Handwritten Mathematical Expression Recognizer

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ABSTRACT : One of the most challenging applications of pattern recognition in deep learning is handwriting recognition. In many fields, including education, engineering, and science, handwritten mathematical expression recognition is helpful. The crux of the issue is recognizing handwritten mathematical formulas written on a tablet or a computer using a mouse. Since many internet programs and websites use handwritten mathematical expressions, they are frequently used. The state-of-the-art model described in this study detects the mathematical statement from the GUI that is produced in real-time with a mouse or pen. A CNN architecture with numerous layers was trained using a dataset of mathematical digits and symbols to make up the suggested design. The proposed model recognizes the mathematical symbols and formulas in an efficient manner.

Keywords: *Convolutional neural network, Handwritten recognition, Neural network, mathematical expression, data processing, Graphical user interface.*

I. INTRODUCTION

With the advent of devices that use digital as an input method, handwriting is still something that is extremely noticeable and that is still possible in today's world of communication. Along with the creation of those gadgets, recognition software was also developed that could translate letters written in human natural handwriting into languages that computers could comprehend [1]. Handwritten text recognition systems have advanced significantly as a result of recent developments in segmentation, recognition, and language models. Mathematical expressions are widely used in almost all scientific fields, including physics, engineering, medicine, economics, etc. In order to enter mathematical expressions into the scientific literature, a procedure is required. To complete this work, a variety of tools are available. However, most of them need some knowledge to utilize them wisely.

As part of our contribution to the field of online handwritten mathematical expressions recognition, we offer simultaneous segmentation, recognition [4], and interpretation of mathematical expressions. In particular, rather than using a classifier that has previously been trained, the system can learn symbols directly from expressions thanks to the global learning strategy utilized by the classifier used to recognize the basic symbols. In section two, we introduce the concept of mathematical expression recognition. Then, in section three, we create our own architecture and present some early findings that are contrasted with those of some other works. We will be able to understand and respond to any handwritten mathematical expression that is written on the device using our convolution neural network technology. Therefore, it is best to think of effective input of handwritten mathematical expressions as a combination of recognition systems and to display the output mathematical expression.

This paper has the following format. The work that has already been done on mathematical expression recognition is briefly summarized in Section II. The process plan implemented in the system is represented in Section III. The methods employed in this system are illustrated in Section IV. The results of this effort are then discussed in section V, which concludes the entire book. We incorporated the paper's references in the final section.

II. LITERATURE SURVEY

Numerous studies on handwriting mathematics expression recognition systems have been conducted in relevant fields over the last few years.

Effective Handwritten Digit Recognition Using Deep Convolution Neural Network. The convolutional neural network [10] method for handwritten digit recognition was proposed in this paper. Recognizing digits is one of the unsolvable problems using machine learning algorithms like KNN, SVM/SOM because of how distinctively they are written. Convolution neural networks are utilized in this study with an MNIST dataset of 70000 digits and 250 different writing styles. On training with 60000 digits and 10000 under validation, the suggested technique obtained 98.51% accuracy for real-world handwritten digit prediction with less than 0.1% loss [6].

Towards Handwritten Mathematical Expression Recognition. Our new framework for online handwritten mathematical expression recognition is presented in this study. Under the constraints of a mathematical expression language, the suggested architecture tries to handle mathematical expression recognition as a simultaneous optimization of symbol segmentation, symbol recognition, and 2D structure recognition. In this instance, the rate of segmentation is 91.2%, the rate of symbol recognition is 75%, and the rate of global ME recognition is 37.1% [7].

In this study, handwritten expression recognition is tackled using convolutional neural networks (CNNs). Using our best CNN model, we construct an end-to-end system that goes from strokes to symbols to a LATEX expression. At the expression level, we were only able to reach 60% accuracy; the accuracy dropped to 23%. Our standard performance SVM classifier has an 87% train and test accuracy [8].

Handwritten Mathematical Recognition Tool. By executing input segmentation based on each pen up and pen down, followed by symbol classification, the suggested architecture intends to handle the handwritten expressions. Extreme Learning Machines and Support Vector Machines are employed as classifiers, and the classifier that produces the best accuracy is chosen. Next, the symbols are trained among a variety of handwritten mathematical expressions, and an encouraging result is obtained at the stage of symbol classification. The ELM classifier is trained using the identical set of test and train data, and a model is created that shows promise by reaching an accuracy rate of 98%, respectively [9].

Offline Handwritten Mathematical Expression Recognition using Convolutional Neural Network. We put up a suggestion for identifying offline HME with CNN classification. Data collecting of handwritten mathematical symbols and expressions is one of the steps. Pre-processing operations are then carried out on the data that was gathered. HME has been divided up into separate symbols. Convolutional Neural Network (CNN) has a very high recognition accuracy of 87.72% for Handwritten Mathematical Symbols (HMS) performance [10-14].

III. PROPOSED WORK

In this section, a detailed explanation of the method and model proposed is illustrated in figure 1. The result of handwritten recognition is already achieved excellently. Numerous studies have revealed brand-new methods for categorizing handwritten numbers, characters, and phrases. The convolutional neural network has enabled recent advances in the field of handwriting recognition. CNN[5] has shown exceptional skill in handwritten digit recognition. As many of them have done handwritten recognizers for digit and character recognition, we want to use the Convolutional Neural Network concept to recognize mathematical expressions and translate them to text.

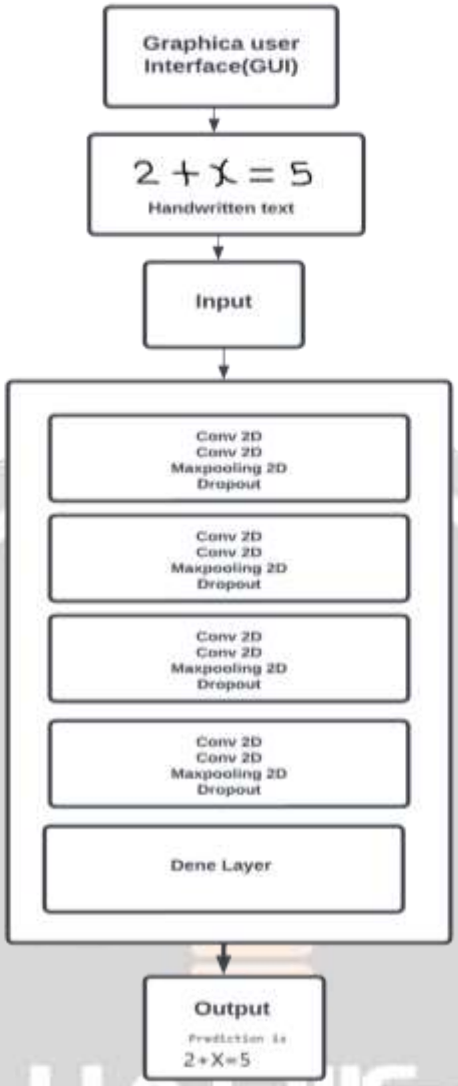

Figure 2: Proposed Architecture

Convolutional Neural network (CNN) is a deep learning algorithm [2] which is mainly used for tasks such as image and video analysis and classification. CNN takes the image as input and assigns importance (weights and biases) to features which are then able to identify the image from one another. The image fed into the CNN is converted into a multidimensional array and in the last layer, it will be flattened. It is made up of max pooling and convolutional layers. These layers facilitate feature extraction from the image. Layers can be multiplied depending on how complicated an image is. The image is classified using the last layer, which is a completely connected layer. The model used is represented in Figure 2.

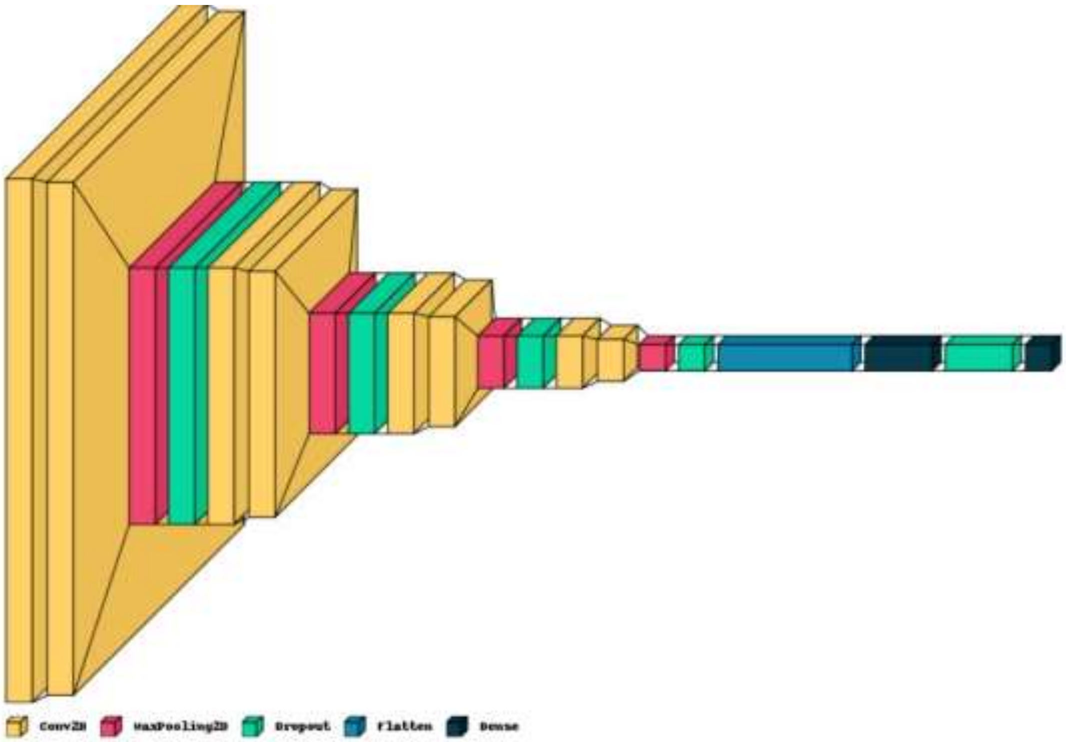

Figure 3: Structure of CNN model

In this study, the mathematical phrase is recognized using CNN architecture. The proposed model uses CNN architecture, which consists of a fully linked layer for classification and four conv2D layers. ConvNets have the capability to find out these filters and properties, whereas in primitive techniques filters are hand-engineered. Through the utilization of pertinent filters, a ConvNet could effectively capture the abstraction and temporal dependencies in a very large image. As a result of there being fewer factors to contemplate and therefore the weights may be reused, the design provides a higher fitting to the picture dataset. To put it another way, the network may be trained to better understand how complicated the image is. The mathematical symbol [3], digit, and alphabet datasets utilized in this study are used to identify the mathematical statement. 8,000 photos make up the dataset, of which 80% have been used for training and 20% for testing. Examples of the training images for the CNN model are displayed in Figure 4.

Figure 4: Example images

The model outputs an accuracy of 0.9954, a loss of 0.0164 with a validation accuracy of 0.9842, and a validation loss of 0.0635.

Figure 5: GUI Interface using Tkinter

A graphical user interface (GUI) shows components that represent actions they can perform and elements that convey information. The objects change in size, visibility, or color when the user interacts with them. Graphical user interfaces became the industry standard for user-centered design in software application programming by enabling users to interact directly with graphical icons including knobs, navigation bars, panels, tabs, menus, cursors, and the mouse pointing device. Recent graphical user interfaces frequently have a touch-screen and voice-command interaction. Drawing mathematical expressions is done using a GUI (Graphical User Interface). For GUI Tkinter is used which is a standard python interface. The Python-built-in Tk GUI toolkit has an object-oriented interface provided by Tkinter. Tkinter doesn't even require any further installation. The GUI creation toolkit Tkinter makes it simple to manage user input and output. The expression written in the GUI (illustrated in figure 5)is converted into an image [3]. Mathematical Expression [5] which is drawn on the GUI is converted into an image illustrated in (figure 1.3) and will be saved. The image is then cut down into parts (100 X100) pixels like the first digit or symbol in the expression and then go on using the sliding window. Picture 1.4 illustrates the mathematical expression (2+x=5) the sliding window goes through one by one first 2 then (+) symbol and till 5. Then the individual image will go through a pre-processing stage in which we have images and labels that correspond to the images. The individual symbols and digits fit into CNN architecture [11] which is already skilled with numbers and symbols. Figure 4 shows the expression written in the GUI is converted into an image.

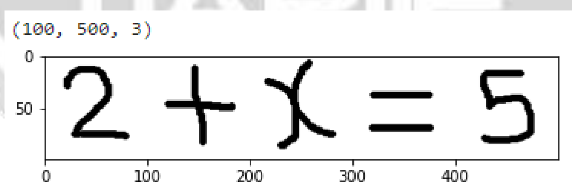

Figure 5: Expression converted to image in GUI

IV. RESULTS AND DISCUSSION

CNN is used for identifying mathematical expressions. The accuracy obtained for the training is represented in Figure 6. An accuracy of 95% is obtained for training.

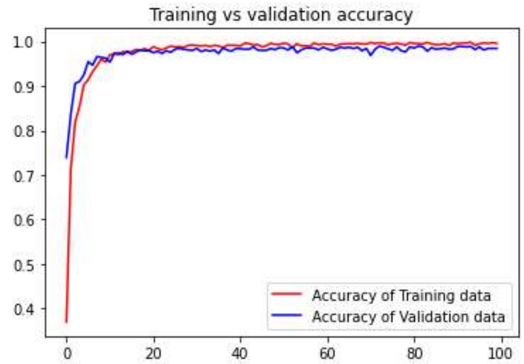

Figure 6: Training Accuracy

The obtained training and validation loss is represented in Figure 7. The training loss obtained is 0.0164 and the validation loss obtained is 0.0635.

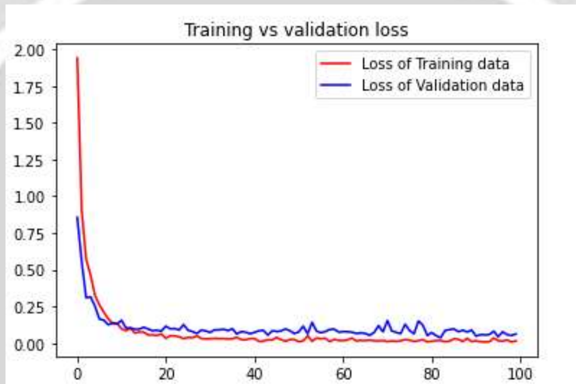

Figure 7: Training Loss

Below table 1 shows the number of layers used for CNN architecture, Conv2D, Maxpooling2D, Dropout, flatten, and dense layers.

	Layers
Conv2d	5
Max pooling 2D	4
Dropout	5
Flatten	1
Dense	2

Table 1: Number of layers used for CNN

Below table 2 illustrates the Precision, recall, and f1 score utilized to depict the experiment outcomes.

	precision	recall	f1-score	support
0	1.00	0.99	0.99	83
1	0.95	0.96	0.96	57
2	1.00	0.98	0.99	45
3	1.00	0.98	0.99	106
4	0.97	0.99	0.98	89
5	0.96	1.00	0.98	92
6	1.00	0.98	0.99	102
7	1.00	0.98	0.99	85
8	0.99	0.97	0.98	95
9	0.99	1.00	1.00	131
10	0.98	1.00	0.99	107
11	0.99	0.95	0.97	86
12	0.98	0.99	0.98	84
13	1.00	1.00	1.00	71
14	0.97	0.98	0.98	101
15	0.96	0.97	0.97	93

Table 2: Transitivity outcomes

Below table 3 describes the transitivity outcomes of the CNN architecture which includes model accuracy, macro aver

	precision	recall	f1-score	support
accuracy			0.98	1427
Macro average	0.98	0.98	0.98	1427
Weighted average	0.98	0.98	0.98	1427

Table 3: Transitivity outcome for CNN model

V. CONCLUSION

The GUI interface using Tkinter where the mathematical expression drawn will be converted into an image with a pixel size of (500X500) will be saved for further analysis. Dataset used in this paper, mathematical symbols, digits, and variables are 7000 images. The dataset is trained on the CNN architecture which has 6 layers as mentioned in table 1. The CNN architecture trained on the dataset outcomes an accuracy of 0.9954, a loss of 0.0164 with a validation accuracy of 0.9842, and a validation loss of 0.0635. The final layer of the CNN flattens the image and recognize the image which is drawn GUI interface.

VI. REFERENCES

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