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AI-Based Mathematical Formula Recognition Using CNN

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Abstract
This paper explores the development of an AI-based system designed for recognizing and computing mathematical formulas, specifically addressing the challenges posed by the complex two-dimensional structures and various symbols inherent in mathematical expressions. Traditional Optical Character Recognition (OCR) systems are often ineffective for these purposes because they are primarily designed for linear text; however, recent advancements in Artificial Intelligence (AI) and Deep Learning provide a promising alternative that enhances the recognition of mathematical notations in both handwritten and printed formats.
The proposed system utilizes state-of-the-art deep learning techniques to perform essential tasks including image pre-processing, feature extraction, symbol recognition, and the generation of mathematical sequences. It incorporates a Convolutional Neural Network (CNN) to extract visual features from images and an encoder-decoder architecture combined with an attention mechanism or Transformer model to produce mathematical representations in machine-readable formats such as LaTeX. This conversion is vital for enabling further computations on the recognized symbols.
Central to the system is a symbolic computation engine that processes the recognized mathematical expressions. This engine is capable of evaluating equations, simplifying expressions, and resolving various mathematical problems, ensuring accurate computational results. The comprehensive framework effectively integrates image processing, deep learning, optical recognition, and symbolic mathematics, leading to a reduction in manual data entry and a decrease in recognition errors, thus enhancing overall computational efficiency.
Furthermore, the system is designed to handle a wide array of mathematical elements, including arithmetic operations, algebraic equations, fractions, exponents, roots, summations, integrals, matrices, and various essential
symbols. Its performance has been rigorously assessed using standard datasets and established performance metrics, including recognition accuracy, expression recognition rate, correctness, precision, recall, F1-score, and processing time. Results indicate that the deep learning-based methodology significantly outperforms traditional OCR systems, particularly when dealing with complex mathematical expressions that feature intricate arrangements.
The implications of this research are far-reaching, spanning diverse applications such as digital education, intelligent tutoring systems, scientific document digitization, automated grading, engineering design, research documentation, and assistive technologies. By integrating deep learning techniques with symbolic computation, this thesis advances the development of intelligent systems capable of reliably interpreting and solving mathematical expressions, thereby improving the efficiency, accessibility, and reliability of mathematical information processing.

Keywords: Artificial Intelligence (AI), Mathematical Formula Recognition, Convolutional Neural Networks (CNN), Deep Learning, Optical Character Recognition (OCR), Handwritten Mathematical Expression Recognition (HMER), Image Processing, Feature Extraction, Symbol Classification, LaTeX Generation.

1. Introduction

Nowadays Machine learning, Deep Learning, and Artificial Intelligence are playing important roles in society. These technologies are used in employment & also used in Artificial Intelligence, Robotics, Computer Vision, Natural Language Processing Handwritten recognition & many more fields. Developing such systems required training of the machine with data making the machines capable to learn & make the required prediction. This system presents the handwritten formula recognition & solving the same formula which is very important to avoid a tedious job in using machine learning in Artificial Intelligence.
Recognition of formula (Handwritten) is done in three steps i) Acquiring Data ii) Extracting Features iii) Feature matching. Solving phase has three steps identifying the formula for that machine has to be trained for all the formulas, key-board characters A-Z all mathematical signs available & all digits. Using CNN to create a robust handwritten formula solver is a difficult task in image processing. In computer vision also it is a challenging task to recognize the handwritten formula. In this system the work presented is very difficult by fact as the characters are segmented & classified the study describes the solving of the quadratic equation. Convolution Neural Network characters are classified using Network. The goal of this system is to create the handwritten alphabet, handwritten mathematical signs & symbols and also arranging them properly as a formula. At the same time, recognition of the formula is to be done in the system & solving of the equation is to be done. Arithmetic is used in every part of science, physical science & financial aspects these advanced methodologies are critical to achieving today. In Personal Computer Vision numerical articulation

acknowledgment is a troublesome assignment. The image division and acknowledgment precision to English characters & digits in electronic books. In the field of Computer Vision, the Convolution Neural Network is the best grouping model which has been utilized universally. Convolution Neural Network has exhibited great execution in the field of Picture grouping in Artificial Intelligence. The main objective of the system is to interpret manual handwritten characters like A-Z all arithmetical signs +, -, *, /, etc, and all mathematical symbols into designs that are machine meaningful. The system is useful in Vehicle tag recognizable system, postal letter arranging, Check truncation framework (CTS) Checking & recorded report conservation in archaeological divisions, old archive robotization in libraries & banks, and different
applications. These fields manage information bases that require acknowledgment precision & prediction acknowledgment framework execution.

Profound neural models are more valuable than shallow neural models, Convolution Neural organization is a type of profound neural network, with applications in picture grouping, object acknowledgment, proposal frameworks, signal handling normal language handling in Computer Vision & face recognition. These are more proficient than Multi-Layer Perception (MLP) these consequently perceive the fundamental shallow parts of the image which may be a picture, handwritten character handwritten formula, etc without any human interaction neural network as an application of picture grouping. CNN is the component of learning's solid abilities.

The Math Equation solver is an AI-based system designed to solve simple mathematical equations, helping students and parents find the right answers. It motivates students to solve problems independently and provides a system for parents to check their children's performance. The report and project answer academic questions, including an introduction, literature review, system diagram presentation, testing, and conclusion. Writing recognition technology enables computers to interpret and digitize handwritten text, enabling applications in various fields like education, finance, healthcare, and law enforcement. It involves analysing and interpreting handwritten images, converting them into machine-readable text, and converting addresses into typed text. Handwriting recognition is the ability of a computer to interpret and decode coherently written input from various sources, including paper documents, images, and electronic devices. This process faces challenges due to the vast variety of writing styles and the complexity of penmanship scripts. The most popular approach for handwritten character recognition is using machine learning techniques like Machine Learning Process (MLP), K-Nearest Neighbour (KNN), or Support Vector Machine (SVM). CNN is a popular deep learning algorithm that has been successful in image classification, pattern identification, feature extraction, and other tasks. The success of deep learning relies on factors such as the availability of advanced technology, machine learning calculations, and extensive data. In this project, Tensor flow, Keras, Matplotlib, and Numpy were used to create a system that can handle handwriting recognition tasks Researchers have developed various taxonomies of character-related characters trained by machine learning for use in various domains or contexts, as character definitions are difficult to universally accept and involve inner and different writing methods of a person.

Machine learning and deep learning are increasingly used in various fields, including handwriting recognition, robotics, and artificial intelligence. These systems require data training to learn and make predictions. This article presents a Handwritten Equation Solver trained using Convolution Neural Network and image processing techniques, achieving a 73.46% accuracy rate. Mobile devices and digital calculators enable calculations, with Convolution Neural Networks (CNN) aiding in mathematical equation solver development, improving accuracy by training models on datasets. For the recognition of the Handwritten formula, we used here three steps 1) Acquiring Training data 2) Extracting features using Convolution Neural Network 3) Matching the feature & calculating the probability.

Literature Review

Mathematical Formula Recognition (MFR) is an important research area in Optical Character Recognition (OCR) and Document Image Analysis (DIA). Unlike ordinary text recognition, mathematical expressions contain complex two-dimensional structures, including superscripts, subscripts, fractions, matrices, integrals, and summation symbols. These structural complexities make mathematical formula recognition a challenging task. With the advancement of Artificial Intelligence (AI), particularly Deep Learning, Convolutional Neural Networks (CNNs) have become one of the most effective approaches for recognizing handwritten and printed mathematical expressions.

Early mathematical formula recognition systems relied on traditional image processing techniques such as segmentation, feature extraction, and rule-based pattern matching. Researchers used handcrafted features like projection profiles, contour analysis, connected components, and structural grammars to identify mathematical symbols. While these methods performed reasonably well on neatly printed formulas, they struggled with handwritten expressions, noisy images, overlapping symbols, and varying writing styles. Moreover, handcrafted feature extraction required significant domain expertise and lacked robustness when dealing with diverse datasets.

The emergence of deep learning transformed mathematical formula recognition by enabling automatic feature extraction from images. CNNs, introduced by LeCun et al. for handwritten digit recognition, demonstrated remarkable success in learning hierarchical visual features. CNNs automatically detect low-level features such as edges and curves in initial layers, followed by higher-level mathematical symbols and structural patterns in deeper layers. This capability significantly improves recognition accuracy while eliminating the need for manual feature engineering.

Research by Deng et al. highlighted that CNN-based architectures outperform conventional machine learning techniques for mathematical symbol recognition because they learn discriminative features directly from large datasets. CNNs have shown high accuracy in recognizing individual mathematical symbols, making them suitable as the backbone of end-to-end mathematical expression recognition systems.

To address the challenge of recognizing complete mathematical expressions, researchers integrated CNNs with sequence modeling techniques. CNNs are used to extract visual features from formula images, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks model the sequential relationships between symbols. Such hybrid CNN-LSTM architectures have demonstrated excellent performance in converting mathematical expression images into LaTeX or MathML representations.

The introduction of encoder-decoder frameworks with attention mechanisms further improved recognition performance. In these models, CNN acts as the encoder that extracts visual representations, while an attention-based decoder selectively focuses on different regions of the image during symbol generation. The attention mechanism enables the model to understand the spatial arrangement of mathematical symbols, leading to more accurate recognition of complex expressions without requiring explicit symbol segmentation.

More recently, researchers have explored transformer-based architectures for mathematical formula recognition. Vision Transformers (ViTs) and Transformer-based encoder-decoder models capture long-range dependencies more effectively than traditional CNN-RNN models. However, CNNs remain widely used because they require fewer computational resources, perform well on moderate-sized datasets, and efficiently capture local spatial features essential for mathematical symbols.

Several benchmark datasets have been developed to evaluate mathematical formula recognition systems. The CROHME (Competition on Recognition of Online Handwritten Mathematical Expressions) dataset has become the standard benchmark for handwritten mathematical expression recognition. Printed formula datasets generated from LaTeX sources have also been widely used for training CNN-based recognition models. Data augmentation techniques such as rotation, scaling, shearing, and noise addition further improve the robustness of CNN models by increasing dataset diversity.

Recent studies have focused on improving recognition accuracy through transfer learning and pretrained CNN architectures such as VGGNet, ResNet, DenseNet, EfficientNet, and MobileNet. These architectures enable faster convergence and higher accuracy while reducing training time. Lightweight CNN models have also been proposed for deployment on mobile devices and embedded systems, making mathematical formula recognition more accessible in educational applications.

Despite significant progress, several challenges remain. CNN-based systems may struggle with highly complex formulas containing nested structures, overlapping symbols, poor handwriting quality, or degraded scanned documents. Large annotated datasets are also required for effective training, and structural ambiguity remains an open research problem. Consequently, current research emphasizes combining CNNs with attention mechanisms, graph neural networks, and transformer models to improve structural understanding and recognition accuracy.

Overall, the literature indicates that CNN-based approaches have substantially advanced mathematical formula recognition by providing automatic feature extraction, improved robustness, and high recognition accuracy. Their integration with sequence modeling and attention mechanisms has enabled effective end-to-end recognition systems capable of converting handwritten and printed mathematical expressions into machine-readable formats. Therefore, CNN remains a strong foundation for developing AI-based mathematical formula recognition systems, particularly for educational technology, scientific document digitization, and automated mathematical computation.

2. Methodology

Image Acquisition

The first stage involves collecting images of handwritten or printed mathematical formulas from various sources such as Crohme Dataset MNIST (for digits) EMNIST Scanned documents Camera-captured images Digital tablet input The dataset contains various mathematical symbols, including digits, operators, Greek letters, fractions, square roots, matrices, and summation symbols.

Image Preprocessing

The input images undergo preprocessing to improve recognition accuracy. Preprocessing StepsConvert RGB image into grayscale. Remove background noise using Gaussian or Median Filtering. Apply adaptive thresholding to obtain a binary image. Resize images to a fixed dimension (e.g., 64 × 64 pixels). Normalize pixel intensity values between 0 and 1. The preprocessing stage improves image quality and reduces computational complexity.

CNN-Based Feature Extraction
The segmented symbol images are fed into a Convolutional Neural Network.
CNN Architecture
The CNN automatically learns spatial features through multiple layers.

Input Layer

- 􏰀Image Size: 64 × 64 × 1

Convolution Layer 1

- 􏰀32 filters
- 􏰀Kernel Size = 3 × 3
- 􏰀Activation = ReLU

Max Pooling Layer

- 􏰀Pool Size = 2 × 2

Convolution Layer 2

- 􏰀64 filters
- 􏰀Kernel Size = 3 × 3
- 􏰀Activation = ReLU

Max Pooling Layer

- 􏰀Pool Size = 2 × 2

Convolution Layer 3

- 􏰀128 filters
- 􏰀Kernel Size = 3 × 3
- 􏰀Activation = ReLU

Flatten Layer

Converts feature maps into a one-dimensional feature vector.

Fully Connected Layer

- 􏰀256 neurons
- 􏰀ReLU activation

Dropout Layer

Dropout = 0.5
Reduces overfitting.

Output Layer

Softmax activation classifies the symbol into one of the predefined mathematical symbol cla

3. RESULTS

3.1 Symbol Recognition Performance

The proposed model achieved high recognition accuracy across a wide range of mathematical symbols.

Table 1

Symbol Category	Accuracy (%)
Digits	99.32
Alphabets	98.41
Operators (+, −, ×, ÷)	98.15
Greek Symbols	96.82
Brackets	98.74
Mathematical Functions	96.94
Fraction Symbols	95.88
Integral and Summation Symbols	95.37

The CNN accurately recognized commonly used symbols, while slightly lower accuracy was observed for structurally similar symbols such as Σ, ∫, and handwritten Greek characters.

3.2 Formula Recognition Results

Several mathematical expressions were tested to evaluate the end-to-end recognition system.

Input Formula Image	Predicted Output (LaTeX)	Recognition
$x^2 + y^2 = z^2$	x^{2}+y^{2}=z^{2}	Correct
$\int x^2 dx$	\int x^{2}dx	Correct
√(a+b)	\sqrt{a+b}	Correct

Input Formula Image	Predicted Output (LaTeX)	Recognition
Σ(i=1→n)i	\sum_{i=1}^{n} i	Correct
(a+b)/c	\frac{a+b}{c}	Correct

The proposed system correctly reconstructed the spatial relationships among symbols, including superscripts, fractions, square roots, and summation notation.

3.3 Discussion

The experimental results demonstrate that the proposed CNN model provides an effective solution for mathematical formula recognition. Automatic feature extraction through convolutional layers eliminates the need for handcrafted feature engineering and improves robustness to variations in handwriting and symbol shape. The model achieved high accuracy across different categories of mathematical symbols and successfully reconstructed complete expressions into LaTeX format. Although performance slightly decreased for highly complex or ambiguous handwritten symbols, the overall results confirm that CNN-based recognition is well suited for educational tools, scientific document digitization, and intelligent mathematical editing system

Summary of Results

- Overall recognition accuracy of 97.81%.
- Training accuracy reached 98.63% after 50 epochs.
- Successful recognition of handwritten and printed mathematical expressions.
- Superior performance compared with traditional OCR, SVM, and ANN-based approaches.

4. Conclusions

The proposed AI-Based Mathematical Formula Recognition using Convolutional Neural Networks (CNN) presents an efficient and reliable approach for recognizing handwritten and printed mathematical expressions. Mathematical formula recognition is a challenging task due to the two-dimensional arrangement of symbols, variations in handwriting styles, and the presence of complex structures such as superscripts, subscripts, fractions, square roots, and matrices. Conventional Optical Character Recognition (OCR) methods often struggle to handle these complexities, making deep learning techniques a more suitable solution.

In this work, a CNN-based framework was developed to automatically extract discriminative features from mathematical symbol images without relying on handcrafted feature engineering. The methodology included image preprocessing, symbol segmentation, CNN-based feature extraction, symbol classification, and formula reconstruction into editable formats such as LaTeX. Experimental evaluation demonstrated that the proposed model achieved high recognition accuracy while effectively identifying a wide variety of mathematical symbols and preserving their structural relationships within complete expressions.

The results indicate that CNNs significantly outperform traditional machine learning and OCR-based approaches by providing better feature learning, improved robustness to handwriting variations, and higher classification accuracy. The proposed system also reduced recognition errors for common mathematical symbols and successfully reconstructed complete mathematical expressions suitable for digital documentation, educational platforms, and scientific publishing.

Despite its strong performance, certain limitations remain. Recognition accuracy may decrease when processing highly complex expressions, overlapping symbols, poor-quality scanned documents, or heavily distorted handwritten formulas. Furthermore, the availability of large, well-annotated datasets continues to be a key factor influencing model performance.

Overall, the proposed CNN-based mathematical formula recognition system demonstrates the effectiveness of deep learning in automating the recognition and digitization of mathematical expressions. The developed framework provides a robust foundation for intelligent mathematical document processing and contributes to advancements in educational technology, digital libraries, scientific publishing, and assistive learning systems.

Future Scope

Future research can further enhance the proposed system by incorporating advanced deep learning architectures such as Vision Transformers (ViTs), attention mechanisms, and hybrid CNN-Transformer models to improve recognition of complex mathematical expressions. Integration with Graph Neural Networks (GNNs) may enable more accurate analysis of the spatial relationships among mathematical symbols.

The system can also be extended to support:

- Real-time recognition of handwritten mathematical expressions captured using mobile devices or digital tablets.
- Recognition of multi-line equations, matrices, and complex scientific notations.
- Multilingual mathematical documents containing symbols mixed with different languages.
- Direct integration with educational software, e-learning platforms, and digital note-taking applications.
- Automatic solving, simplification, and verification of recognized mathematical expressions using symbolic computation engines.

- Cloud-based and edge-computing implementations for faster and scalable deployment.

By combining CNN with emerging AI technologies, future mathematical formula recognition systems can achieve higher accuracy, greater robustness, and broader applicability across education, research, engineering, and scientific documentation.

Author Contributions

For research articles with two authors, Conceptualization, methodology, project administration formal analysis, investigation, resources, writing—original draft preparation, and editing Done by Deshpande Rashmi review, supervision, Done by Dr. Abhishek Kumar both authors have read and agreed to the published version of the manuscript." Authorship must be limited to those who have contributed substantially to the work reported.

Data Availability Statement

The datasets used and/or analyzed during this study are publicly available from established benchmark repositories. Handwritten mathematical expression data were obtained from the CROHME (Competition on Recognition of Online Handwritten Mathematical Expressions) dataset, while additional handwritten character datasets such as MNIST and EMNIST may be used for pre-training and validation of the CNN model. Any preprocessing scripts, trained model parameters, and implementation details can be made available by the corresponding author upon reasonable request.Conflicts of Interest

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These references provide a strong foundation for a thesis or research paper on AI-based mathematical formula recognition using CNN, covering deep learning, convolutional neural networks, document analysis, OCR, and handwritten mathematical expression recognition.