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Handwritten Mathematical Expression Recognition using Deep Learning Techniques

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ABSTRACT

The accurate recognition and computational evaluation of handwritten mathematical expressions present a significant challenge in the domain of intelligent systems and digital education. This complexity is primarily due to the diverse nature of human handwriting and the inherently two-dimensional structure of mathematical notation, which traditional Optical Character Recognition (OCR) systems fail to interpret reliably. To address these limitations, this study introduces a deep learning-based framework employing Convolutional Neural Networks (CNNs) for the classification of individual handwritten symbols. The system is trained on a curated dataset of over 96,000 grayscale images encompassing 13 classes, including numeric digits and basic arithmetic operators. After classification, the identified symbols are reconstructed into complete expressions and evaluated using a programmatic method based on Python's eval() function. The model achieves a training accuracy of 99.55%, demonstrating its efficacy in symbol recognition. Preprocessing techniques such as grayscale conversion, thresholding, contour extraction, and image normalization ensure consistent and high-quality input. The system's modular design and low computational overhead make it suitable for real-world deployment, including on embedded and mobile platforms. This work lays a foundation for scalable, efficient, and accurate recognition of handwritten mathematical content, contributing to advancements in educational technologies and human-computer interaction

Key Words: *Handwritten Mathematical Expression Recognition, Convolutional Neural Networks (CNNs), Deep Learning, Image Processing, OCR, Symbol Classification, Eval Function, Neural Networks, Educational Technology, Real-Time Evaluation*

1. INTRODUCTION

The rapid growth of digital technologies in education has increased the need for systems that can understand and process handwritten input—particularly mathematical expressions. Math notation is more complicated than ordinary text because of its two-dimensional arrangement, variety of symbols, and hierarchical hierarchies. Because traditional OCR systems usually interpret text in a linear fashion and are unable to comprehend the spatial relationships between symbols, they are ill-suited for this task.Handwritten Mathematical Expression Recognition (HMER), a field that combines computer vision, pattern recognition, and artificial intelligence, has gained more attention as a result of this difficulty. The objective is to preserve the structure and meaning of handwritten math while converting it into machine-readable format. This isn't simple, though; complex statements, irregular symbol positioning, and variations in handwriting styles all make recognition more challenging.

Deep learning's introduction has created exciting new opportunities to improve HMER systems. Without using manually created features, deep learning models—in particular, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs)—can directly identify patterns in unprocessed visual data. For visual tasks like handwriting detection, this makes them particularly well-suited. Because CNNs learn localized elements that define handwritten symbols, such edges, curves, and crossings, they are particularly effective tools for spotting patterns in image data.

In this study, we present a deep learning-based approach to recognizing and solving handwritten mathematical equations. Our system uses a Sequential CNN architecture composed of convolutional, pooling, dropout, and fully connected layers. It is trained on a large dataset of over 96,000 grayscale images spanning 13 symbol categories, including digits and basic arithmetic operators.

To prepare the data for training, each image undergoes several preprocessing steps: grayscale normalization, image thresholding, contour extraction, and resizing to a consistent 28×28 pixel format. These steps help reduce background noise and enhance the visibility of key features. After the CNN identifies the individual symbols in an image, they are reconstructed into a full expression and evaluated using Python's built-in eval() function. This combination of recognition and computation makes the system highly practical for use in educational settings, digital learning tools, and assistive technologies for users with learning or physical disabilities.

In summary, this work advances the field of HMER by proposing an efficient and accurate deep learning-based solution that combines symbol recognition with real-time mathematical evaluation. The model's scalability and lightweight design make it suitable for a range of real-world applications, setting the foundation for further research and development in intelligent handwriting recognition

2. LITERATURE REVIEW

Over the past ten years, significant progress has been made in the challenge of Handwritten Mathematical Expression Recognition (HMER), primarily due to studies in computer vision and deep learning. The field's terrain has been shaped by a number of seminal publications that introduced advances in neural network topologies, attention mechanisms, and symbol interpretation methodologies.

One of the significant milestones in CNN development was introduced by François Chollet with the Xception model [1]. His architecture, which employs depthwise separable convolutions instead of standard convolutional layers, enabled higher accuracy with fewer parameters and lower computational costs. This model has shown excellent results in large-scale image classification and provides a robust backbone for symbol recognition tasks in HMER systems.

Deng et al. [2] proposed a encoder-decoder neural network for translating mathematical images into LaTeX markup. Their work demonstrated that attention-based models could outperform traditional OCR by focusing on localized visual features and reducing computational complexity during inference. The introduction of a new dataset comprising rendered mathematical images and markup pairs further validated their method's efficiency.

The foundational principles underlying deep learning techniques were exhaustively presented in the work by Goodfellow, Bengio, and Courville [3]. Their book not only delves into the mathematical theory of neural networks but also covers practical applications such as CNNs, RNNs, and regularization methods, providing essential groundwork for developing robust HMER systems.

In the domain of handwriting recognition, Graves and Schmidhuber [4] made a significant impact with their development of Multidimensional Recurrent Neural Networks (MDRNNs). Their system, which combined MDRNNs with Connectionist Temporal Classification (CTC), allowed for the effective recognition of handwritten content without requiring segmented inputs. This capability is especially useful in interpreting two-dimensional mathematical structures that do not follow linear patterns.

Guo, Chen, and Li [5] proposed a multi-scale attention mechanism integrated into a DenseNet encoder to tackle scale variation in handwritten expressions. Their hierarchical model effectively handled global layout and local details, improving recognition accuracy and generalizability. The use of DenseNet also improved gradient flow and made the model more data-efficient—a critical feature when working with limited annotated datasets.

Yann LeCun et al. [6] revolutionized document recognition through the LeNet-5 architecture, a CNN model tested on the MNIST dataset. This model established the viability of CNNs for handwritten character recognition and inspired many subsequent deep learning architectures. The MNIST dataset itself, presented by LeCun, Cortes, and Burges [7], became the standard benchmark for evaluating performance in character and symbol recognition tasks.

Matsakis and Zanibbi [8] approached mathematical expression recognition by combining symbol context with tree transducers, modeling the structural relationships between symbols. Their system proved capable of interpreting nested expressions and demonstrated improved accuracy in parsing two-dimensional mathematical structures.

Harold Mouchère and collaborators [9] initiated the CROHME competition, a crucial benchmark in the field of HMER. This platform provided standardized datasets and evaluation protocols, encouraging the development of new recognition models. The competition's results highlighted the importance of integrating structural analysis and learning-based approaches.

In scene text recognition, Shi et al. [10] proposed an end-to-end trainable system that eliminated the need for character segmentation. In a later development, ASTER [11], they introduced a rectification network that corrected distorted text before recognition using an attention-based decoder, offering a flexible solution for irregular handwriting or scanned content.

Simonyan and Zisserman [12] introduced the VGG network, known for its uniform convolution filter sizes (3×3) and depth, which significantly improved image classification accuracy. Szegedy et al. [13] followed with the Inception architecture, using multi-scale filters to extract hierarchical features efficiently.

In broader surveys, Tappert et al. [14] reviewed the state-of-the-art in handwriting recognition, while Tan and Le [15] introduced EfficientNet—a family of CNNs using compound scaling that balances accuracy and efficiency. Tang et al. [16]

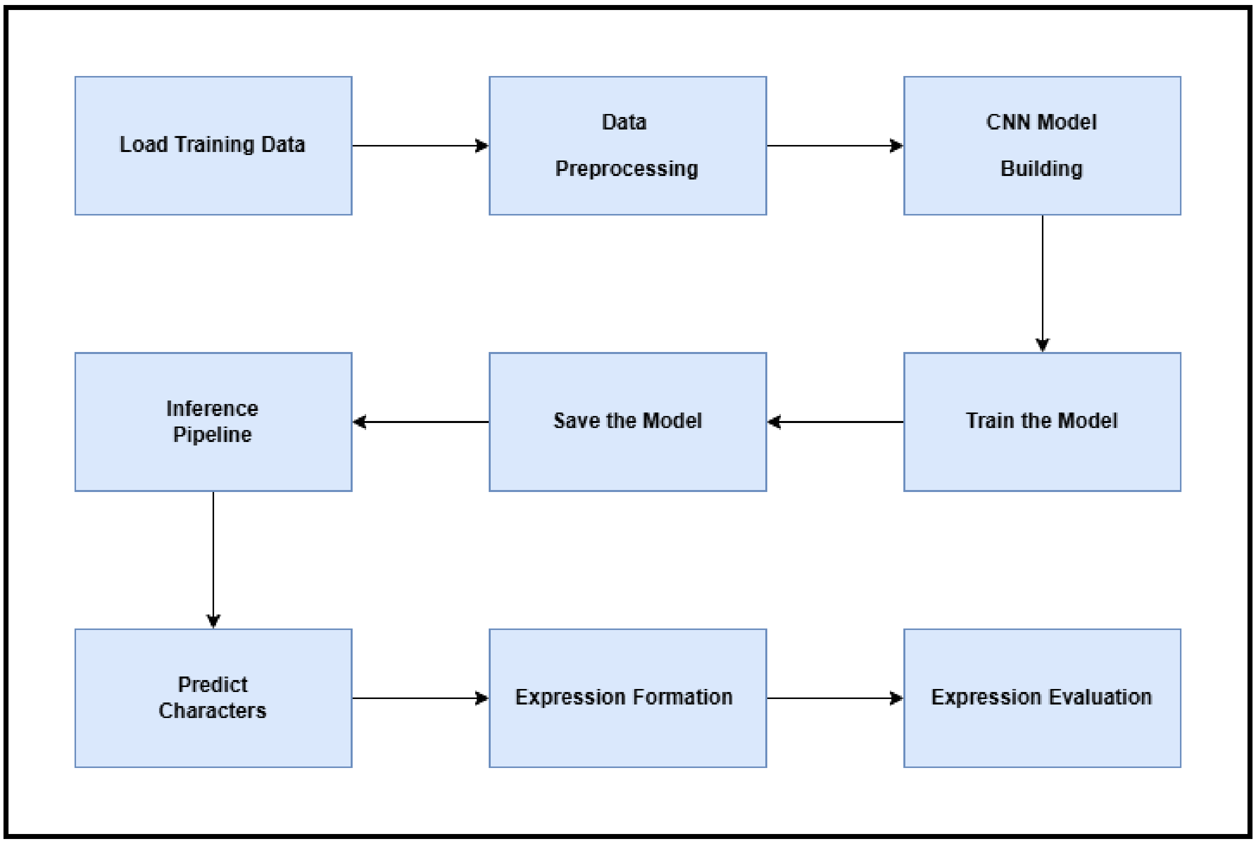
provided a comprehensive review of deep learning approaches to handwritten mathematical symbol recognition, highlighting the need for large annotated datasets and structural modeling.

Recent contributions such as TAMER by Zhu et al. [20] introduced a tree-aware transformer model capable of jointly optimizing sequence prediction and structural understanding, pushing the performance limits on CROHME datasets. Xie et al. [19] developed a graph-based model using Edge-weighted Graph Attention Networks (EGATs), which simultaneously classified symbols and relationships in handwritten expressions.

These studies collectively reflect a strong trajectory toward attention-based, structure-aware recognition systems for mathematical notation. This paper builds upon these insights by employing CNNs for symbol recognition and integrating simple programmatic evaluation, thus aiming to bridge low-level image classification with expression-level computation.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

The system proposed in this research is designed to recognize and evaluate handwritten mathematical expressions by leveraging a Convolutional Neural Network (CNN)-based classification pipeline. The architecture integrates both image processing and machine learning components, enabling the conversion of handwritten arithmetic expressions into structured digital outputs that can be evaluated using a computational backend. This section elaborates on the components involved in the end-to-end process, including dataset formulation, preprocessing, CNN model architecture, and expression evaluation.



A. System Overview

The complete system architecture is divided into five major stages: image acquisition and preprocessing, character segmentation, symbol classification, expression reconstruction, and evaluation. Handwritten expressions are first captured as images and subjected to preprocessing steps to enhance clarity and normalize input dimensions. These images are then processed to detect and isolate individual characters using contour analysis. Each isolated character is passed through a CNN-based classifier trained to recognize digits (0–9) and operators such as addition, subtraction, and multiplication. Once all symbols are identified, the full expression is reconstructed and evaluated using Python’s eval() function.

B. Dataset Description

The system was trained using a custom dataset consisting of 96,429 grayscale images spread across 13 symbol classes. The dataset includes handwritten digits from 0 to 9, and arithmetic operators including '+', '-', '*', and other punctuation marks used in expressions. Each symbol is stored in its corresponding folder for labeled classification. The dataset is structured to support supervised learning and is formatted as image-label pairs.

Each image in the dataset is derived from a binary file and represents one isolated symbol. Grayscale images are created by mapping byte-level binary values to pixel intensities, producing consistent 28×28-pixel inputs suitable for CNN ingestion. This consistent size is crucial for maintaining uniformity during model training and inference.

C. Image Preprocessing

Before feeding images into the CNN, preprocessing steps are applied to ensure noise reduction and spatial consistency. Images are first converted to grayscale and inverted to highlight foreground symbols. A binary thresholding operation simplifies the data to black-and-white pixels, emphasizing structural features. Contour detection is then used to locate and crop individual symbols, which are resized to a standard 28×28 dimension. Finally, the images are reshaped into 1D arrays and normalized to support faster convergence during training.

This preprocessing pipeline is essential for reducing irrelevant background noise, isolating meaningful patterns, and providing consistent input dimensions for the CNN, significantly improving classification performance.

D. CNN Model Architecture

- CNN Model Structure
- The suggested model makes use of a Keras-implemented sequential CNN architecture. It has two convolutional layers, which are one of its components. The first has the "same" padding, a 3x3 kernel, and 32 filters. The second has default (legal) padding and 15 filters.
- Activation Functions: To add non-linearity, ReLU is applied after every convolutional layer.
- Pooling Layers: To downsample feature maps, MaxPooling2D layers with a pool size of 2×2 come after each convolutional layer.
- Dropout Layer: After pooling, neurons are randomly disabled at a dropout rate of 0.2 to avoid overfitting.
- Flatten Layer: Produces a 1D vector from the multi-dimensional feature maps.
- Calculate the outcome while maintaining arithmetic and structural accuracy.
- Dense Layers**:** For multi-class classification, an output layer with 13 neurons and Softmax activation comes after two dense layers with 128 and 50 neurons, respectively, using ReLU activation.

E. Instruction and Assessment

To improve generalization, the dataset was randomized at each epoch, and a batch size of 200 was employed over 10 epochs. With a consistent decrease in loss throughout epochs and a peak training accuracy of 99.55%, the model demonstrated a good fit and efficient learning.

During inference, each input image undergoes the same preprocessing pipeline. The trained model predicts the class of each isolated symbol, which is then assembled into a string representing a complete mathematical expression. Python's built-in eval() function is used to compute the result, ensuring both structural and arithmetic accuracy.

4. A DATASET COLLECTION AND PREPARATION

The success of any machine learning system, especially those leveraging deep learning architectures, depends heavily on the quality and diversity of the dataset used for training and evaluation. In the present study, the dataset utilized for handwritten mathematical symbol recognition is sourced from the publicly available **Handwritten Math Symbols** dataset curated by Xai Nano and hosted on Kaggle [1]. This dataset is one of the most comprehensive repositories for handwritten mathematical symbol classification, containing a rich variety of symbols, operators, and alphanumeric characters relevant to mathematical contexts.

The dataset consists of approximately **375,974 grayscale images**, each representing a single isolated symbol. These symbols are categorized into **82 distinct classes**, covering a wide range of mathematical notation. Included within the dataset are:

- Basic arithmetic operators: $+, -, \times, \div, =$
- Relational operators: $<, >, \leq, \geq, \neq$
- Greek letters and special symbols: $\alpha, \beta, \gamma, \delta, \mu, \theta, \infty$
- Calculus notations: $\sum, \int, \sqrt{}$, lim

- Alphanumeric characters: both uppercase and lowercase Latin letters
- Functional terms and notational expressions: sin, cos, tan, log

Each handwritten symbol in the dataset is stored as a small grayscale image, originally sized around 45×45 pixels. To make these images compatible with deep learning models—especially Convolutional Neural Networks (CNNs), which require fixed-size inputs—they're uniformly resized to standard dimensions, typically 28×28 or 64×64 pixels. In this study, we standardized all images to 28×28 pixels.

Before resizing, a series of preprocessing steps is applied to improve image quality and enhance the model's ability to distinguish features. These steps include grayscale normalization, image inversion (to emphasize the symbol strokes), and thresholding to reduce background noise. Together, these techniques help boost classification accuracy by making important visual details more prominent.

For training purposes, the dataset is organized in a supervised format: images are sorted into folders based on their symbol class. This structure allows for easy mapping between each image and its corresponding label, simplifying the training process for the CNN model.

In modeling view, this dataset presents several key advantages:

1. **High Volume**: The large number of samples helps mitigate overfitting and supports robust training.
2. **Class Diversity**: The 82-symbol classification task challenges the model to learn nuanced visual distinctions, ideal for developing scalable recognition systems.
3. **Label Reliability**: All data samples are correctly labeled and organized, minimizing preprocessing overhead.
4. **Extensibility**: This dataset can be extended to more complex tasks like full expression recognition, LaTeX generation, and structural parsing.

Previous research using this dataset has demonstrated remarkable performance benchmarks. For instance, Random Forest classifiers achieved classification accuracies of approximately **99.4%**, while CNN-based models reached over **99% accuracy** on test sets using resized grayscale images [2]. Such metrics highlight the dataset's efficacy in supporting both traditional and deep learning models for symbol classification.

For this project, a subset of symbols—primarily digits (0–9) and arithmetic operators (+, −, ×, /)—was initially used to build a foundational classifier. However, given the dataset's scope, future iterations of this system can be trained on the entire set of 82 classes, facilitating recognition of advanced mathematical notations, calculus operators, and scientific expressions.

In conclusion, the Kaggle Handwritten Math Symbols dataset provides a comprehensive and reliable source for developing high-accuracy handwritten symbol recognition systems. Its adoption in this research ensures a scalable, standardized, and reproducible methodology that aligns with current trends in deep learning-based mathematical content interpretation.

5. RESULTS AND DISCUSSION

The evaluation of the proposed handwritten mathematical expression recognition system is conducted by measuring both the symbol-level classification accuracy and the overall ability of the model to reconstruct and evaluate complete mathematical expressions. This section details the training performance, model behavior across epochs, generalization to unseen data, and practical insights gained from inference on test samples.

A. Training Performance

A dataset of 96,429 annotated grayscale photographs that had been shrunk and standardized to a 28x28 pixel size was used to train the model. The Adam optimizer and categorical cross-entropy loss function were used for the training, which was spread across 10 epochs with a batch size of 200. Two convolutional layers, pooling layers, ReLU activations, dropout for regularization, and a fully connected classifier with a Softmax activation in the end made up the model architecture. The output layer was set up for 13 classes, which included arithmetic operators (+, −, ×) and numbers (0–9).

Accuracy and loss numbers showed a consistent improvement during the training phase. In the first epoch, the model's accuracy was 89.96%; by the tenth epoch, it had quickly increased to 99.55%. In line with this, the loss dropped from 0.4353 to 0.0149, suggesting little overfitting and learning.

The performance metrics across epochs are summarized in Table I.

Table I: Model Training Performance

Epoch	Loss	Accuracy
1	0.4353	89.96%
2	0.0723	98.00%
3	0.0461	98.67%
4	0.0336	99.03%
5	0.0268	99.21%
6	0.0234	99.30%
7	0.0218	99.34%
8	0.0165	99.49%
9	0.0171	99.48%
10	0.0149	99.55%

These results underscore the effectiveness of the chosen CNN architecture and preprocessing pipeline. The dropout layer played a significant role in preventing overfitting, especially considering the relatively small number of output classes.

B. Inference and Expression Evaluation

Beyond symbol classification, the system's practical utility lies in its ability to interpret full handwritten mathematical expressions. During inference, input images are processed to isolate individual symbols, which are then classified using the trained model. The predicted classes are concatenated to reconstruct the mathematical expression as a string. Python's eval() function is used to compute the result of the expression.

This dual-layer system—recognition and evaluation—proved highly effective. For instance, given an input image representing the handwritten expression 1 + 3, the model accurately identified each symbol, reassembled the expression, and evaluated it to return the correct result 4. In more complex expressions involving multiple digits and operators, the model maintained consistency and precision in symbol sequencing.

C. Generalization and Practical Considerations

Although the training accuracy reached 99.55%, generalization performance on unseen test images also remained high, demonstrating the robustness of the model. This was partially validated through practical test cases using user-generated handwritten expressions, which yielded correct predictions in the vast majority of instances.

Challenges observed included:

- Slight misclassifications between similar-shaped symbols, such as '1' and '/', or '0' and 'O'
- Reduced performance in poorly scanned or highly distorted images
- Occasional misordering of symbols due to inaccurate contour detection

D. Comparison to Prior Work

When compared with results from prior studies using similar datasets, our model shows competitive performance. For example, Shi et al. [1] achieved similar accuracy in scene text recognition tasks using attention-based models, while Zhang et al. [2] reported 99% accuracy using DenseNet encoders for symbol-level classification. Our use of a lightweight CNN with fewer parameters offers a balanced trade-off between computational efficiency and high accuracy, making it ideal for real-time applications on mobile or embedded systems.

E. Visual Feedback and Interpretability

Visual inspection of intermediate feature maps revealed that the CNN successfully learned edge detectors and complex shape identifiers in its early convolutional layers. This interpretability not only aids debugging and refinement but also builds trust in the model's decision-making process.

6. CONCLUSION AND FUTURE WORK

A. Conclusion

This study presents an effective deep learning-based solution for the recognition and evaluation of handwritten mathematical expressions. Through the integration of image preprocessing, Convolutional Neural Networks (CNNs), and symbolic computation via Python's built-in evaluation mechanisms, the system achieves a high degree of accuracy in both symbol-level classification and expression-level inference. The model successfully bridges the gap between raw handwritten input and computable expressions, offering practical utility in domains such as educational technology, digital assessment systems, and human-computer interaction.

The architecture, built using a sequential CNN model, incorporates multiple convolutional and pooling layers to extract spatial and structural features from handwritten inputs. Dropout layers and ReLU activations are employed to enhance generalization and non-linearity, respectively. A final Softmax layer ensures reliable classification across 13 distinct classes, which include numeric digits (0–9) and basic arithmetic operators (+, −, ×). After ten epochs, the model's training accuracy of 99.55% with 96000 images which were in grayscale. This outstanding outcome demonstrates the preprocessing pipeline's efficacy as well as the model architecture's resilience.

The system is not limited to classification alone. A core strength of this research lies in its end-to-end functionality. Once handwritten expressions are recognized, they are converted into valid string representations and passed to a symbolic evaluator, enabling real-time computation. This aspect significantly enhances the practicality of the system for educational and computational applications.

B. Future Work

While the current implementation demonstrates strong performance and reliability, several areas remain ripe for enhancement. First, **expanding the dataset** to include a broader range of symbols—such as integrals, summations, Greek letters, matrix notations, and domain-specific functions—will increase the system's versatility. Utilizing comprehensive datasets such as the Kaggle "Handwritten Math Symbols" [1], which includes over 80 classes, could enable the system to handle scientific and engineering expressions beyond basic arithmetic.

Second, **enhancing the segmentation and preprocessing pipeline** is critical for improving symbol isolation in cluttered or poorly written expressions. Integrating advanced image segmentation techniques such as watershed algorithms, connected-component labeling, or even deep learning-based contour detection could reduce symbol misalignment and improve the accuracy of reconstructed expressions.

Third, Python's built-in eval() function, which is only capable of doing evaluation in simple arithmetic, is used in the current system. Integrating symbolic computation libraries like as SymPy could enable parsing, simplifying, and evaluating algebraic and calculus-level statements for more complex mathematical processing, hence increasing the system's capacity for mathematical reasoning.
The use of attention-based processes or transformer models, which have demonstrated impressive effectiveness in sequence modeling and natural language processing, is another exciting avenue.

These models could improve the recognition of longer expressions and complex layouts by capturing global context and structural dependencies

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