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HANDWRITTEN TEXT TO DIGITAL TEXT CONVERSION USING MACHINE LEARNING NETWORK

P Sandeep Reddy[1]

Final Year student (Department of Computer Science Engineering), Ballari Institute of Technology and Management, Ballari, India[1]

Abstract: This novel technique digitizes handwritten text using Optical Character Recognition (OCR), Mobile Nets, and Convolutional Neural Nets (CNNs). The concept is to use CNNs and Mobile Nets to extract features and classify handwritten characters, with the goal of accurately understanding them. The addition of OCR technology improves the process even further by strengthening the model's capacity to identify different handwriting styles. Combining these techniques results in a significant improvement in character recognition efficiency and accuracy, which opens up new possibilities for document digitization, language processing, and computer interaction. This paper presents a robust framework for handwritten text interpretation in a variety of applications.

Keywords: CNN, MOBILENET, AND OCR TECHNIQUE

I. INTRODUCTION

Ensuring secure and user-friendly identity verification is crucial in the current digital landscape. Handwritten data have been a reliable means of identity verification for a very long time. However, since everything is now done online, it's critical to have an automatic method for reading handwritten content. Our project's main goal is to use machine learning techniques—specifically, MobileNet, a portable and effective kind of convolutional neural net to solve this challenge.

We're using MobileNet in a new way called Handwritten Text Recognition. This uses deep learning and computer vision in developing a strong system that can tell if handwritten text is real or not, just by looking at images or documents. MobileNet is perfect for this because it's lightweight, meaning it can work quickly on phones and computers without using up too much power.

We present a novel application of MobileNet dubbed Handwritten Text Recognition. This builds a powerful system that can determine if handwritten text is real or fake based only on viewing the photographs or documents by utilizing deep learning and computer vision. Because MobileNet is lightweight and can operate swiftly on computers and phones without consuming a lot of power, it is ideal for this kind of application.The potential of this technique is to improve safety, streamline procedures, and provide businesses and individuals with an easier way to verify identities.

II. LITERATURE REVIEW

1. Ghandali et al. [1] Biometrics, often known as biometric authentication, is the technique of identifying people according to their physical attributes. In computer science, biometrics is utilized for access control and identification, making it one among the safest ways to protect people's privacy. Biometrics can be divided into two groups: physiological (fingerprint, iris traits, etc.) and behavioural (signature verification, keystroke dynamics, etc.). One among the earliest biometrics to be utilized, even before computers were invented, was the handwritten signature. An authentication technique called ”offline signature verification” examines the actual act of signing and measures the dynamics of a person's handwritten signature. In this research, we offer an off-line text verification and identification system utilizing pixel matching technique. The fundamental component of a text biometric system is behavior. The user's signature is checked using PMT (Pixel Matching Technique) against a sample text that is kept in the database. The suggested approach's result is checked with the SVM (Support Vector Machine) technique and the back-propagation method of present ANN (Artificial Neural Network).

2. Miguel A.Ferrer et al. [2] Based on inner stroke distribution in Cartesian coordinates and polar and the data of the text envelope,This work proposes a collection of geometric signature features for offline automatic signature verification.

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The features were generated using 16-bit fixed-point arithmetic and then tested using a set of classifiers, such as hidden Markov models ,the Euclidean distance classifier and support vector machines. Experiments on the problem of differentiating between simple and random forgeries have produced promising results.

3. B. Fang et al. [3] One of the main challenges in offline signature verification is non-linear rotation of signature patterns. In the order to address the issue, this work provides 2 models that use the rotation invariant structure properties. The intricately extracted ring-peripheral features have the potential to explain periodic variations in the internal and exterior structure of signatures. A distance model is utilized for verification, and discrete fast Fourier transform is utilized to remove phase shift in the order to get a numerical match score evaluation. Furthermore, a ring-hidden Markov model (HMM) is built to assess test signature and training sample similarity directly. Regarding the adverse influence of outlier training samples on threshold estimates and stable statistical models, we provide a selection technique to enhance system performance. The outcomes of the experiments showed how successful the suggested strategies were in raising verification accuracy.

4. Liwicki et al. [4] Digital tablets are utilized to obtain online signatures, and they offer complete signature trajectories and pressure variations over time. Consequently, recognition rates for online signature verification are greater than for offline signature verification. These days, forensic document examiners make a distinction between disguised signatures, where the genuine author purposefully seeks to conceal his or her identity in the order to later deny the authenticity of the document, and forgeries, in which an impostor attempts to copy a particular signature of another person. Masked signatures are important in real forensic scenarios, even if they are not considered in the work that is being done right now. In this study, we provide a novel approach to online signature verification that can detect both disguised and forgeried signatures. Both the reference signature and the questioned signature have features extracted by this approach. Several classifiers are utilized to combine the characteristics, and this results in great performance on multiple signature databases.

5. Ashish Chaturvedi [5] This project demonstrates how to use neural networks to create a system that can recognize handwritten English alphabets. Every letter in the English alphabet is represented by binary values in this system. These are sent into a simple feature extraction system, and our neural network system receives the result.

6. Savitha Attigeri et al. [6] Handwritten character identification has been one of the busiest and most challenging areas of pattern recognition and image processing research.It can be used for many things, such as organizing handwritten documents into a structured text format and bank checks for blind readers. The goal of this project is to use a multilayer feed forward neural network to recognize handwritten characters for English alphabets without the need for feature extraction. There are 26 alphabets in a set of character data sets. The neural network is trained using fifty distinct character data sets. Classification and recognition are performed using the trained network. Each character in the suggested method is immediately learned after being shrunk to 30 by 20 pixels. Put another way, each scaled character's 600 pixels are used as properties while training the neural network.The results show that the proposed approach achieves good recognition rates comparable to feature-based extraction schemes for handwritten character recognition.

7. Palak Patel et al. [7] This paper's goal is to identify the characters in the given scanned document and investigate the consequences of altering the ANN models.These days, pattern recognition tasks are the main application for neural networks. The actions of several neural network models employed in OCR is described in the paper. OCR is a popular Neural Network application.We have considered parameters like the number and size of hidden layers and epochs.

There is now a layered feed-forward network that uses backpropagation. A few basic preprocessing methods have been applied, including character segmentation, character normalization, and deskewing. We ran the test set through several neural network models in are arranged to calculate each neural network's accuracy.

8. Anita Pal et al. [8] The main aim is to train an expert system for "HCR (English) utilizing Neural Network" that, with the help of an artificial neural networks, can accurately identify a certain character of type format. Since neural computing is still in its infancy, its design elements are not as well defined as those of other architectures. Data parallelism is implemented via neural computers.

The manner that neural computers are operated is entirely distinct from how conventional computers are controlled. When given a particular initial state (data input), neural computers are taught (not programmed) to either classify the data into 1 of the many classes or cause the original data to evolve in a way that optimizes a desired attribute.

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III. METHODOLOGY

Convolutional Neural Network

Step1: the convolutional process Convolution operations are the first building component in our attack tactics. In this step, we will talk about feature detectors; these are essentially the filters of neural network. We'll also discuss feature maps,how to learn about their parameters, to know how to identify patterns,how to arrange the results and map out the detection layers.

Step (1b):Level Return The 2nd part of this process will address the Rectified Linear Unit, or Relook. We'll talk about Relook layers and look into how linearity relates to Convolutional Neural Nets. Although it's not required to comprehend CNNs, taking a little lesson to sharpen your abilities can't hurt.

Step 2: Pooling Layer of This section will cover pooling and provide an overview of its general operation. However, we'll concentrate on maximal pooling in this instance. However, we'll look at a set of tactics, including mean pooling. An interactive visual representation that will be helping you grasp the concept in its entirety will wrap up this part.

Step 3: In this part, the flattening process and the procedures to go from pooled to flattened layers in Convolutional Neural Net applications will be briefly reviewed.

Step 4: Whole URL This part will cover every topic we covered in the previous section. If you comprehend this, you'll be able to see Convolutional Neural Nets and how the final "neurons" learn image classification more clearly.

Summary: We'll wrap things up and give a quick rundown of the concept covered from this part. If you believe it will be of any assistance at all, as it probably will be, you want to know the further tutorial on Cross-Entropy and Soft ax. While not necessary for the course, knowing these concepts will be very beneficial to you since you will come to know them when working with Convolutional Neural Nets

MOBILENET:

Tensor Flow's first mobile computer vision model, called MobileNet, is developed to be used in mobile applications, as its name implies. MobileNet leverages depth-aware separable convolutions. It significantly reduces the amount of parameters when matched with the network with traditional convolutions at same depth in the nets. The output will be lightweight deep neural networks. Two processes are used to make a depthwise separable convolution. Convolution in depth. The CNN class known as MobileNet, which Google made publicly available, gives us a fantastic beginning for training our incredibly compact and incredibly quick classifiers. amount of fused Multiplication and Addition operations, or MACs (Multiply-Accumulates), is directly correlated with the speed and power consumption of the network.

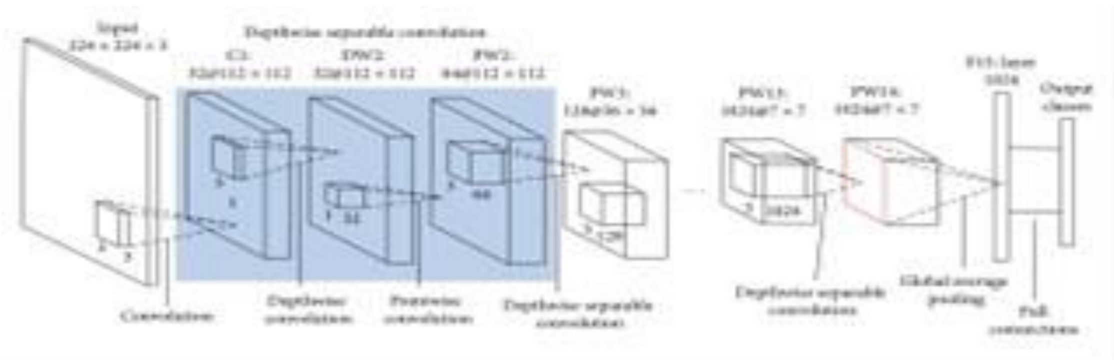

Fig 1

Depth wise Convolution:

The term "separable" for this convolution comes from the concept that a filter's depth and spatial dimension can be separated. Take this example with us of the Sobel filter, which can be utilized to identify edges in images. These filters' width and height measurements are separable. You can take the Gx filter as a matrix product of [1 2 1]. Use [-1 0 1] to transpose. We can observe that the filter has taken on a disguise. Although it has six, it appears to have nine parameters. Its width and height measurements being apart has made this possible.

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-1	0	+1
-2	0	+2
-1	0	+1

Gx

+1	+2	+1
0	0	0
-1	-2	-1

Gy

Fig 2

Pointwise convolution:
Convolution that only mixes the features produced by the depthwise convolution with a kernel size of 1x1. M * N * Df2 is the computational cost of it. The primary distinction between the architecture of MobileNet and a conventional CNN is the absence of one 3x3 convolution layer, which is followed by the batch norm and ReLU. Mobile Networks divided the convolution into a 1x1 pointwise convolution and a 3x3 depth-wise convolution, as displayed in the image.

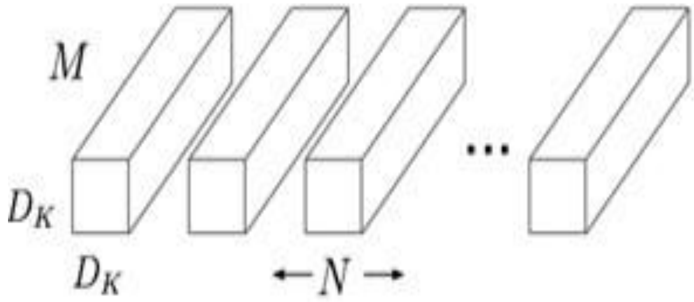

Fig 3

IV. PROPOSED SYSTEM

To identify the issues with the previous system, we created a new one. Our approach recognizes handwritten writing by utilizing deep learning and computer vision. It's good at recognizing and understanding characters. The handwritten writing is recognized and categorized using deep learning techniques.

V. IMPLEMENTATION

System:

• Create Dataset:
The training datasets and testing datasets, each with a test size of 20–30, are separated with in the dataset that contains pictures of the target objects to be recognized.

• Pre-processing:
To train our model, we resize and reshape the photos into the proper format.

• Training:
Utilizing the preprocessed training dataset, the MOBILE NET technique is utilized to train our model.

User:

• Register:
The information is kept in a MySQL database, and the user must register.

• Login:
To utilize an application, a registered user must log in to the website using proper credentials.

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• Upload Image:
The user has to upload an image which needs to be classify the images.

• Prediction:
The output of our model will display the correct text which we have assigned to it.

• Logout:
Once the prediction is over, the user can logout of the application.

V. RESULTS

The project's final outcomes demonstrated notable advancements in the capability to rapidly, precisely, and consistently identify handwritten text utilizing a mix of OCR and Mobilenet in machine learning.Beyond that could be accomplished with conventional OCR approaches, the system's handwriting recognition performance was enhanced by combining OCR with Mobilenet's lightweight neural network.

Additionally, Mobilenet sped up the process by rapidly identifying key features in the text, which sped up the recognition of handwriting, particularly when done in real time.

Fig 4: Data set Upload Page

Fig 5: Result Page

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Fig 6: . Image Upload Page

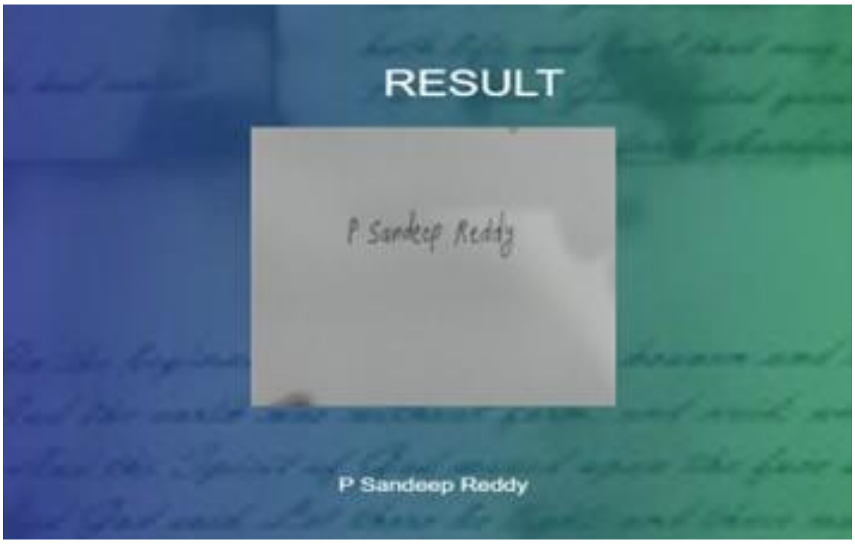

Fig 7: Result Page

VI. FUTURE SCOPE

Our objective is to improve the efficiency and user friendliness of the MobileNet model in the future for handwritten text recognition. It has to be strengthened and made capable of handling various handwriting styles in practical settings. The aim of research should be to optimize the model's performance throughout a broad spectrum of handwriting characteristics and styles. They can accomplish this by developing novel methods to expand the pool of data and investigating strategies to ward off cunning attacks. To enhance recognition, we could also consider applying pre-existing models and learning from smaller datasets. It is critical to confirm that this recognition can happen quickly on mobile devices without jeopardizing security or privacy.

VII. CONCLUSION

In conclusion, MobileNet for recognition of written text is a great illustration of how machine learning can authenticate individuals. Because of its rapid operation on mobile devices, MobileNet's design makes it ideal for real-time signature recognition. The model learns a wide variety of handwriting styles, which improves its ability to precisely recognize and validate signatures. This improves security when performing operations like document verification and financial transactions. This technology is helpful for preventing fraud, streamlining document processing, and improving user experiences in scenarios where written text is needed for confirmation because it is accurate and works with smartphones.

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