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Recognition of Handwritten Mathematical Expression and Using Machine Learning Approach

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Abstract - *The goal of this research is to give a general overview of handwritten mathematical expression recognition and its applications. Mathematical expressions are frequently entered by hand from a computer, which is substantially slower than writing them down on paper with a pen. We'll use machine learning technology to identify a handwritten expression on a piece of paper. In this work, we go over the various processes we take to recognise mathematical expressions in handwriting using CNN. The Convolutional Neural Network (CNN) Method offers the greatest accuracy for handwritten mathematical expression recognition. We may be able to enhance overall expression accuracy considerably with more time and computer resources. The task's future scope involves the creation of an improved user interface.*

Key Words: Handwriting recognition, CNN, data processing, Classification, data augmentation

1.INTRODUCTION

Handwriting is a natural part of everyday human interaction. These days, in addition to widespread smartphones and tablets, new types of devices such as interactive panels, digital pens and smart writing surfaces have become widely adopted in workplaces and mainly in educational institutions, resulting in the increased demand for recognizing specific handwritten content such as mathematics, diagrams, charts, tables, sketches, etc.

Another reason for this is the sudden outbreak of COVID-19 pandemic which publicized another scene to users and lays forward new requirements for handwriting interaction applications in education and distance learning.

To address this problem, over the past decade, many advances were made in sequence recognition models, based on convolutional neural networks (CNN), keeping in mind the need of handwritten document processing. Mathematical expressions are an essential part of engineering, science, finance, education, and other domains.

Mathematical expressions differ in many ways from the textual data due to the presence of a very large codebook of more than 1,500 symbols, recognized in mathematics, and the characters are often very similar to each other, especially in handwritten expressions. Handwriting input of Mathematical expressions is often done by users from a keyboard, which is much slower than writing it down on paper using a pen.

We will take this technology and implement it to recognize a handwritten mathematical expression on a paper and solve it using a mobile application, to improve the user interface and interactivity.

We will be able to capture an image from a mobile phone and produce the mathematical expression and the solution of the equation, where UI and UX play an important role in the implementation and deployment of handwritten mathematical expression applications.

This paper presents the prospective survey of handwritten mathematical expression recognition and their applications, while proposing an app interface for the same.

2. METHODOLOGY:

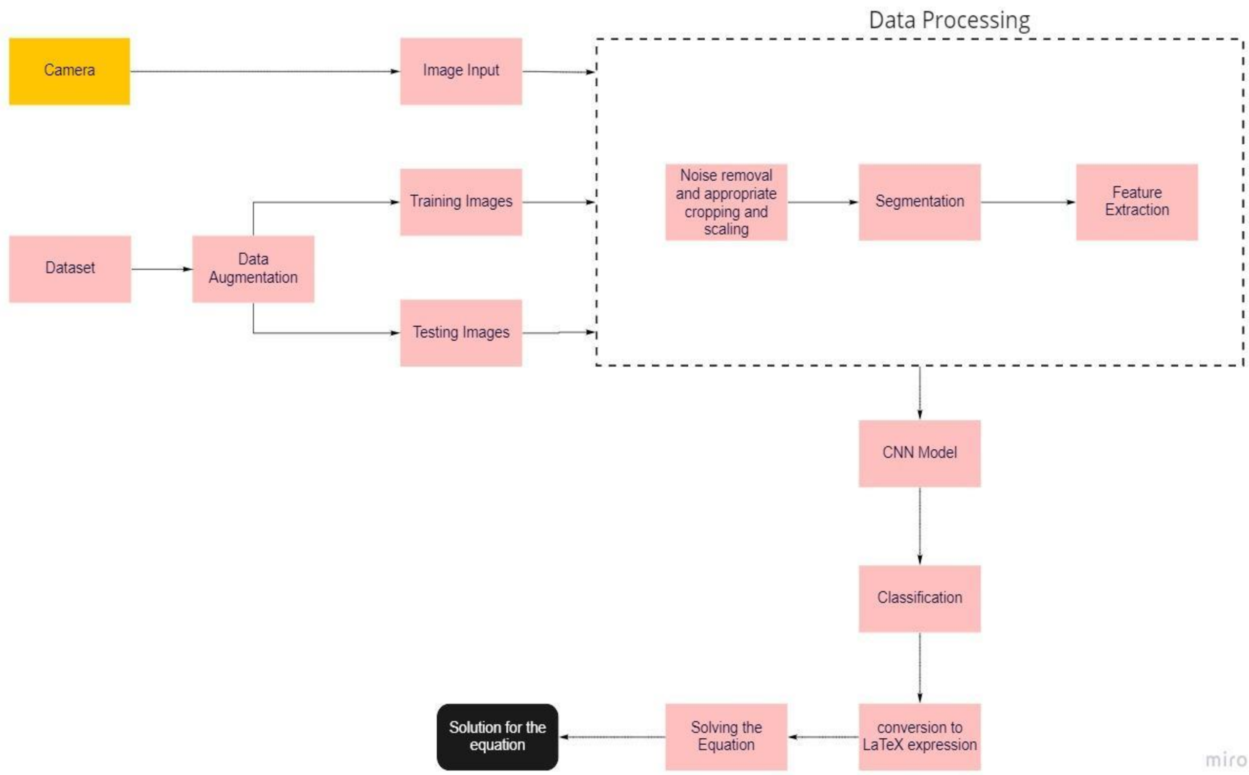

Fig -1: Flow diagram of handwriting recognition using CNN

Deep Learning has emerged as a key tool for self-perception issues such as picture interpretation, human speech recognition, and robot exploration of the world. We want to use the Convolutional Neural Network idea for digit and symbol recognition. The suggested approach aims to understand CNN and apply it to a handwritten mathematical expression recognition system.

2.1 Data Augmentation:

In data analysis, data augmentation refers to increasing the quantity of data by adding slightly changed copies of current data or creating new synthetic data from existing data. We can use geometric modifications, flipping, colour alteration, cropping, rotation, noise injection, and random erasure to enhance images for data augmentation. After this step we split the dataset into training and testing sets.

2.2 Data Processing:

(a) Noise Removal:

We need to pre-process the image before passing it onto the next stage. The images will then be clear to read, or there will be more/less gaps between edges, characters, and so on. Some of these approaches are classified as morphological operations.

(b) Segmentation:

Segmentation is the process of dividing a document picture into smaller pieces depending on certain criteria. The images are segmented into homogenous components using segmentation (numbers, letters, symbols). It is a necessary step in every system of recognition or categorization. In a HME recognition pipeline, segmentation is the most difficult and important process.

(c) Feature Extraction:

In Feature Extraction each character is represented as a feature vector, which serves as its identification, throughout the feature extraction step. The primary purpose of feature extraction is to find a collection of features that optimises recognition rate while using the fewest number of elements possible.

Obtaining these attributes is a tough process due to the nature of handwriting, which has a significant degree of unpredictability and imprecision.

2.3 CNN Model:

Convolutional Neural Network (CNN), a common deep neural network architecture, may be used to accomplish HME Recognition. Traditional CNN classifiers are capable of learning and classifying essential 2D characteristics in pictures, with the classification accomplished using the soft-max layer.

(a) Input Layer:

The Input Layer serves as a buffer for the input before it is sent on to the following layer.

(b)Convolution Layer:

The main operation of feature extraction is performed by the Convolution Layer. It uses the supplied data to conduct a Convolution process. Sliding the kernel across the input and performing the sum of the product at each position is how the convolution process is carried out. Stride is the size of the step in which the kernel slides. The number of feature maps created in a convolutional layer is also known as the depth of the layer. Several convolutional operations are done on the input using various kernels, resulting in distinct feature maps.

(c) The Rectified Linear Unit (ReLU):

It is an activation function that is used to inject nonlinearity into a system. Negative values are replaced with zero, which speeds up the learning process. Every convolution layer's output is routed via the activation function.

(d) Pooling layer:

Pooling employs a sliding window that moves in sync with the feature map, converting it into representative values. It also minimises the spatial size of each feature map, which reduces the network's computation. The terms "minimum pooling," "average pooling," and "max pooling" are often used.

(e) Fully connected layer:

Every neuron in a fully linked layer is connected to every neuron in the previous layer. It learns a non-linear mixture of characteristics that it may use to categorise or forecast the output. The fully connected layer is usually followed by a soft-max layer for classification issues, which generates the probability of each class for the supplied input. It is then followed by a regression layer to forecast the output for regression issues.

2.4 Classification

Classification is the next stage. CNN was employed as the classifier, and it has 83 distinct classifications. SpNet-CNN is the name of the projected CNN. The layers input, convolutional, max pooling, convolutional, max pooling, convolutional, max pooling, fully connected, and softmax make up the SpNet-CNN. The input picture is applied to a 3x3 filter in the convolution layer. When a subsampling size of 2x2 is applied to the pooling layer, the output size of the image from pooling is half the size of the input image to the layer.

2.5 Conversion to LaTex expression:

In this step we convert the recognised characters from the images to a LaTex format for better and understandable representation of the equation.

Example:

$\frac{a}{b+c}$ /frac{a}{b+c} →

3. LITERATURE SURVEY

Table -1: Literature Survey

Title	***Journal/Conference name***	***Methodology used***	***Results***	***Advantages of methodology***
A Review of Various Handwriting Recognition Method **[1]**	International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 2 (2018) pp. 1155-1164 © Research India Publications. http://www.ripublication.com	1)Convolutional Neural Network (CNN), 2)Semi-Incremental , 3.)Incremental, 4)Lines and Words Segmentation, 5)Parts based method, 6)Slope and Slant Correction, 7)Ensemble, 8)Zoning.	In virtually every situation, CNN's accuracy is excellent. The Slope and Slant Correction Method has the lowest accuracy. In writing recognition, zonation approaches, line and word segments, ensemble methods, and part-based algorithms are all quite reliable.	1)After CNN has been trained, image recognition will be accurate. 2) It has been demonstrated to be effective in a variety of handwriting and computer recognition applications. The % accuracy of each technique may be determined using the technologies, reinforcing the author's conclusion that CNN has the best accuracy.
Recognition of Online Handwritten Mathematical Expressions Using Convolutional Neural Networks	cs231n Project Report Stanford (2015)	approach relies heavily on CNNs, which are widely used for a variety of vision recognition problems. pipeline has five distinct phases: (1) data set enrichment, (2) image segmentation, (3) data extraction, (4) character-level classification, and (5) expression-level classification	The author discovered that CNNs are an effective method for recognising handwritten expressions. With more time and greater computational resources, it may be able to improve overall expression accuracy dramatically. Because symbol accuracies are compounded at the expression level, small percent increases in accuracy at the symbol level have dramatic effects at the expression level.	The CNN-based system outperforms SVM-based system by 3-4%
Handwritten Mathematical Recognition Tool	Second International Conference on Computational Intelligence in Data Science (ICCIDS-2019)	This technique uses pipeline with 4 different phases namely i) Segmentation of the given input, ii) Symbol Classification, iii) Grouping of Symbols iv) LATEX Format. To recognize the mathematical symbols, two different methods are adopted for classification, i) SVM and ii) ELM.	We are easily able to enter the math expression into our machines but the real problem is to recognize it. In this paper HME is written using Inkscape which is a vector graphics editor. After that the expression is segmented based on when the user lifts the pen up and down while writing the mathematical expression.. After that they are classified based on two	Symbol recognition has very high accuracy: RESULTS FOR SVM: About 90% RESULTS FOR ELM: About 95%

			methods: i)SVM ii)ELM. Once the symbols are classified that expression is sent to get converted into LaTeX format.	
Offline Handwritten Mathematical Expression Recognition using Convolutional Neural Network	2018 International Conference on Information, Communication, Engineering and Technology (ICICET) Zeal College of Engineering and Research, Narhe, Pune, India. Aug 29-31, 2018	This technique uses 4 steps: A. Data collection B. Preprocessing C. Segmentation D. Classification	We can create a system which will recognize offline handwritten mathematical expressions by converting it into LaTeX format. We also conclude that this system will give best results only for isolated symbols.	We found very good results of about 88% using Convolutional Neural Network(CNN) which is very good in terms of recognizing HME.
Handwritten Mathematical Expressions Recognition using Back Propagation Artificial Neural Network	Communications on Applied Electronics (CAE) – ISSN : 2394-4714 Foundation of Computer Science FCS, New York, USA Volume 4– No.7, March 2016	Feed forward back propagation neural network technique is used for recognition. It has 4 stages of execution - 1. Training the data, 2. Pre-processing, 3. Segmentation, 4.Feature extraction	In the proposed system, recognition of the straight line equation $y = mx + c$ has been done with better accuracy and recognition rate. the neural network trained using gradient descent with momentum and adaptive learning. Neural Network developed using one input layer, two hidden layers and one output layer. By repeatedly presenting data set to the network performance of the network is increased.	(1). The system presented an approach to recognize handwritten MEs such as quadratic equations with improvement in recognition rate, processing time and accuracy. (2). Centroid and bounding box are the key features extracted from each character and uprightness of the system using back propagation neural network
Online Handwritten Mathematical Expression Recognition and Applications: A Survey	1)Faculty of Computer Science and Cybernetics, Taras Shevchenko National University of Kyiv, 01601 Kyiv, Ukraine 2)Samsung Research and Development Institute Ukraine, 01032 Kyiv, Ukraine	End to end solutions(main focus), Integrated solutions, Sequential solutions	The research is now centred on DML techniques, ensuing in third generation end to end solutions. Although these solutions have taken the lead in lots of areas, in handwritten Mathematical equation recognition, these techniques are nonetheless at an early phase of implementation and improvement with a few limitations.	This survey demonstrates that interest in online HME recognition has been growing over the past 40 years. The development of integrated solutions made it possible to combine various methods (grammatical, statistical) minimizing the accumulation of recognition errors.
Recognition of Online Handwritten Math Symbols using	IEICE Transactions on Information and Systems -	Bidirectional Long short-term memory(BLSTM)	MQDFs perform worse than CNNs. Depth is the best feature of deep neural	Because of the Markov assumption, RNNs with LSTM blocks can integrate

Deep Neural Networks	October 2016	recurrent neural networks for online recognition and offline using Deep Maxout Neural Network (DMCN)	networks. Because of the depth of CNNs, each of their layers can compute complicated features that represent larger and more complex object parts. Current systems performed worse than BLSTM.	the influences of previous nodes without suffering from the gradient vanishing problem, whereas MRFs can only consider neighbouring points.

4. CONCLUSION AND FUTURE SCOPE

Handwriting has been one of the most fundamental methods for communication for ages, since it is an important component of the learning process. This paper addresses useful methods of character recognition. The major goal was handwritten mathematical expression recognition, as printed text recognition did not require a large number of datasets to train the algorithm.

We have explored seven methods for recognition of handwritten mathematical expressions and the one that has the highest accuracy is the Method of Convolutional Neural Network (CNN). CNNs are a strong way to tackle handwritten expression recognition, according to our study.With more time and greater computational resources, it may be able to dramatically improve overall expression accuracy.

We learned about the various processes done by CNN to identify HME.

We have studied how HMM improves accuracy and what improvements can be done. We also learned about alternative symbol categorization algorithms such as ELM and SVM.

We also explored a variety of datasets for training and testing of CNN models.

In the next phase we would work on finding the solutions of the mathematical expressions.

Our studies suggest combining mathematical expression recognition capabilities with existing algebra solving software, graphing tools, and simulation systems would be a first step toward developing a superior user interface for performing the task.

In the future by implementing the technologies, the % accuracy of every method can be found to further strengthen the author's statement in [1] that CNN has the best accuracy.

In [3] Author mentions improving the character-level classification will give much better expression-level accuracy. In future, merged or connected or joined symbols will be segmented to give better recognition results according to [2]. Combining online and offline classifiers [6] takes advantage of both online and offline classification methods. More specifically, there are some characters making online classifiers difficult to discriminate from other symbols, this can be explored in future.

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