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Digital Digit Recognition System Using DCNN

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Abstract— A digital digit recognition system using deep learning convolutional neural networks is a technique used to recognize numbers that are not written accurately. It is an effective way to identify numbers that differ in size and shape, which may be difficult for humans to do. This system uses the MNIST dataset as its training data, which contains images of handwritten digits from 0-9. By using neural networks, this system can recognize those digits with high accuracy and speed. The accuracy of the recognized digit is represented using a graphical user interface. The DCNN architecture consists of multiple layers of interconnected nodes trained using a large dataset of labeled images. The system uses a process called convolution to analyze the features of the images and learn how to differentiate between digits.

A. INTRODUCTION

A digital digit recognition system using Deep Convolutional Neural Networks (DCNNs) is a state-of-the-art machine learning system that can automatically identify and classify handwritten digits. DCNNs are a type of deep learning neural network that is particularly effective at recognizing complex patterns in images, making them well-suited for image recognition tasks such as digit recognition.

The system works by using multiple layers of interconnected neurons that are specifically designed to extract features from images of digits. The network architecture consists of convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply a set of filters to the input image while pooling layers down sample the output of the convolutional layers. Fully combined layers take the output of the pooling layers and produce a probability distribution over the possible digit classes.

During the training process, the DCNN is fed a large dataset of labeled examples of handwritten digits. The

network learns to extract increasingly complex features of the digit images by adjusting the weights of the neurons through backpropagation. This allows the system to achieve higher accuracy than traditional digit recognition systems.

We make use of the tensor flow framework to recognize digital digit recognition systems.

B. LITERATURE SURVEY

In comparison to the most commonly used classification models like SVM and KNN, CNN using Keras with Theano and TensorFlow offers the highest precision and RFC. Due to its most elevated precision, Convolutional Neural Network (CNN) is being utilized for an enormous scope in photo arrangement, and video investigation, and soon numerous specialists are attempting to interpret sentiment in a statement, often in the processing of natural language and the identification of sentiment CNN is used, by shifting various boundaries [1]. Scientists are dealing with this issue to diminish the error rate however much as could reasonably be expected, in one test using 3-NN,

trained and tested on MNIST, the error in recognition of writing using hand was 1.19 percent [2]. It is being used in convalescing sentences in a picture. A few analysts are attempting to connect new techniques to stay away from the drawbacks of the usual convolutional layers. Ncfm (No combination of function maps) is a tool that can be used to improve MNIST dataset execution [3]. It has a precision of 99.81 percent and is used for large-scale data, in general. With Each passing year, new CNN frameworks emerge with numerous sorts of examinations. Scientists are making a decent attempt to reduce the number of errors.

Error costs are calculated using MNIST datasets and CIFAR[4]. CNN is often used to clean up blurry images. As a result, another model has proposed the usage of the MNIST dataset. This strategy arrives at a precision of 98 percent, with losses ranging from 0.1 percent to 8.5 percent[5]. CNN's traffic sign discernment approach has been suggested in Germany. It suggested a quicker general execution with 99.65% precision[6].

C. METHODOLOGY:

We categorize this classification into six phases which are image digitization, image preprocessing, image segmentation, feature extraction, image classification, and image post-processing.

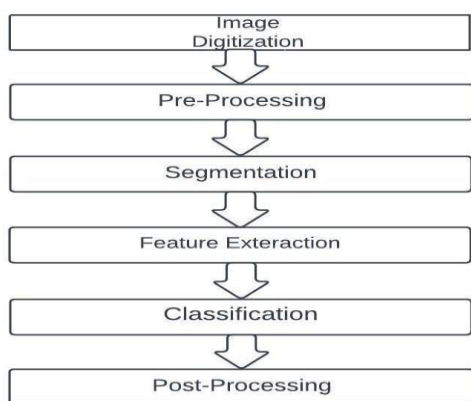


Fig1: System Architecture

IMAGE DIGITIZATION:

A digit is drawn by the human using a mouse or joystick in the GUI. This

procedure is also referred to as the procedure of acquisition. We will make use of GUI to generate an input image and then send it for further processing and classification.

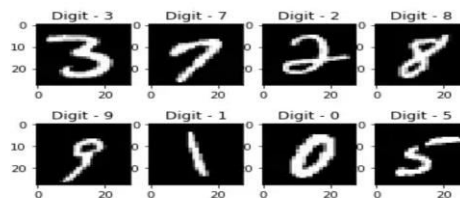


Fig2: Digit Images from MNIST DataSet

IMAGE PRE-PROCESSING:

We need to prepare the image data such that it will fit the model, the required image dimensions are 60000*28*28*1, and the dimensions we have are 60000*28*28. It is a crucial step in digital digit recognition system methodology. There are 5 steps involved here; they are normalization, resizing, grayscale conversion, data augmentation, and splitting the data.

Normalization scales the pixel values in a range of 0 and 1, as it minimizes the contrast differences in the given input image. Resizing reduces the computational complexity in the deep learning model. Grayscale converts the RGB images into grayscale images.

Data augmentation performs different kinds of transformations to the input images such as rotation, flipping, and scaling which prevents overfitting. The dataset is being split into testing, validation, and test datasets.

The training set is used to test the deep learning model, the validation set is used to fine-tune the model's hyperparameters, and the test set is used to evaluate the model performance.

IMAGE SEGMENTATION:

It becomes more significant and easier to evaluate. The primary goal of digit segmentation is to distinguish between the clear digit print area and the non-digit print area. Because of the variety of writing styles, this is the most difficult stage in handwritten digit recognition.

IMAGE CLASSIFICATION:

Image classification is done by the output of the neural network, as we will be giving the number of classes as 10, the network will classify the digit into one of the 10 predefined classes. And the output will be displayed in the GUI interface that we are using.

It is a very important stage in the process, as it helps in classifying the images into respective classes. It happens inside our convolution neural network, it is done over a process of continuous learning by our training dataset.

We would be training the model to be able to detect these features which will be done during the training phase. The model will be further tested in the validation/testing phase where we assess the desired accuracy.

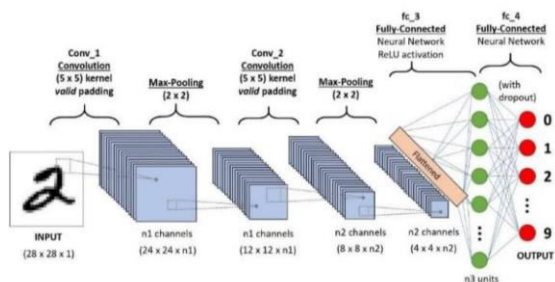


Fig 3: Convolution Neural Network

It is the most crucial stage of the recognition process. It is a method of collecting relevant information by converting input data into a set of features. It is essentially connected to dimensionality reduction; when there is a significant amount of input data to be processed and some redundancy, the input data is transformed into a reduced representation of features. The primary goal of feature extraction is to boost recognition rates.

IMAGE POST-PROCESSING:

This is not a required step in digit recognition, although it can help enhance the system's accuracy in some cases.

Results:

Existing System:

-

The existing system for digital digit recognition involves various techniques, including template matching, neural networks, support vector machines, and K-nearest neighbors. These techniques have been widely used to recognize handwritten digits in various applications such as optical character recognition, signature verification, and automatic bank check processing. However, these techniques have limitations in terms of accuracy and processing time, especially when dealing with large datasets.

Template matching involves comparing a test image with pre-defined templates to find a match, but this technique is sensitive to variations in handwriting styles and may not work well for complex datasets. Neural networks can learn complex patterns in data and can achieve high accuracy, but require extensive training and may overfit the training data. Support vector machines and K-nearest neighbors are also effective techniques but may suffer from the curse of dimensionality when dealing with high-dimensional data.

The previous system used a different machine-learning algorithm for the recognition of handwritten digits. In any recognition process, the important problem is to address the feature extraction and correct classification approaches. The proposed machine learning algorithm that is SVM (Support Vector Machine) tries to address both factors well in terms of accuracy and time complexity.

The overall highest accuracy 90.37% is achieved in the recognition process by Multilayer Perceptron. But the drawback is that the existing system didn't use any classification techniques in attaining higher accuracy. And also Anuj Dutt in his paper showed that by using Deep Learning programs, he was able to achieve a high degree of accuracy.

By using the Convolutional Neural Network with Keras and Theano as a backend, he was gaining 98.72% accuracy.

Proposed System:

The proposed system for digital digit recognition is based on deep learning techniques, particularly convolutional neural networks (CNNs). CNNs have shown significant improvements in accuracy compared to traditional techniques. The proposed system involves training a CNN on a large dataset of handwritten digit images to learn features that can accurately distinguish between different digits. The trained CNN model can then be used to recognize digits in real-time applications.

The proposed system also includes pre-processing techniques such as image normalization, noise reduction, and edge detection to improve the accuracy of digit recognition. Additionally, data augmentation techniques such as rotation, scaling, and shearing can be used to increase the size of the training dataset and prevent overfitting.

Overall, the proposed system for digital digit recognition using deep learning techniques offers improved accuracy, faster processing times, and better scalability compared to traditional techniques. The system can handle complex datasets and is particularly effective for recognizing handwritten digits.

Previously, several algorithms for feature classifications and extraction have been utilized for the purpose of digit recognition. But, with the advent of CNN in deep learning, no separate algorithms are required for this purpose. However, in the area of computer vision, deep learning is one of the outstanding performers for both feature extraction and classification.

However, DNN architecture consists of many nonlinear hidden layers with an enormous number of connections and parameters. Therefore, training the network with a very small amount of samples is a very difficult task. In CNN, only a few sets of parameters are needed for training the system. So, CNN is the key solution capable of correcting datasets for both input and output by varying the trainable parameters and number of hidden layers with high accuracy.

Hence, in this work, CNN architecture with a Deep Learning framework is considered the best fit for digit recognition from handwritten digit images. For the experiments and verification of the system's performance, the normalized standard MNIST dataset is utilized. CNN performance using Tensorflow provides an astonishing 99.70% better result. Despite the fact that the complexity of the process and the codes seem to be much greater compared to conventional machine learning algorithms, the accuracy gain is becoming increasingly apparent.

GUI Interaction:

We collected a dataset of handwritten digit images and trained a DCNN model using a deep-learning framework called TensorFlow. Developed a GUI using a programming language called Python and a GUI library such as Tkinter.

The GUI has included a canvas where users can draw a digit using the mouse or touchpad. When the user submits the drawing, the GUI can pass the image to the DCNN model for digit recognition.

The DCNN model will classify the digit and return a result to the GUI. The GUI displays the recognized digit along with a confidence score or probability distribution. The GUI also includes options for the user to save the drawing or clear the canvas to start a new drawing. It is used for various applications such as educational tools, digital signature recognition, and automated form processing.



Fig4: GUI Display

When we draw the digit using this canvas, it process and classifies the features and then recognizes the given digit, later it displays the accuracy of the digit in the form of a graph as shown below.

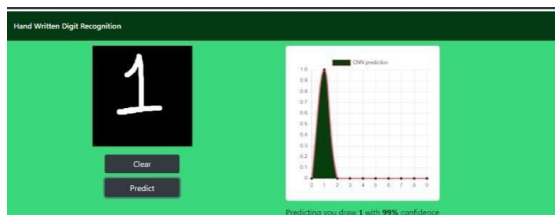


Fig5: Digit Accuracy Display

Conclusion:

We conclude that the digital digit recognition system is the power tool that numerous applications run using deep learning convolution neural networks used to recognize and classify handwritten digits accurately.

Our project reduces the errors and improves the efficiency as the deep learning model is created by applying the CNN algorithm refined and a vast amount of data is fed into the system. This shows that it has the potential to become even more accurate and reliable.

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