IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

IDENTIFYING HANDWRITTEN LETTERS WITH DEEP LEARNING

Karri Uday sai ganesh

Computer science and Engineering, Sathyabama Institute of Science and Technology, Chennai. [UG]

K.V.S. Aditya Reddy

Computer science and Engineering, Sathyabama Institute of Science and Technology, Chennai. [UG]

K. Anita Davamani, Asst.Professor

Department of Computer science and Engineering, Sathyabama Institute of Science and Technology, Chennai.

Abstract - Two crucial technological areas that are uniting the world are machine translation and natural language processing. The barrier to communication with others who speak a different language is removed via machine translation. Finding the word's native language and then translating it into the target language are the foundations of machine translation. If each letter in the word can be recognized, determining the language of the word may be simpler. We now arrive at "Character Recognition."

This thesis focuses on evaluating the available techniques for handwritten character identification using deep learning and those techniques to recognize handwritten characters. The intriguing thing about machine learning is that the computers that are programmed to interpret, say, Chinese, can also be programmed to translate, say, Hindi or Telugu. This is a key characteristic that the thesis seeks to investigate because it is so potent. Beyond just detecting the characters, modern technology can also translate such characters between different languages. Depending on the character, the machine learning model created for this thesis can accurately identify the character or alphabets with a 70–90% rate of success.

All data is saved and documented in datasets for further sharing and project usage. A large database of handwritten numbers is nee ded to train different methods for analyzing im ages.the MNIST database, which is frequently u sed. The database is commonly used for developing and evaluating machine learning algorithms. It was created by recombining samples from the initial runs.2017 saw the publication of EMNIST, an expanded dataset that is identical to MNIST and contains 240,000 training photos and 40,000 testing images of handwritten numbers and characters.

Keywords: - Machine learning, Deep learning, Sci-kit learn, Denoising, K-nearest neighbor, Pooling, CNN, Convolutional Layers.

I. INTRODUCTION

Researchers have been investigating various methods for testing handwritten character recognition over the past few decades. Learning becomes harder as our assignments become more challenging. We employ deep neural networks, which is suitable. Make a neural network design with higher performance metrics and train it. Deep learning and neural networks enable us to train the model we independently constructed to learn for itself from our experiences.

Convolutional Neural Network is of the of method of Deep Learning Algorithms. Characters present in the image are successfully recognized by the CNN classifier. Convolutional layers for feature extraction and fully linked layers followed by a soft-max layer for classification make up the architecture of conventional CNN classifiers. One of the effective feature extractors is CNN.

Data exploration is a methodology that integrates methods from machine learning, statistics, and computer systems to find patterns in enormous volumes of data. The neurons in CNN's architecture are arranged in layers. This design consists of an input layer, many hidden levels, and an output unit. Typically, networks with a lot of hidden layers are referred to as deep neural networks. The neurons in the hidden layers of CNN are connected to only a fraction of the input space produced by the preceding layer, as opposed to entirely important factor like Multi Laminated Perceptron (MLP) networks. The inversion process produces an extracted feature when the convolution kernel passes across the input matrix for the layer, adding to the input of the following layer. Then, further layers like normalizing, pooling, and entirely linked levels are introduced.

In conclusion, handwritten digit recognition is a significant, quickly developing topic with a wide range of real-world uses. We may anticipate significant advancements in precision and performance as deep learning and computer vision technologies keep evolving, making them even more beneficial in a variety of fields.

II. RELATED WORK

The first attempt to recognize the handwritten character was made in Grimsdale in 1959 while conducting research on word recognition. This mid-'60s study demonstrated the application of Eden's 1968 examination-by-combination approach. He gave an example to show how the number of schematic highlights is the limit for every single handwritten character.

Different pre-handling systems linked to character recognition were proposed by K. Gaurav and Bhatia P. K. The process attempted numerous picture formats, ranging from a straightforward picture-based report to a colored and altered forces incorporating foundation.

R. Bajaj, S. Chaudhari, L. Dey, et al. used distinctive features including clear portion, thickness, and minute highlights to group the Devanagari numbers. The paper also suggests multi classifier unshakable quality for handwritten Devanagari numerals to further improve recognition capacity.

In her essay on Four characteristics, Sandya Arora provided illustrations using the terms shadow, histogram of chain code crossing point, and horizontal line fitting. One of these highlights was the character image's shadow, while the other three were processed by segmenting the image into the different sections. The dataset of 4900 instances was used in one practical execution, which showed a 90.8% accuracy rate for Devanagari handwritten characters.

In this study, we will classify handwriting using three (3) different methods: SVM, KNN, and Neural Network. Their handwriting recognition system uses Local Binary Pattern (LBP) as a feature extraction method and KNN in "Handwriting Digit Recognition using Local Binary Pattern Variance and K-Nearest Neighbors Classification."

III. EXISTING SYSTEM

Even if the results of existing algorithms for handwritten digit recognition are excellent, there are still several restrictions and issues that need to be resolved:

Several algorithms are sensitive to the input image's quality, especially in terms of contrast, illumination, and noise. The algorithm could have trouble correctly identifying the digit if the input picture is unclear. Some algorithms can only detect digits written in a particular handwriting or style. Due to this, they are not as generalizable to new datasets or handwriting types as what they were trained on. Modern handwritten digit recognition algorithms are frequently complicated and computationally costly, making it challenging to apply them on limited-resource devices like mobile phones or embedded systems. Results from algorithms that were trained on skewed datasets might be skewed. For instance, if some digits are better represented in the training dataset than others, the algorithm may perform less well when trying to identify those digits. As many deep learning algorithms are "black boxes," it might be challenging to comprehend how they make their predictions. This can be an issue in situations where interpretability and openness are crucial, such as in the legal or medical fields.

IV. PROPOSED SYSTEM

Offline and online handwriting identification systems are two distinct types of handwriting recognition. Online techniques use a digital pen or stylus and may see the pen position and stroke information while text is being typed. It is typically possible to classify them quite accurately since they frequently carry an extensive amount of information about the language's flow, which makes it easier to distinguish between the various characters in the text. Offline techniques rely on reading text that has already been written down, therefore they are not aware of the writing strokes or directions used, and they may also have some background noise from the paper used to write the text. Depending on their functionalities, separated the project into several components.

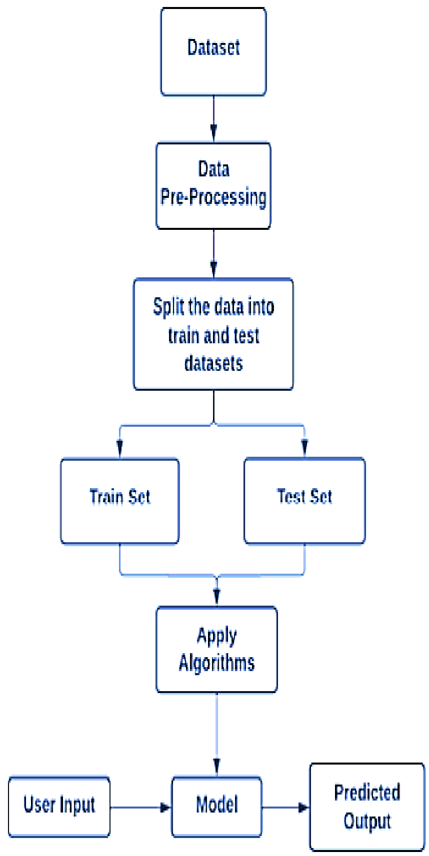

Fig .1 Architecture Diagram

A sequential model is created. Five hidden Conv2D layers are present in this sequential model. Every Hidden layer is activated using the ReLU function. ReLU speeds up training and introduces nonlinearity. ReLU aids in accelerating computations. Pooling is used to follow every hidden layer. For decreasing the dimensions and calculations, we employ MaxPooling. Due to the smaller number of parameters, Max Pooling also lowers overfitting. Location-invariant feature detection is achieved through Conv + Pooling. Each Previous Input is Connected to the Next Layer by a Dense Layer. Finally, we flatten the layers to make them 1D. The SoftMax Function is used to anticipate outcomes with the greatest degree of certainty. Train the model using an improved optimizer, such as Adam. Adam's optimizer has a higher rate of learning. A Sparse Categorical Crossentropy should be used. Pass the metrics for accuracy. To train the data for 10 epochs, use the .fit() function. Show the Accuracy and Loss on a graph. We have to go through several processes for making the data better and usable.

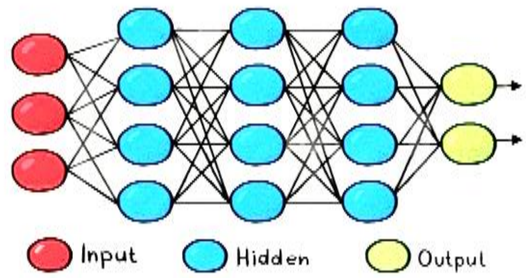

Fig .2 Basic CNN layers

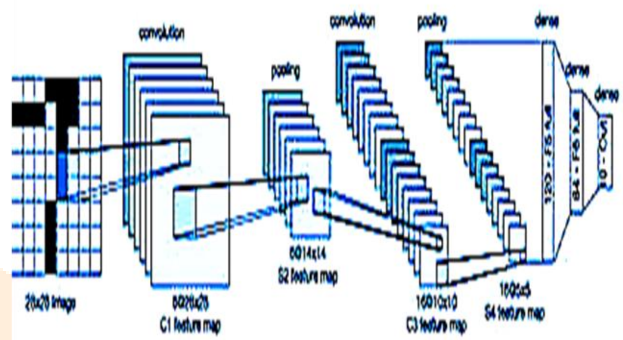

Fig .3 Layering in CNN

Data cleaning is an important step in the machine learning process that involves identifying and correcting errors or inconsistencies in a dataset. It is an important step that might have a big impact on how accurate and successful machine learning models are.

There are several techniques that can be used for data cleaning, including:

Handling Missing Data: This involves identifying missing values and either imputing them with a value or removing them from the dataset.

Handling Outliers: Outliers are extreme values that can skew statistical analyses. They can be handled by either removing them or transforming them using techniques like winsorization.

Handling Inconsistencies: Inconsistent values can occur when different sources of data are merged. These can be handled by identifying and correcting errors or standardizing values.

Handling Duplicates: Duplicate records can be removed to avoid bias in the analysis.

Handling Irrelevant Data: Data that is not relevant to the analysis can be removed to reduce noise and improve the accuracy of the model.

To ensure that the data cleaning process is effective, it is important to have a clear understanding of the data and the problem being addressed. This involves exploring the data, identifying patterns and trends, and selecting appropriate cleaning techniques.

The process of eliminating extraneous features from the feature set is known as denoising or noise reduction. Although the term "denoising" refers to the elimination of noise, the process involves preserves features.

Making each feature's value have a zero mean and a single variation is the process of standardization. Calculating the mean and standard deviation for each characteristic is part of the broader standardization process. The easiest method for transforming any image into a binary image is by thresholding. A binary image is one in which each pixel may only have one of two potential values. The fundamental concept is to swap every pixel for a black or white one based on whether the pixel's intensity is either less than or larger than a predetermined constant. The threshold value is another name for this amount.

V. RESULTS&DISCUSSION

In order to verify that the CNN model will function as we expected ,we undertook a series of tests to analyze its performance. Various metrics helped in measuring the performance of the proposed model.

Fig .4 Plotting the character data.

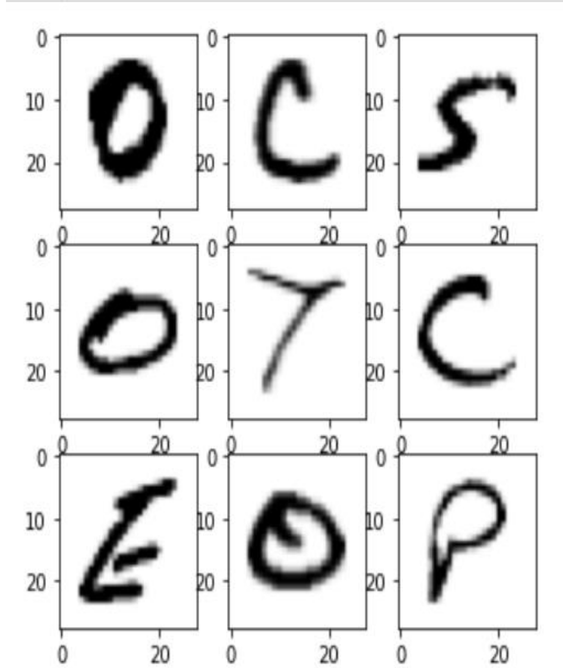

Fig .5 After applying threshold on image.

The metrics that we determined for CNN to measure the model's performance, and the results are shown below.

```
The validation accuracy is : [0.9723587036132812]
The training accuracy is : [0.9532219171524048]
The validation loss is : [0.09842836856842041]
The training loss is : [0.17315390706062317]
```

Fig .6 Performance measures.

VI. CONCLUSION

In summary, handwritten text recognition is a growing area of study with applications in a variety of industries, including document digitalization, signature authentication, and handwriting analysis. Despite recent considerable progress in this area, the intricacy and diversity of handwriting make precise and reliable handwritten identification a difficult challenge to solve.

Researchers may investigate different strategies in the future to enhance handwriting recognition systems. The following are some prospective future research areas:

Data augmentation: Adding new training data by rotating, scaling, and skewing already-existing data may help script recognition algorithms become more resilient.

Transfer learning: Pre-training models on massive amounts of printed text or other visual tasks and refining them on smaller amounts of handwritten text may increase recognition accuracy.

End-to-end systems: Improving the accuracy and effectiveness of recognition may require the development of end-to-end systems that can analyze unprocessed handwriting input without the requirement for manual feature extraction or segmentation.

These are only a few instances of possible directions for further research in the identification of handwriting. It will be fascinating to observe the various methods and strategies that are developed as this topic develops to deal with the difficulties of handwritten text identification.

REFERENCES

[1] Handwritten Character Recognition of South Indian Scripts: A Review by Jomy John, Pramod K. V, Kannan Balakrishnan, National Conference on Indian Language Computing.

[2] Multilingual OCR for Indic Scripts by Minesh Mathew, Ajeet Kumar Singh and C. V. Jawahar

[3] Telugu handwritten character recognition using adaptive and static zoning methods. Sanugula Durga Prasad, Yashwanth Kandhuri.

[4] Handwritten Character Recognition for Telugu Scripts Using Multi - Layer Perceptrons (MLP). C. Vikram, C. Soba Bindhu, C. Sashikala

[5] S. Xiao, L. Peng, R. Yan and S. Wang, "Deep Network with Pixel-Level Rectification and Robust Training for Handwriting Recognition," *2019 International Conference on Document Analysis and Recognition (ICDAR)*, Sydney, NSW, Australia, 2019, pp. 9-16.

[6] M. Yadav and R. K. Purwar, "Integrating Wavelet Coefficients and CNN for Recognizing Handwritten Characters," *2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES)*, Delhi, India, 2018, pp. 1160-1164.

[7] P. Voigtlaender, P. Doetsch and H. Ney, "Handwriting Recognition with Large Multidimensional Long Short-Term Memory Recurrent Neural Networks," *2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR)*, Shenzhen, China, 2016, pp. 228-233.

[8] Shima Alizadeh and Azarr Fazel, "Convolutional Neural networks for Facial Expression recognition", *Computer Vision and Pattern Recognition Cornell University Library ArXiv:1704.06756v1*, April 2017.

[9] M. D. Zeiler and Fergus, "Visualizing and understanding convolutional networks", European Conference on Computer Vision, vol. 8689, pp. 818-833, 2014.

[10] Caifeng Shan, Shaogang Gong and Peter W. McOwan, "Facial expression recogniton based on Localbinarypatterns:Acomprehensivestudy", *ELS ELSEVIER Image and Vision Computing*".