

A LITERATURE SURVEY ON A NOVEL METHOD FOR HANDWRITTEN DIGIT RECOGNITION SYSTEM

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ABSTRACTION:

Handwritten character recognition is a translational problem of human writings into machine editable text format. In this paper, Convolutional Neural Networks (CNN) is presented for handwritten character recognition.

Handwritten character was transformed into graphs based on its underlying skeleton structure. Edges of the extracted graph were categorized into shape types and vertices were extracted from each of the edges and their layer wise evaluation using deep learning. Matching procedure of the graph was performed in Convolutional Neural Networks (CNN) approach. Performance evaluation of the proposed method was conducted using validated kaggle dataset which exclude ambiguous and unidentified writing samples. The use of neural network can improve the quality of recognition while achieving good performance and encouraging.

KEYWORD: Deep learning, Hand writing detection, Artificial Neural Network, Convolution Neural Network

INTRODUCTION:

Handwriting digits and character recognitions have become increasingly important in today's digitized world due to their practical applications in various day to day activities. It can be proven by the fact that in recent years, different recognition systems have been developed or proposed to be used in different fields where high classification efficiency is needed. Systems that are used to recognize Handwriting letters, characters, and digits help people to solve more complex tasks that otherwise would be time-consuming and costly.

A good example is the use of automatic processing systems used in banks process bank cheques. Without automated bank cheque processing systems, the bank would be required to employ many employees who may not be as efficient as the computerized Processing system.

The human visual system is primarily involved whenever individuals are reading Handwriting characters, letters, words, or digits. It seems effortless whenever one is reading handwriting, but it is not as easy as people believe. A human can make sense of what they see based on what their brains have been taught, although everything is done unconsciously. A human may not appreciate how difficult it is to solve Handwriting.

RELATED WORKS:

- * The main objective of this research is design an expert system for Handwriting character recognition using neural network approach.

- * To address the issue of accuracy in Handwriting character recognition systems by developing a system that will use efficient technology for recognizing Handwriting characters and words from image media.

- * To investigate and demonstrate the usefulness of neural network technology in development of efficient Handwriting character recognition systems.

METHODOLOGY

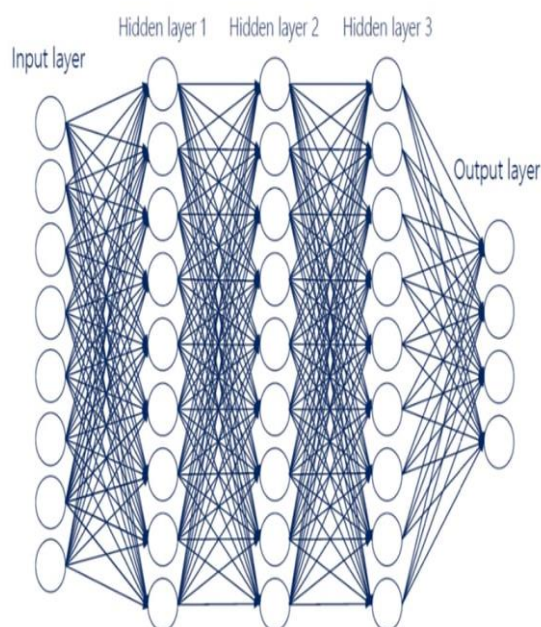
1. Neural Networks:

Neural network is a system inspired by human brain function, consists of neurons connected in parallel with the ability to learn. A basic design of neural network has input layer, hidden layer, and output layer. Neural networks, with their remarkable ability to derive meaning from complicated or imprecisedata, can be used to extract pattern and detect trends that are too complex to be noticed by eitherhumans or other computer techniques.

2. Network Layers:

The commonest type of artificial neural network consists of three groups, or layers, of units: a layer of “input” units is connected to a layer of “hidden” units, which is connected to a layer of “output” units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units.

The behaviour of the output units depends on the activity of the hidden units and the weights between the hidden and output units. This simple type of network is interesting because the hidden units are free to construct their own representations of the input. The weights between the input and the hidden units determine when each hidden unit is active, and so by modifying these weights, a hidden



unit can choose what it represents.

CONVOLUTIONAL NEURAL NETWORKS

In this paper, Convolutional neural network (CNN) framework was used for handwritten character recognition. In that framework, proper sample generation, training scheme and CNN network structure was employed according to the properties of handwritten characters. That CNN-based framework achieved better performance compared with other CNN-based recognition methods. That CNN-based framework mainly consists of three parts.

The Sample generation, CNN models and voting. Sample generation used distortions such as local and global distortion. CNN model was for better training and Voting can significantly improve recognition rate. The error-rate by this CNN-based framework for character recognition for MNIST data set was 0.18%. So we can still improve this framework by enlarging the CNN scale or input image size. Also we can find better sample generation methods, training scheme and network structure of CNN.

A special type Neural Networks that works in the same way of a regular neural network except that it has a convolution layer at the beginning. A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, RELU layer i.e. activation function, pooling layers, fully connected layers for softmax layers.

1. Input Layer:

The input layer is used to feed the system with the image with the handwriting. The layer can be colored image (RGB values) or grayscale. It can have dimension $W \times H \times D$, depending on the input image. The $W \times H$ refers to the width and height of the image, while D refers to the depth of the image.

2. Convolution Layer:

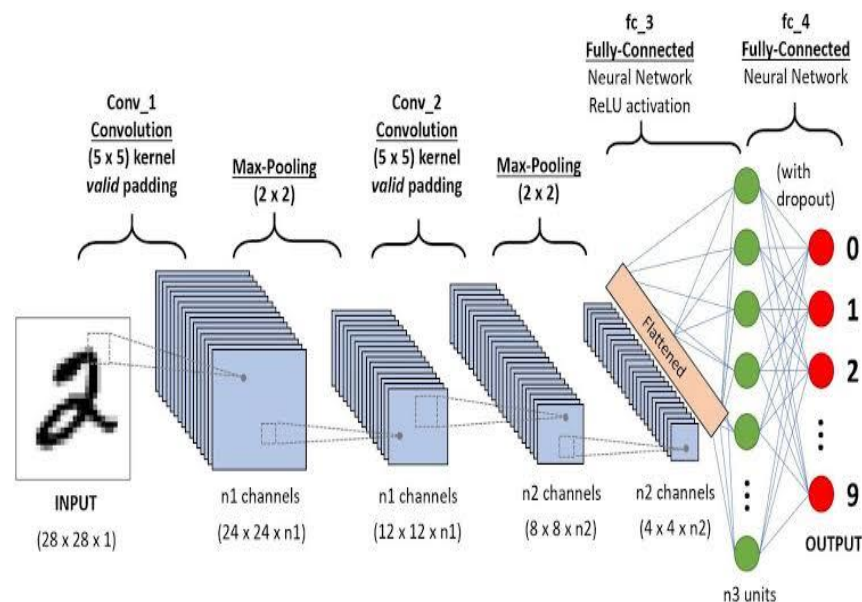
The convolution layer is the building block of the whole network. Most of the computational work that is required to recognize characters from the input is done in this layer (Aggarwal, 2018). The layer consists of a set of learnable filters known as parameters of the convolution layer.

3. Pooling Layer:

The pooling layers are found between the convolutional layers in the CNN architecture. They are responsible for progressively reduce the spatial size of computational work in the network. They help to streamline the underlying computation. They do so by reducing the dimension of the input data by combining the outputs of the neuron clusters. They operate independently. That way, the system can achieve the intended outputs.

4. Fully Connected Layer:

Neurons in a fully connected layer are fully connected to all activations in the previous layer. Hence, this layer, activations, can be computed with matrix multiplication. Based on the architecture, a system can have multiple fully connected layers. In summary, CNN can be used to achieve a solution to every pattern recognition issue. The architecture demonstrated above shows how OCR systems using neural networks can read handwriting. The convolutional networks work in the hierarchy and can be used to solve complex structures found in handwriting inputs. Humans inspire the whole idea can recognize writing objects and process what they see in their brains.



MODULES

The current OCR system will consist of five phases. The phases are image acquisition and digitization, preprocessing, segmentation, feature extraction, and recognition.

1. Image Acquisition and Digitization:

The image acquisition step involves acquiring an input image that contains handwriting. The image, in this case, should be in specific formats

such as PNG and JPEG. The image is acquired through a digital camera, scanner, or any other suitable input device. The digitization step, on the other hand, involves converting the input paper into electronic format. The conversion is achieved by first scanning the original document and representing it in the form of an image that can be stored on a computer. The digital image is essential for the pre-processing phase.

2. Preprocessing:

Preprocessing is the second phase of OCR after the digital image. The digitized image is pre-processed to remove noise, and then it is checked for skewing. Preprocessing is essential for developing data that are easy for optical character recognition systems. The main objective of pre-processing is to remove the background noise, enhance the region of interest in the image, and make a clear difference between foreground and background.

Image Enhancement Techniques:

To modify attributes of the image to make it more suitable and to improve the quality of the image by reducing noise, increasing contrast, image blurring, and providing more details. Hence, to process an image so that result is more suitable than the original image and providing better input for automated image processing techniques.

Noise removal:

Additive noises of different types can contaminate images. Hence there is a need to remove noise to improve the quality of the image. Binarization: This method is used to transform the grayscale image and converting it to black and white, substantially reducing the information contained within the image from different shades of gray into a binary image.

Skew Correction, Thinning: This is one of the first operations to be applied to scanned documents when converting data to digital format. This process helps to get a single-pixel width to allow easy character recognition.

3. Segmentation:

Segmentation can be argued to be the most critical process in character recognition techniques. Segmentation of images is done in the testing stage only. It checks for any error point inclusion by checking all points against the average distance between segmentation points in complete image. The process involves separating individual characters from an image. The process results in multiple segments of the image known as super pixels. The main aim of segmentation is to simplify the representation of an image into something that can be analyzed easily. Hence it has a positive impact on the

recognition rate of the scriptbest results were obtained when they used elastic deformation. At the end results shows that they achieved the highest performance known to date on the MNIST data set, using elastic distortion and convolutional neural network.

4. Feature Extraction:

In this phase, features of the image are extracted and are defined based on the following attributes: height of the character, numbers of horizontal lines, widths of the character, number of circles, pixels, position of different features and number of vertically oriented arcs, to mention a few.

5. Recognition:

In this phase, the neural network is used for classification and recognition of the characters from the image. The most neural networks that are used by optical character recognition systems are the multiplayer perception (MLP) and Korhonen's Self Organizing Map.

IMPLEMENTATION:

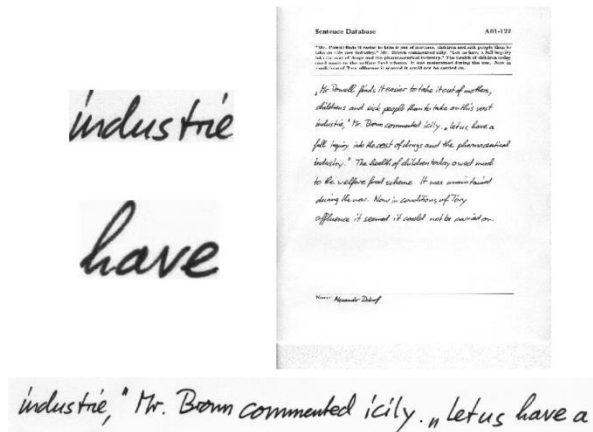
To implement our CNN architecture, we will use MatConvNet. MatConvNet is an implementation of Convolutional Neural Networks (CNN) for MATLAB [12]. It exposes the building blocks of CNN as easy-to-use MATLAB functions, providing routines for computing linear convolutions with filter banks, feature pooling and many more. In this manner, MatConvNet allows fast prototyping of new CNN architectures; at the same time, it supports efficient computation on CPU and GPU allowing to train complex models on large datasets such as Image Net ILSVRC.

Convolutional Neural Networks (CNN) are the current state-of-art architecture for the image classification task. Our proposed 2-D Convolutional Neural Network (CNN) model is designed using MatConvNet backed for the well known MNIST digit recognition task. The whole workflow can be to preparing the data, building and compiling of the model, training and evaluating the model and saving the model to disk to reuse. Preparing the data is the first step of our approach. Before we build the network, we need to set up our training and testing data, combine data, combine labels and reshape into the appropriate size. We save the dataset of normalized data (single precision and zero mean), labels, and miscellaneous (meta) information.

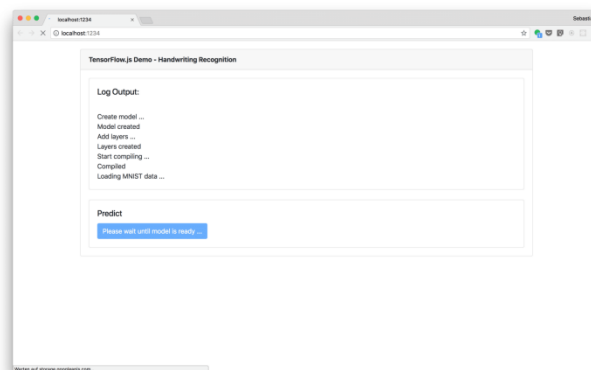
RESULTS:

In this project we have given image as an input then it predicts the output by loading the model which is already previously created and saved.

INPUT MESSAGE



OUTPUT MESSAGE:



CONCLUSION AND FUTURE SCOPE:

In this project classification of characters takes place. The project is achieved through the conventional neural network. The accuracy we obtained in this is above 90.3%. This algorithm will provide both the efficiency and effective result for the recognition. The project gives best accuracy for the text which has less noise. The accuracy completely depending on the dataset if we increase the data, we can get more accuracy. If we try to avoid cursive writing then also its best results. Future Work: In future we are planning to extend this study to a larger extent where different embedding models can be considered on large variety of the datasets. The future is completely based

on technology no one will use the paper and pen for writing. In that scenario they used write on touch pads so the inbuilt software which can automatically detects text which they writing and convert into digital text so that the searching and understanding very much simplified.

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