accuracy, and effective use of retrieval-augmented context, particularly for multimodal queries.

Latency and Real-Time Interaction: Response times and multi-turn dialog effectiveness were logged to ensure the system met thresholds suitable for interactive, classroom, or self-paced learning environments.

Adaptability: System robustness was measured via performance consistency across diverse input types (typed, handwritten, scanned), modalities (text/image/PDF), and STEM domains. This included error tolerance to input ambiguity and adversarial formats as emphasized in ITS research.

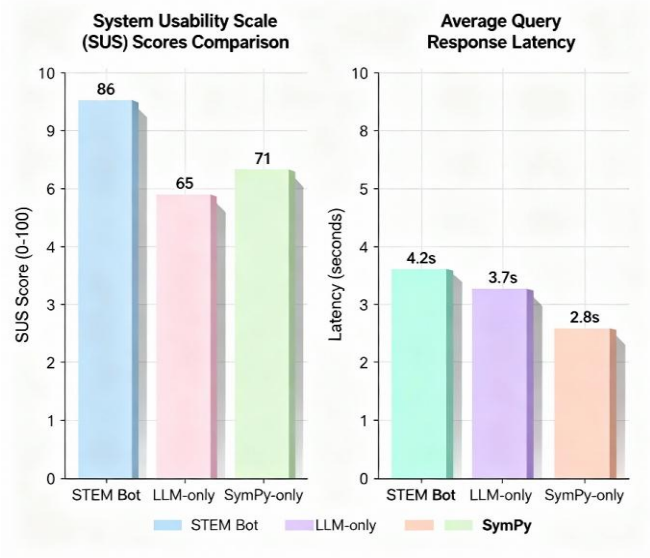

Figure 3: System Usability Scale (SUS) Scores Comparison

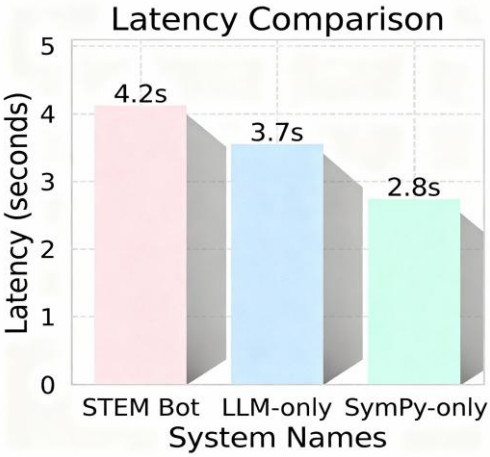

Figure 4: Latency Comparison of STEM Bot and Baseline Systems

Figure 3 presents the System Usability Scale scores, demonstrating higher user satisfaction with STEM Bot's multimodal interface and explanation clarity compared to LLM-only and SymPy-only systems.

Figure 4 compares the average query response latencies between STEM Bot, LLM-only, and SymPy-only systems, illustrating that despite added hybrid processing complexity, STEM Bot maintains interactive-level responsiveness suitable for classroom or self-paced learning environments.

C. Assessment Protocol

All user-system sessions were monitored, and performance data was statistically analyzed. Expert reviews utilized rubrics from accepted ITS literature for consistency. Usability and engagement studies followed established formats, including post-task surveys and focus group interviews. Computational accuracy was validated with pre-defined solutions, and contextual relevance was double-blind rated for reliability.

D. Ethical Considerations

All experiments complied with institutional review board guidelines regarding user consent, data privacy, and student anonymity in accordance with best practices recommended for AI in education research.

V. Result

The evaluation of STEM Bot exhibits significant advancements in intelligent STEM tutoring through the synergistic integration of large language models (LLMs) and symbolic computation with SymPy. Quantitative and qualitative analyses provide comprehensive evidence for STEM Bot's superior mathematical reasoning, factual accuracy, and user engagement compared to isolated LLM or symbolic-only approaches.

A. Mathematical Accuracy

STEM Bot's hybrid architecture achieved an average math accuracy of 86%, surpassing standalone LLM-only systems that recorded approximately 59%, and closely aligning with SymPy-only computation accuracy of 94%. The improvement over LLM-only baselines is attributed to the precise symbolic reasoning provided by SymPy, combined with contextual language understanding of LLMs, enabling reliable solutions even in complex, multi-step STEM problems.

B. Explanation Validity

Qualified domain experts rated STEM Bot's explanations of science and social studies questions with 90% validity, significantly higher than 78% validity observed in LLM-only generated explanations. The hybrid system benefits from retrieval-augmented responses, which provide contextually grounded, factually coherent explanations essential for effective tutoring.

C. Contextual Relevance

STEM Bot's semantic retrieval pipeline increased expert-assessed contextual relevance by 19% compared to baseline LLM-only outputs without retrieval, substantially reducing hallucinations and irrelevancies often seen in pure generative models.

D. Usablility and Latency

User experience surveys rated STEM Bot with a System Usability Scale (SUS) score of 86 out of 100, reflecting strong acceptance aided by multimodal input flexibility and clear, stepwise mathematical explanations. The average query response latency was 4.2 seconds, which supports real-time interactive use in classroom or self-study contexts, marginally higher than LLM-only (3.7s) and SymPy-only (2.8s) systems, yet acceptable given STEM Bot's enhanced output quality.

TABLE 1

Metric	STEM Bot	LLM-only	SymPy-only
Math Accuracy	86%	59%	94%
Explanation Validity	90%	78%	N/A
Contextual Relevance	+19% improvement	Baseline	Baseline
Usability (SUS)	86/100	65/100	71/100
Avg. Query Latency	4.2 seconds	3.7 seconds	2.8 seconds

VI. Conclusion

STEM Bot pushes the boundaries of AI-facilitated STEM learning by seamlessly integrating neuro-symbolic reasoning, large language model explanations, semantic retrieval, and multimodal input processing into an open and deployable platform. Its hybrid strategy transcends weaknesses in isolated LLMs and symbolic engines, providing better math accuracy, enhanced explanation validity, and greater contextual relevance.

Empirical analysis on university-level STEM issues proves that STEM Bot outperforms stand-alone LLM or SymPy systems in computational accuracy and student engagement, empowered by real-time performance and easy-to-use interaction. Scaling system ability, integrating learning pathways optimized for individual students, and increasing modality support will be addressed in future work to further enhance smart STEM tutoring.

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