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Offline Handwritten Mathematical Expression Recognition using CNN and Xception

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ABSTRACT

Mathematical expressions generally play a requisite role in scientific communications. They are not just used for numerical calculations, on the other hand, are also employed for fetching scientific information with less ambiguity, and facilitate researchers to exactly outline and formalize target problems. It takes far longer to manually enter mathematical formulas into a computer than it does to write them down on paper using a pen. Recently, we proposed deep learning methods that can identify images of trigonometric expressions from 2dimensional layouts to 1dimensional strings in order to solve this issue. As densely connected convolutional neural networks (CNN) can boost accuracy, we utilize CNN to improve the results in this study. In order to compare performance, the Transfer Learning framework Exception is employed, which obtains 90% accuracy when recognizing handwritten mathematical expressions. CNN provides 98% accuracy in this regard. Therefore, the CNN model that we created has a higher accuracy rating than the Transfer Learning model Xception.
Keywords : Mathematical Handwriting recognition, data processing, Classification, CNN.

I. INTRODUCTION

These days, due to the growing technology usage of electronic gadgets like smartphones and tablets, new gadgets like digital pens, smart writing surfaces, and interactive panels have also become popular primarily in educational institutions and offices. As a result, there is a greater need for handwritten content recognition for a particular type of content, such as diagrams, tables, mathematics, charts, sketches, etc[10]. The AI research community faces a hurdle in creating computer algorithms that can automatically solve math word problems (Bobrow, 1964). It is difficult to automatically solve mathematical word problems (MWPs), primarily because there is a semantic divide between human-readable terms and machine-understandable logic [12].

Another factor for this is the abrupt COVID-19 pandemic outbreak, which made another situation known to users and established new specifications for handwriting interface software used in distant learning and education. In many fields, including engineering, science, business, and education, mathematical expressions are a necessary component. The presence of a very extensive codebook of more than 1,500 symbols, recognized in mathematics, and the character's frequent similarity to one another, especially in handwritten expressions, cause mathematical expressions to differ from textual data in many ways. Mathematical expressions are frequently entered by handwritten notes. Convolutional neural network (CNN)-based sequence recognition models have seen significant advancements over the past 10 years as a result of the necessity to process handwritten documents.[10]

The headway in the sector of Artificial intelligence and Machine learning has stirred up computer vision. Effectual, Deep Learning tactics are tested to be very impactful for image classification, object detection, and pattern recognition. Convolutional Neural Networks (CNNs) are used extensively to draw out patterns and features from images and have revealed exceptional work in the area of handwritten recognition.

The proposed method uses densely linked convolutional neural networks to operate on mathematical expressions and transform them into equivalent text (CNN).

The organization of this document is as follows: section 1 introduction, section 2 is a literature survey, section 3 is the methodology, section 4 is the result and the last section 5 is the conclusion.

II. LITERATURE SURVEY

TITLE/ AUTHORS	METHODOLOGY USED
[1] Recognition of Online Handwritten Mathematical Expressions Using Convolutional Neural Networks [C. Lu and K. Mohan]	The approach relies heavily on CNN, the dataset containing 75 different mathematical symbols was taken from chrome, data enrichment was done by interpolation scheme, followed segmentation using straightforward heuristic finally character-level classification using CNN and SVM for comparison, and expression-level classification using Hidden Markov Models (HMMs) with binary plus unary potentials The CNN-based system outperforms the SVM-based system by 3-4%
[2] Offline Handwritten Mathematical Expression Recognition using Convolutional Neural Network [Lyzandra D'souza and Maruska Mascarenhas]	The author has done Segmentation using a recursive projection profiling algorithm and using Classification(CNN). Found very good results of about 88% using Convolutional Neural Network(CNN).
[3] Neural network approach to mathematical expression recognition system [S. Ramteke, Dhanashri V. Patil, N. Patil]	A centroid and bounding box are the main components in feature extraction and segmentation. Written data is in jpg format. Neural networks are used and presented a 90% recognition rate. Compared with other existing techniques
[4] Recognition of Online Handwritten Math Symbols using Deep Neural Networks [Dai Hai Nguyen, Masaki Nakagawa and Anh Le Duc]	Bidirectional Long short-term memory (BLSTM) recurrent neural networks for online recognition and offline using Deep Maxout Neural Network (DMCN) Because of the depth of CNN, each of their layers can assess complicated features that imitate larger and more

	complex object parts. CNN performs better than modified quadratic discriminant functions (MQDFs).
[5] End-to-end Parsing Text into Math Expressions [Yanyan Zou, Wei Lu]	A unified structured prediction approach is proposed for Text to conversion. The proposed work can be applied to resolve distinct math-related problems along with arithmetic word problems and equation parsing problems.
[6] Online recognition of handwritten mathematical expressions with support for matrices [Chuanjun Li; Robert Zeleznik; Timothy Miller; Joseph J. LaViola]	Presented interactive computational tool math paper. Segmentation & recognition using the spacing algorithm, that leverages symbol identification, and size. relevant location. The system is designed for 7 subjects each having 890 symbols (a total of 6237) in forty-three different expressions. The average result is 91.6%.
[7] Identification of Handwritten simple mathematical equation based on SVM & projection histogram. [Sanjay S. Gharde, Pallavi V. Baviskar, K. P. Adhiya]	Projection Histogram &OCR(SVM). Bounding box and labeling. With projection histogram features and SVM classifier, they have presented results of 98.4%.
[8] Handwritten Mathematical Recognition Tool [M.Abirami,Suresh Jaganathan]	In the proposed work segmentation was done using the Histogram approach of the given data, Symbol Classification using a support vector machine (SVM), and extreme learning machine ELM. Symbol recognition has very high accuracy: results for SVM were About 90% and for ELM was about 95%.
[9] Recognition of handwritten mathematical symbols with PHOG features. [Nicolas D. Jimenez,Lan Nguyen]	Transforming handwritten formula to Latex. Support vector machines (SVM) are trained using The Pyramid Histogram of Oriented Gradients (PHOG) features. CHROME-12 dataset is used. Presented result 92%.(images of 75 handwritten symbols and 1400 equations).
[10] Progressive structural analysis for dynamic recognition of online handwritten mathematical expressions. [Vuong Ba-Quy,Hui, Sui-Cheung , He, Yulan]	Proposed PSA for dynamic recognition. A mathematical expression tree is used to represent an expression. Presented result as 97%.

From the literature survey, we understood that there is scope for recognizing handwritten mathematical expressions.

III.METHODOLOGY

The proposed work includes the following steps: data collection, data augmentation to increase the size of the dataset, splitting up of data into 2 parts training set and testing set, data pre-processing, and training of the CNN model to finally generate text equivalent to mathematical expression. Figure: 1 indicates the framework of the proposed system.

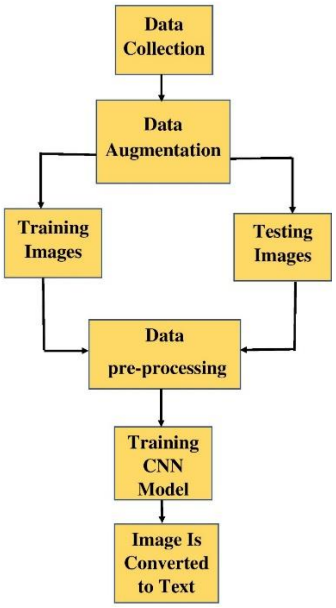


Figure 1: System Architecture

3.1 Database: we have collected images of handwritten mathematical expressions from different people and classified them into 30 different classes. There are thirty thousand images in our dataset. Here are a few samples of the same in figure-2.

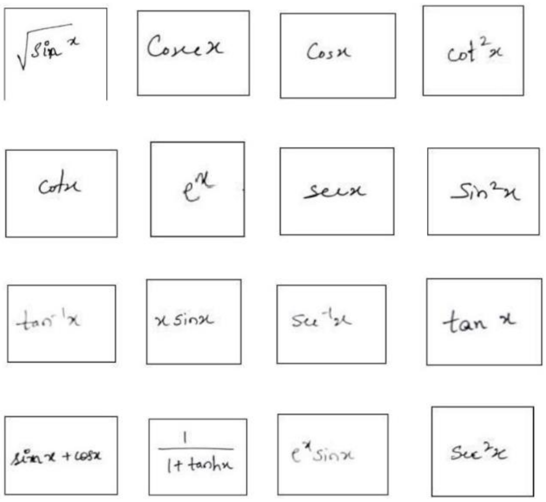


Figure 2: Sample idols of the dataset

3.2 Data Augmentation: In the analysis of data, data augmentation cites to increase the quantity of data by adding up moderately altered copies of present data or producing new synthetic data from existing data. We can use geometric modifications, flipping, cropping, rotation, noise injection, and random erasure to enhance images for data augmentation. Figure 3 shows a sample of the augmented dataset.

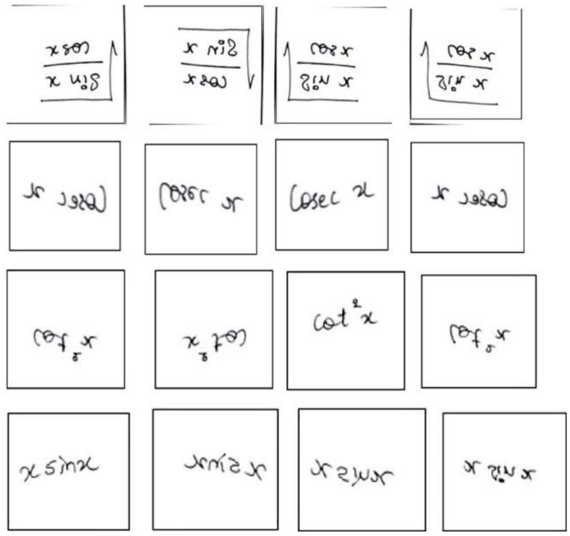


Figure 3: Sample images of Augmented dataset

3.3 Data Pro-cessing

It is a procedure that is applied to transform the raw data into a clean data set. Due to the heterogeneous nature of handwriting datasets need to be pre-processed before training.

- Resize Images: Some images vary in size, therefore, we establish a base size for all images and fed them to our CNN model. We have used a base size of 128 * 128
- Decode the JPG content to an RGB grid of pixels with channels.
- Normalization: is cited as *data re-scaling,* it is the procedure of protruding image data pixels (intensity) to a deliberate range (normally (0,1). In the first image, values range from 0 to 255, in normalization we convert this value to a 0 to 1 range.
- Exploratory Data Analysis (EDA): is a data analytics process to understand the data in detail and learn the divergent data characteristics, frequently with visual mean

3.4 CNN Model: Convolutional Neural Network (CNN), a common deep neural network architecture, that may be utilized to accomplish HME Recognition. CNN has an input layer, hidden layers, and an output layer. The hidden layers customarily comprise convolutional layers, ReLU layers, pooling layers, and fully connected layers.

(a) Input Layer: accepts an input image of size 128X128 and changes it to a series of hidden layers.

(b) Hidden Layers:

The Convolutional Layer draws out an attribute from an input image. Convolution retains the link between pixels by understanding image features using small squares of input data. The image is converted to the numerical format. When the picture proceeds through one convolution layer, the output of the first layer becomes the input for the second layer this continues with every further convolutional layer. The proposed work has a convolution mask of size 3X3 and 4 convolution layers.

- Rectified Linear Unit (ReLU) layer: it is a non-linear activation function. The major whip hand of using the ReLU function over other activation functions is that it doesn't activate all the neurons at a time. For the negative input values, the result is zero, i.e., the neuron doesn't get activated. The main aim of this layer is to convert negative values to zero.

- Pooling layer: from the previous layer we get the plot of 0's, Role of the pooling layer is to turn down the matrix size by avoiding the 0's but retaining features of the map required for classification. There are many pooling techniques Max pooling, and mean pooling in our work we have used Max pooling. **Max pooling** is where we take the largest of the pixel values of a segment. We have performed Max pooling four 4 times. Next, we flatten every pooled image into a single long vector. Figure 4 shows the sample of max pooling.

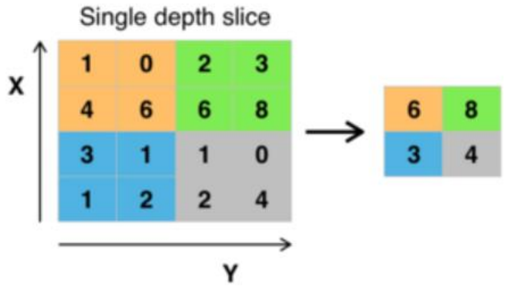


Figure 4 : Example of Max pooling

(c) Fully Connected layer / Output layer: After the execution of a sequence of convolutional, nonlinear, and pooling layers, it is essential to fix a fully connected layer. This layer bridges the output facts from convolutional networks. Connecting a fully connected layer to the end of the network results in a 1 * N-D vector, where N is the number of classes from which the model selects the desired class, here the value of N is 30.

The below graphs show the loss and accuracy plot of the trained CNN module which has an accuracy of 98%. Figure 6 shows the donut chart of the CNN model of thirty classes and their % of contribution to the whole dataset.

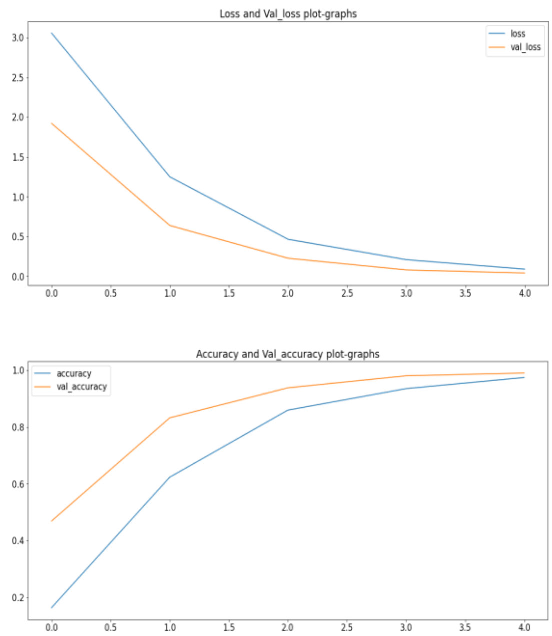


Figure 5: Graph showing loss and accuracy function

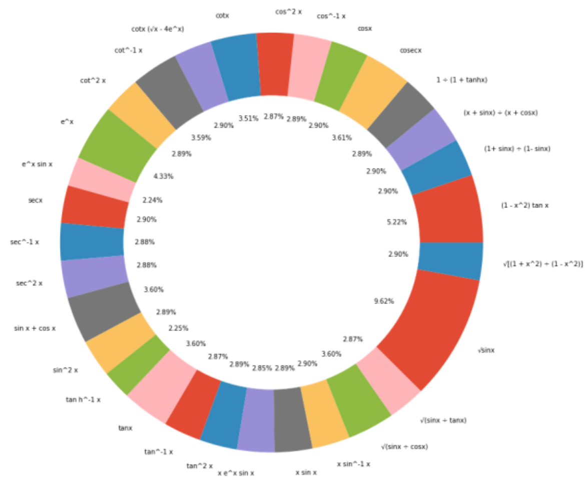


Figure 6: Donut chart of the dataset

IV. RESULTS

The dataset consists of 30,000 mathematical handwritten images, these images are classified into 30 different classes. we have used two algorithms Xception and CNN for comparing the accuracy,70% of images are used for training, and the rest of the 30% of images are tested. We have achieved 90% accuracy for the Xception model and 98% accuracy for the CNN model. Therefore, we conclude that the CNN model is suitable for our work. Here are some of the samples of images and their equivalent results in text form. Following figure 7. Shows the obtained result and figure 8. Shows the record size comparison for 30 classes.

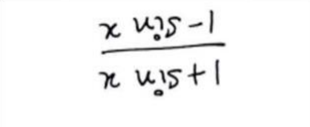
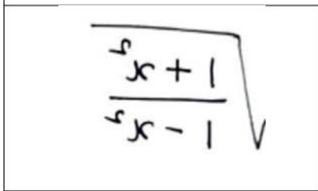
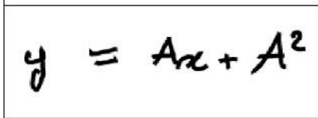
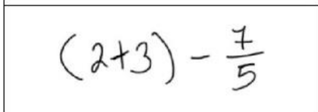
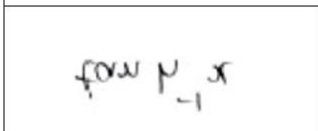
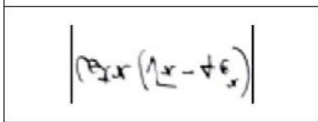
INPUT IMAGES	RESULTS
	e^x
	(1+ sinx) ÷ (1- sinx)
	√[(1 + x^2) ÷ (1 - x^2)]
	y= ax + a^2
	(2 + 3) – (7 ÷ 5)
	tan h^-1 x
	cotx (√x - 4e^x)

Figure 7: Results of proposed work

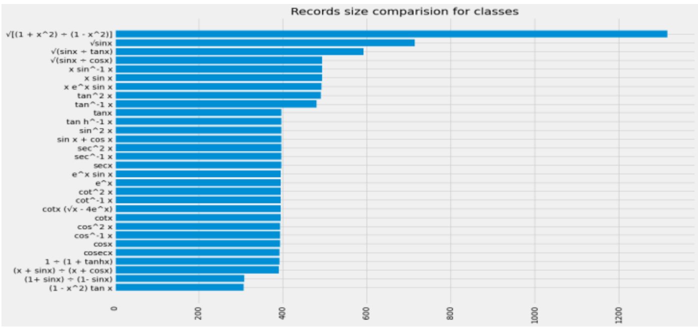


Figure 8: Bar graph for record size comparison of classes

Figure 9 shows the confusion matrix of the trained CNN model.

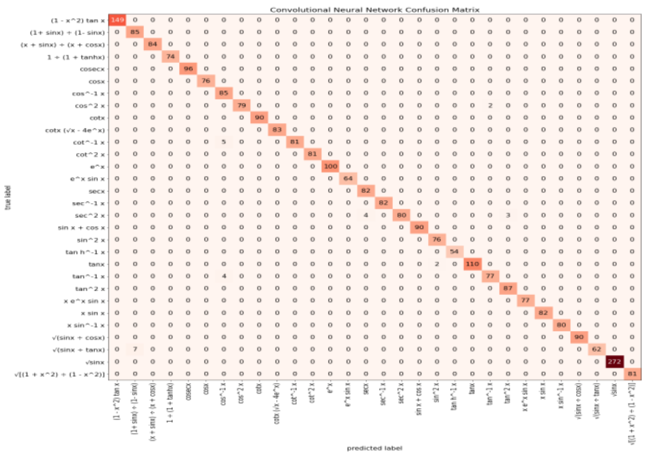


Figure 9 : Confusion matrix of CNN algorithm

V. CONCLUSION

We have learned that CNNs are a powerful approach to solving handwritten mathematical expression recognition. The proposed model converts the image of a handwritten mathematical expression to its parallel text and obtained a result of 98% accuracy. We found limitations in the following areas recognizing images with complex content within the square root, exponential expression, limit function, etc. In the future, we need to propose a better algorithm to overcome this problem.

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