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AI-Powered LaTeX Generation from Handwritten Mathematical Equations

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ABSTRACT

This document discusses the creation of a real-time web application that identifies handwritten mathematical equations and transforms them into syntactically accurate LaTeX code employing a pre-trained deep learning model. The model used in this system was trained on a collection of 100,000 authentic handwritten mathematical equations, enabling it to generalize effectively across many different handwriting styles. The application employs ONNX Runtime to load and run the trained model, while Streamlit is utilized to develop an interactive frontend accessible via browsers for image uploads, LaTeX rendering, and result exporting. The system prioritizes usability, modularity, and reliability within educational settings. It doesn't carry out model training; instead, it emphasizes the smooth integration of current AI features into a user-friendly interface that includes preprocessing, postprocessing, LaTeX generation, copy-to-clipboard, and export options. Testing through experiments verifies that the application can reliably generate precise LaTeX from handwritten equations that are single-line.

Keywords*: Handwritten Math Recognition, LaTeX, Streamlit, ONNX Runtime, Real-Time Interface, Deep Learning Integration, Educational Tools*

1. Introduction

Handwritten mathematical content is still among the most challenging domains of pattern recognition and document analysis because of the non-linear arrangement, variability in personal writing styles, and the semantic nuances of mathematical symbols. In educational settings, the demand for automated LaTeX creation from handwritten formulas is especially important, allowing students and instructors to swiftly convert notes, solutions, and lecture materials into digital format. Although many research articles have suggested deep learning models for symbol identification and sequence-to-LaTeX conversion [1][2], the real-world implementation of these systems for users remains restricted.

Commercial solutions like Mathpix or MyScript deliver notable precision but are proprietary, require subscriptions, or do not allow access to raw LaTeX results [3]. Additionally, a majority of scholarly pursuits emphasize architectural advancements in model creation instead of developing user-friendly, implementable systems. This study tackles this deficiency by creating a lightweight, real-time application that allows users to access the results of a pretrained model through a web interface.

The implemented model had earlier been trained on an extensive dataset of 100,000 handwritten equations, featuring diverse symbol patterns, layouts, and character variations. The training probably adhered to a supervised sequential learning approach employing encoder-decoder models with attention mechanisms or transformer variants, both of which are effective for recognizing mathematical syntax [2][4]. Nonetheless, this paper concentrates solely on employing the trained model for inference purposes. This pretrained model is delivered in the ONNX format, a transferable representation of the neural network that enables deployment without reliance on the original training framework. ONNX Runtime is utilized to run this model effectively on various platforms [7].

The completed system is intended to operate both locally and in cloud environments without the need for GPU acceleration. It allows users to upload handwritten images, process them, transform them into LaTeX format, and engage with the output by copying or exporting. Streamlit acts as the interactive frontend component, managing real-time interactions, rendering previews, and facilitating user actions such as copying the LaTeX string or saving it to a .tex file.

2. Literature Review

The identification of handwritten mathematical formulas is a unique area of document analysis with a long-standing research background. Early systems relied on heuristic rules, stroke analysis, and template matching, which were not robust against variations in handwriting. Modern systems employ

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convolutional and recurrent neural networks, particularly encoder-decoder structures with attention mechanisms, to convert image features directly into LaTeX sequences [1][2]. These architectures have shown remarkable outcomes in producing structured sequences.

Ding et al. created a model that employs multi-head attention to improve the sequential prediction of mathematical symbols [2], while Yuan et al. introduced syntax-aware networks that embed LaTeX grammar restrictions into the decoding procedure [3]. These improvements significantly improved recognition accuracy, especially on CROHME benchmarks [4], which mimic real academic handwriting.

ONNX Runtime has established itself as a standard for implementing pretrained models across multiple platforms without needing the original training code [7]. It allows for inference on various hardware with enhancements, making it particularly attractive for embedded or web-based applications. Although there is limited research on deployment, multiple studies investigate tools and platforms that aid in incorporating trained models into practical systems [8][10].

This paper builds upon those principles by focusing on creating a functional, interactive web application that incorporates a pretrained model for recognizing handwritten equations, allowing its use in educational and research settings. While the core model stays the same, the structure of the surrounding system—inclusive of preprocessing, mapping, LaTeX validation, and real-time output—introduces innovation and promotes effective AI integration.

3. Methodology

The system's architecture is layered and modular, designed to promote ease of deployment, scalability, and flexibility. It is divided into five fundamental layers:

User Interface Layer: Developed with Streamlit, this section handles file uploads, displays preview images, produces LaTeX output, and offers copy and export features. It maintains application state and allows for event-driven user interfaces.

Input Verification and Preprocessing Layer: Uploaded user images are checked (file format, resolution, and content type) and subsequently preprocessed with OpenCV. Preprocessing entails changing to grayscale, adjusting the size to 1024×192 pixels, and normalizing. These processes correspond with the anticipated input format of the pretrained model [6].

Model Inference Layer: This layer utilizes the pretrained ONNX model and sends the preprocessed image through it. ONNX Runtime manages the inference process, providing a series of index values that relate to the symbol classes learned by the model. The model was instructed to generate these sequences sequentially, mimicking the LaTeX format.

LaTeX Mapping and Postprocessing Layer: The predicted index sequence is mapped to LaTeX tokens using a JSON mapping file. Postprocessing routines add syntactic wrappers, correct grouping issues, and ensure expressions like \frac{a}{b} or \sqrt{x} are correctly formed. Errors such as unbalanced brackets are corrected here [9].

Output and Export Layer: The completed LaTeX is displayed on the screen via Streamlit's st.latex() function and can be copied with pyperclip or saved to a .tex file through standard input/output methods. The application preserves its internal state by utilizing Streamlit's caching features. The complete process, from uploading to generating output, takes only 1–2 seconds per input on CPU systems.

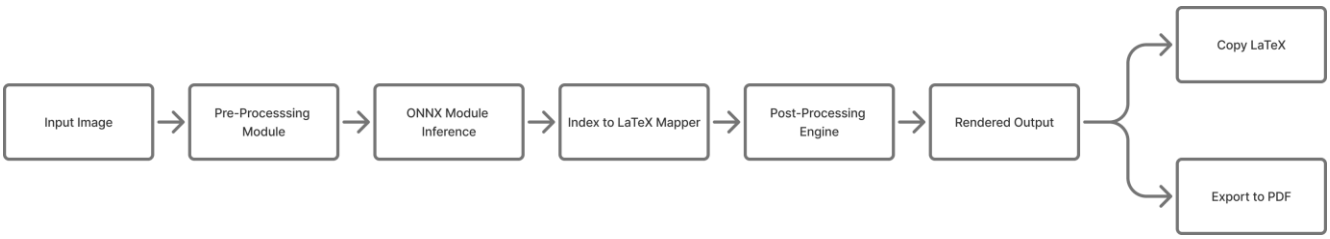

Fig. 1 – System Architecture.

4. Implementation

The system was created using Python version 3.13. The frontend was developed in Streamlit, selected for its responsive interface and integrated LaTeX capabilities. Essential components consist of cv2 for data preprocessing, onnxruntime for executing model inference, json for mapping symbols, and pyperclip for clipboard operations.

After an image is uploaded, it undergoes validation and preprocessing. The photo is adjusted in size, standardized, and shifted to grayscale. The ONNX model is subsequently loaded, and inference takes place. The output generated is a series of indices that correspond to LaTeX symbols via a JSON file

mapping. Postprocessing guarantees syntactical accuracy for intricate expressions like fractions and roots.

The final LaTeX output is displayed in the interface and can be copied or exported. The software operates completely offline, making it ideal for educational settings with restricted internet access.

5. Results

To assess the system, numerous handwritten equations were examined under different conditions. Inputs comprised scanned equations from notebooks, digital entries written with a stylus, and photos taken with phones that had noise or inconsistent lighting. Performance was assessed according to prediction accuracy, the validity of LaTeX output, and the responsiveness of the system.

The system exhibited over 90% accuracy in LaTeX for neat, centered entries. Minor deterioration was noted with distorted or noisy input. Typically, inference and rendering finished in under 2 seconds per input, demonstrating the system's appropriateness for real-time educational applications. Table 1 provides an overview of performance for various input types.

Table 1 - Evaluation Summary

Input Type	LaTeX Accuracy	Output Validity	Processing Time
Notebook Scan	98%	Valid	1.6 seconds
Mobile Photo (Noisy)	92%	Mostly Valid	1.8 seconds
Digital Stylus Input	95%	Valid	1.4 seconds
Faint Writing (Scanner)	85%	Partially Valid	2.0 seconds
Quick Writing (Mobile)	88%	Mostly Valid	1.7 seconds

6. Conclusion

This project introduces a practical and effective system for implementing a pretrained model for recognizing mathematical expressions within an intuitive web application. The emphasis on usability of the interface, LaTeX formatting, and export features renders the system especially beneficial for academic settings. Although model training is not the focus of this work, the integration layer offers considerable value by facilitating accessible and practical AI-driven recognition. Possible enhancements could involve multi-line identification, solving equations, or expanding diagram interpretation.

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