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Handwritten Recognition of Character and Number Using Convolutional Neural Network and Support Vector Machine

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***Abstract*: Handwritten character recognition has become a major study topic as a result of the rising use of digital technology in many industries and in practically all day-to-day activities to store and convey information. Although handwritten copies are still useful, individuals prefer to have them turned into electronic versions that can be shared and saved online. Handwritten recognition is the capacity of a computer to recognize and understand comprehensible handwritten input from a variety of sources, including touch screens, pictures, paper documents, and other sources. Because diverse people have distinct handwriting styles, handwritten characters remain complicated. The purpose of this work is to describe the creation of a handwritten character and number recognition system that will be used to read handwritten notes from students and lecturers. For feature extraction and higher end classification, the Learning model uses Convolution Neural Networks (CNN) and Support Vector Machines (SVM). Handwritten inputs are scanned, noise is removed, and numbers and characters are retrieved to complete this operation.**

***Keywords*: CNN, SVM, MNIST, handwritten character and number recognition.**

1. Introduction

Human's dependence on technology has never been higher, to the point that deep learning and machine learning algorithms can conduct anything from object detection in images to adding sound to silent movies. Similarly, handwritten text recognition is a major field of research and development with a plethora of possibilities.

Handwriting recognition (HWR), also known as Handwriting Text Recognition (HTR), is the capacity of a computer to recognize and interpret comprehensible handwritten input from a variety of sources, including paper documents, pictures, touch displays, and other devices. Apparently, we used MNIST datasets to conduct handwritten letter and number recognition using Support Vector Machines (SVM) and Convolution Neural Network (CNN) models in this article.

The model pipeline includes the stages, image preprocessing, feature extraction and classification to convert the features to the text. In the image preprocessing stage, image is binarized, scaled, contrast is improved, and the noises are removed. The handwritten are extracted from the preprocessed images.

Due to its practical uses in numerous day-to-day tasks, handwritten digits and character recognitions have become increasingly significant in today's electronic environment. It may be demonstrated by the fact that several recognition systems have been created or suggested in recent years for application in various sectors where high categorization efficiency is required. Biological neural networks, which allow people and animals to learn and model non-linear and complicated interactions, can be used to inspire handwritten recognition systems. That is to say, they can be created using an artificial neural network Individuals can distinguish distinct Handwritten items such as numerals, letters, and characters thanks to the human brain.

The images extracted from the inputs, still cannot be fed to the CNN model as the CNN classifiers need images of each character. So, using OpenCV's, individual characters are identified.

2. Literature Review

1) Handwritten numerical string recognition based on SVM verifier

Although the challenge of isolated handwritten number recognition has been solved, segmentation and recognition of handwritten numerical strings remains a challenging topic in this field. In this study, we will use an experiment model for handwritten numerical string recognition, which will address issues like as over segmentation and under segmentation.

2) Human-perception handwritten character recognition using Convolutional neural network

This paper provides a unique technique for handwritten character identification based on human perception. Horizontal or diagonal letters are not recognized by this programme. We employed vision's multiresolution capacity to extract information such as fixation points and picture details in horizontal, vertical, and diagonal orientations for this project.

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3) Human identification of letters in mixed-script Handwritten: an upper bound on recognition rates using Convolutional Neural Network.

The focus of this research is on a reading task that involves identifying letters in mixed-script handwritten words. Humans accomplish this job in a language environment that is either expansive or confined. Many recognition algorithms are being developed at research centers, but none of them have yet shown to be successful. We can build a model that recognizes mixed writing, such as integers and characters.

4) Online handwritten Indian script recognition: A human motor function-based framework Using SVM Algorithm

The approach's main focus is on simulating human motor functioning when creating characters. The suggested similarity measure appears to be rather weak against broad variances in writing styles, according to the proposed low-complexity classifier. We can build a model that can identify a large variety of handwritten characters.

5) Handwriting recognition for security Problems in web services using convolutional neural network

Despite decades of research and development, computer recognition of unconstrained handwriting remains a challenging problem. This is because handwritten text poses significant hurdles, such as character identification and handwriting style diversity. In this research, we investigate the gap between humans and computers' capacity to read handwritten language in order to offer solutions to security issues in Web services.

3. Model Architecture

Design is a multi-step process that focuses on data structure, software architecture, procedural details, procedure, and the interface between modules, among other things. Before coding begins, the design approach decodes the requirements into a presentation of software that can be accessed for quality assurance. As new methodologies, enhanced analysis, and boundary knowledge grew, so did the design of computer software. The revolution in software proposal is still in its early stages.

As a result, software design approach lacks the breadth, flexibility, and quantitative character associated with traditional engineering disciplines. However, software design approaches do exist, design quality standards do exist, and design notation may be used.

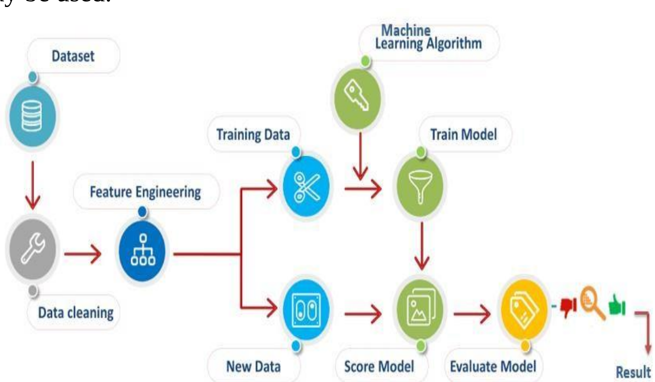

Fig. 1. System architecture

4. Data Flow Diagram

A flow diagram is a general name for a diagram that depicts a system's flow or collection of dynamic interactions. Flow diagram is occasionally used as a synonym for flowchart and as a counterpoint to the flowchart.

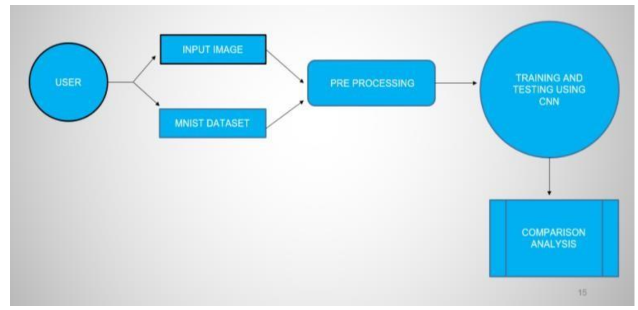

Fig. 2. Data Flow Diagram

5. Module Description

A. Data Collection

Data Collection is one of the most important tasks in building a machine learning model. It is the gathering of task related information based on some targeted variables to analyze and produce some valuable outcome. Two different types

1. Character (image converted into pixels)
2. Numbers (loaded directly from MNIST Data set)

B. Data Pre – Processing

Data pre-processing is a process of preparing the raw data and making it suitable for Deep learning model. In data set the images are in different sizes (image height and width). So, it is rescaled by converting 28x28 pixels. Transform colored image to greyscale image.

C. Noise Removal

To eliminate the unwanted or undesired patterns, a technique called noise removing is used.

While compressing the picture, some noise will be produced. To remove the noise produced, we use Gaussian Blur method.

D. Training and Testing

Train/Testing is the method to measure the accuracy of the model. It is called train/test because we split the dataset into two sets.

- Training Set (80%)
- Testing Set (20%)

We create the model by training the model.

E. Using Convolutional Neural Network (CNN) and Support Vector Machine (SVM)

Two different algorithms used for two different datasets. Convolutional neural network algorithm (CNN) used for characters and Support vector machine algorithm (SVM used for number dataset.

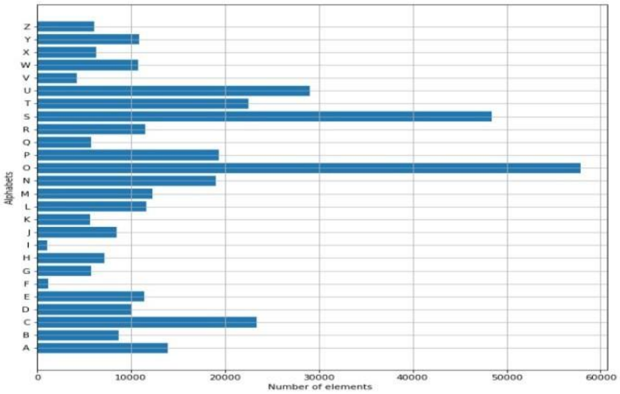

Fig. 3. MNIST dataset for characters

In overall dataset, the number of elements are checked (eg.: Element A has trained in more than 13000 or 15000.

Different handwriting). When the number of elements I is higher, and the accuracy will be better.

CNNs are made up of a large number linked neurons with weights and biases that may be learned. The neurons in CNN's architecture are arranged in layers. It has an input layer (pixel image), several hidden layers, and an output layer. Deep neural networks are referred to as such if the network contains a significant number of hidden layers. Instead of connecting to all of the input space provided by the preceding layer, the neurons in the hidden layers of CNN are coupled to a restricted region (receptive field). As a result, CNN requires less time to train for networks of comparable size. A typical CNN's input is a two-dimensional (2D) array of data, such as photographs. The layers of a CNN, unlike those of a standard neural network, are organized in three dimensions (width, height and depth).

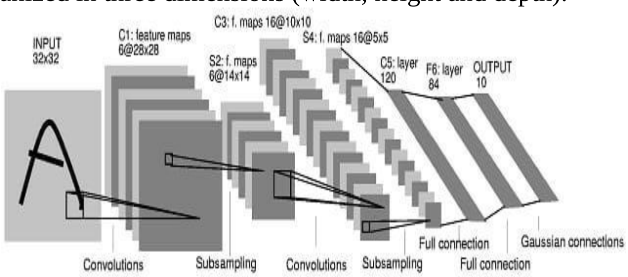

Fig. 4. Convolutional Neural Network

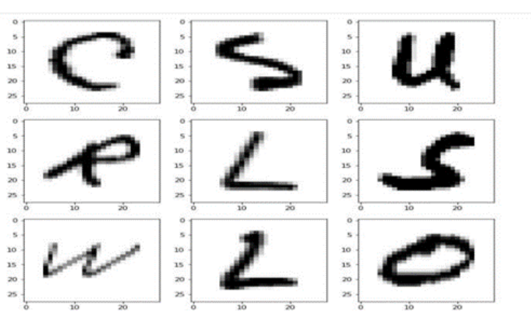
Fig. 5. Grayscale scale image (CNN)

SVM is a collection of supervise learning methods that may be used to detect outliers and perform classification regression. SVM methods use a collection of label data to train and classify data into several categories. In high-dimensional spaces, it works well. When the number of dimensions exceeds the number of samples, the method is still successful. It is incompatible with huge datasets. When there is greater noise in the data set, SVM does not perform well. (That is, the target classes overlap.)

SVM is used to classify handwritten digits from the MNIST dataset into numbers ranging from 0 to 9. The collection is made up of grayscale pictures of handwritten digits, each measuring 28 pixels in height and width (28x28). 30000 training samples and 30000 testing samples were used efficiently. Grayscale images are created from the samples.

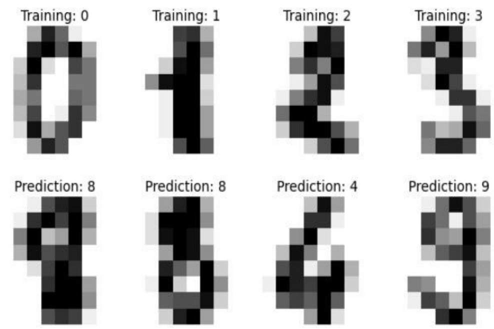

Fig. 6. Gray Scale Image (SVM)

Some of the random images from the test dataset compared with prediction level.

6. Accuracy Comparison

Accuracy depends on the size of the dataset. Here we have attained above 92% accuracy in Support Vector Machine and above 95% in Convolutional Neural Network.

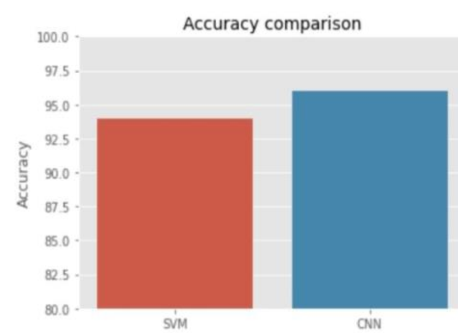

Fig. 7. Accuracy comparison

7. Results

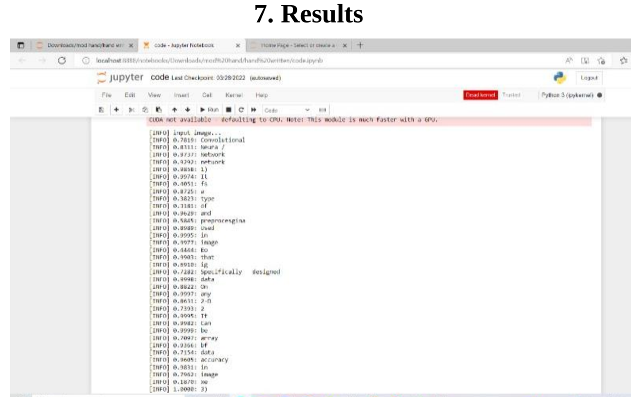
Fig. 8. Detected text from the input image (1)

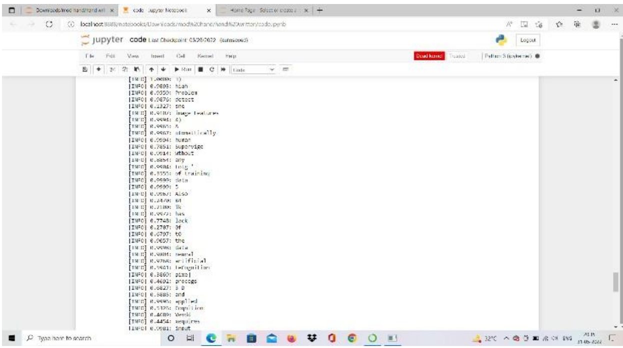

Fig. 9. Detected text from the input image (2)

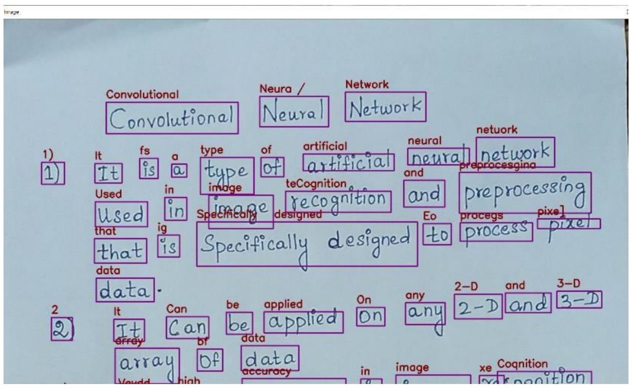

Fig. 10. Recognized image

8. Future Enhancement

It can be used as a Real time deployment model. In schools and colleges, it can be used to find students handwriting with the help of predefined. In future we are expecting to explore the Convolutional neural network (CNN) and Support vector machine (SVM) algorithm to make recognition of digits and character faster and more efficient and improve the overall performance.

9. Conclusion

The model achieves maximum accuracy with Sequence-to-Sequence implementation utilizing CNN and SVM. If we can train the model on a larger number of datasets, the model's performance will improve. The model's performance can be enhanced if we can train it on more samples with larger spacing between the characters. The model accuracy was above 95% when CNN classification was used with the MNIST dataset. The mode model accuracy was around 92% Percent utilizing SVM and the MNIST dataset. The picture was sent into the model, which generated the sequence of characters and numbers based on the coordinates of each character and number. The MNIST dataset was used to train the model, and it was discovered that the model could predict better numbers and characters. We can increase model accuracy by training the model using a balanced dataset.

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