Handwritten Text Recognition Using Python

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Abstract- The process of recognizing handwritten text (HTR) is crucial in the digitization of handwritten documents. It allows for efficient text search and analysis. In this research paper, we present a comprehensive approach for handwritten-to-text recognition using Python-based techniques. Our methodology integrates preprocessing steps such as image enhancement and binarization to prepare handwritten samples for feature extraction. We employ convolutional neural networks (CNNs) for feature learning. Additionally, we discuss optimization strategies and potential applications of the developed system in document digitization and archival tasks. Through experimentation and analysis, our work contributes to advancing the field of handwritten text recognition using accessible Python tools and frameworks.

Keywords- Convolutional Neural Networks(CNNs), TF(TensorFlow), OpenCV (Open Source Computer Vision Library)

I.INTRODUCTION

Handwriting is the most common and regular means of communication used by humans. It is also an effective and efficient way to record information, even with the introduction of new technologies such as SwiftKey keyboards and sound commands. A handwriting recognition system is a mechanism that is used to recognize human handwriting in any language, either from scanned handwritten images or real-time handwriting using a stylus pen on an electronic device. This system can be categorized into three types: numeral, character, and cursive word. Additionally, it has numerous applications such as language translation, bank cheques, and keyword spotting.

II.OVERVIEW

The process of handwriting recognition typically involves several key steps. First, the image of the handwritten text is acquired, often through scanning. Then, pre-processing techniques such as noise removal and thresholding are applied to enhance the quality of the image. Next comes segmentation, where the text is divided into individual characters or words. This step is crucial for accurately extracting features from each segment in the subsequent stage. Feature extraction follows, where distinctive characteristics of each segment are identified. These features serve as input for classification, where various algorithms such as Convolutional Neural Networks (CNNs), Neural Networks, or Support Vector Machines (SVMs) are employed to recognize the text. In this project, the focus is on developing online

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handwritten recognition using CNNs. Two commonly used databases, MNIST and EMNIST, are utilized for their clean data. The CNN architecture handles feature extraction and classification, using image pixels as input features. Performance evaluation uses metrics such as confusion matrices to assess classification accuracy. networks, or Support The process of handwriting recognition typically involves several key steps. First, the image of the handwritten text is acquired, often through scanning. Then, pre-processing techniques such as noise removal and thresholding are applied to enhance the quality of the image. Next comes segmentation, where the text is divided into individual characters or words. This step is crucial for accurately extracting features from each segment in the subsequent stage. Feature extraction follows, where distinctive characteristics of each segment are identified. These features serve as input for classification, where various algorithms such as Convolutional Neural Networks (CNNs), Neural Networks, or Support Vector Machines (SVMs) are employed to recognize the text. The CNN architecture handles both feature extraction and classification, using image pixels as input features. Performance evaluation is conducted using metrics such as confusion matrices to assess classification accuracy.

III.PROCESS

A. Flow chart

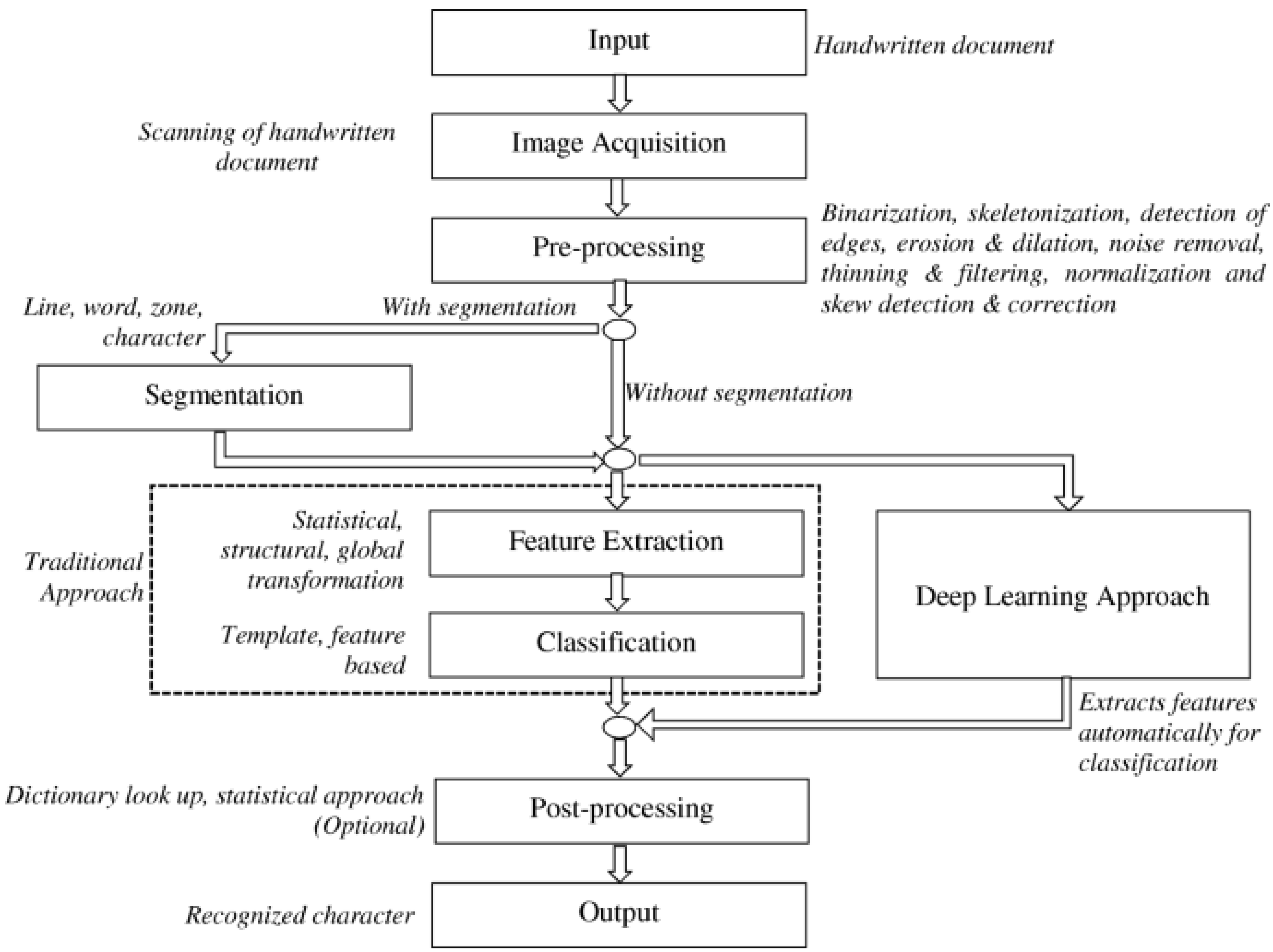

Figure 1. Representation of a common handwritten text recognition (HTR) system.

Develop a system or model that can accurately recognize and transcribe handwritten text into machine-readable format.The goal of this project is to create a robust and efficient system capable of automatically recognizing and transcribing handwritten text. Image acquisition, preprocessing, segmentation, feature extraction, and classification are the typical processes of an HCR system, as shown in **Figure 1**. The initial step is to receive an image form of handwritten characters, which is recognized as image acquisition that will proceed as an input to preprocessing. In preprocessing, distortions of the scanned images are removed and converted into binary images. Afterward, in the segmentation step, each character is divided into sub-images. Then, it will extract every characteristic of the features from each image of the character. This stage is especially important for the last step of the HCR system, which is called classification. [1] Image Acquisition: This step involves obtaining images containing handwritten text. These images can be acquired from various sources such as scanned documents, photographs, or directly from digital input devices like tablets.Pre-processing: In this step, the acquired images are pre-processed to enhance their quality and make them more suitable for further processing. Pre-processing techniques may include resizing, noise removal, contrast enhancement, and normalization.

Segmentation: Segmentation involves dividing the pre-processed image into smaller, more manageable components. In the context of handwritten text recognition, segmentation is typically used to separate individual characters or words from the rest of the image.Feature Extraction: Once the image has been segmented, features need to be extracted from the segmented regions. These features capture important characteristics of the handwritten text, such as shape, size, and texture. Common techniques for feature extraction include histogram of oriented gradients (HOG), scale-invariant feature transform (SIFT), and convolutional neural networks (CNNs).Classification: Finally, the extracted features are used to classify the segmented regions into the corresponding characters or words. This is typically done using machine learning algorithms such as support vector machines (SVM), k-nearest neighbors (KNN), or deep learning models like convolutional neural networks (CNNs).

B. Convolutional Neural Networks (CNNs)

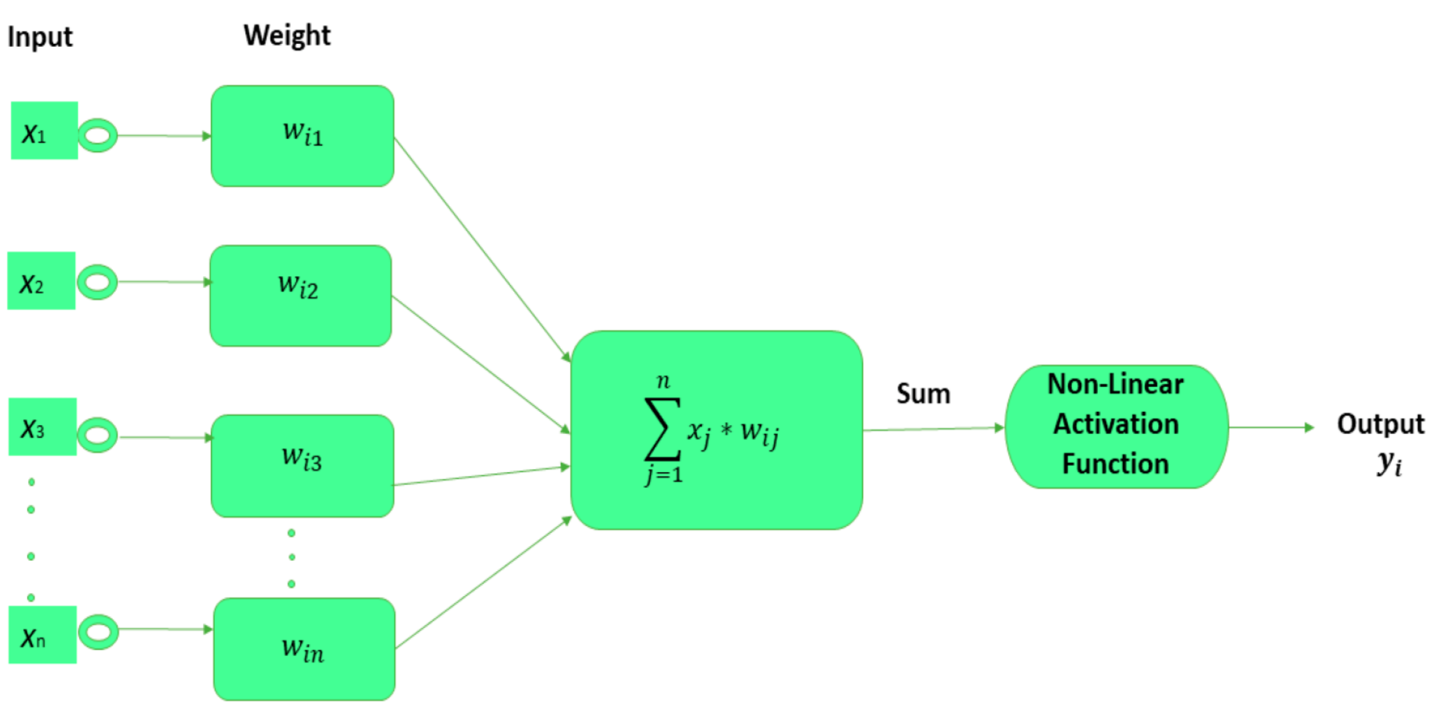

Figure 2. Representation of a basic neural network (NN).

A type of machine learning includes neural networks (NNs), which are inspired by the biological process of the human brain. The basic neural network is represented in Figure 2. The number of layers in a neural network indicates deep learning. Neurons are the information-processing components that form the foundation of neural networks, drawing parallels from the biological neural network. The primary components of an NN are the weights associated with the connection links, bias, inputs, and outputs. Each node in a neural network (NN) is called a perceptron [3]. Researchers are working to achieve the best accuracy, but the accuracy using a CNN is not outstanding, which compromises the performance and usability for handwritten character recognition. Therefore, this paper aims to obtain the highest accuracy in handwritten character recognition (HCR) by introducing a CNN system that can automatically extract important features from images better than multilayer perceptron (MLP) [4,5,6,7,8,9]. CNNs were first used in 1980. [10]Convolutional neural networks (CNNs) were inspired by the human brain's ability to recognize objects from visual images. CNNs work similarly by using deep learning algorithms that are fully connected, meaning each neuron in a layer is connected to all neurons in the next layer. Some well-known CNN architectures include AlexNet, VGG, GoogLeNet, and ResNet. CNNs don't require prior knowledge of designer features, making them excellent for object recognition, and they're not dependent on the rotation of input images. Researchers have used CNN models for handwritten character recognition (HCR) with the MNIST dataset, achieving up to 99.81% accuracy. One experiment combined multiple CNN models for MNIST digits and achieved 99.73% accuracy. Another experiment extended this to a 35-net committee, resulting in 99.77% accuracy. Niu and Suen integrated support vector machines (SVM) for MNIST digit recognition and achieved an accuracy of 99.81%. Chinese handwritten character recognition was also investigated using CNN. Alvear-Sandoval et al. used deep neural networks (DNN) for MNIST and obtained a 0.19% error rate. However, the highest recognition accuracy of the MNIST dataset can be achieved using ensemble methods, which improve classification accuracy. Convolutional neural networks (CNNs) were inspired by the human brain's ability to recognize objects from visual images. CNNs work similarly by using deep learning algorithms that are fully connected, meaning each neuron in a layer is connected to all neurons in the next layer. Some well-known CNN architectures include AlexNet, VGG, GoogLeNet, and ResNet. CNNs don't require prior knowledge of designer features, making them excellent for object recognition, and they're not dependent on the rotation of input images. However, there are tradeoffs, i.e., high computational cost and increased testing complexity [18]. In the proposed CNN model, four 2D convolutional layers are kept the same and unchanged to obtain the maximum comparable recognition accuracy into two different datasets, Kaggle and MNIST, for handwritten letters and digits, respectively. This proves the versatility of our proposed model.

➢ A custom-tailored, lightweight, high-accuracy CNN model (with four convolutional layers, three max-pooling layers, and two dense layers) is proposed by keeping in mind that it should not overfit. Thus, the computational complexity of our model is reduced.

➢ Two different optimizers are used for each of the datasets, and three different learning rates (LRs) are used for each of the optimizers to evaluate the best models of the twelve models designed. This suitable selection will assist the research community in obtaining a deeper understanding of HCR.

➢ To the best of the authors' knowledge, the novelty of this work is that no researchers to date have worked with the classification report in such detail with a tailored CNN model generalized for both handwritten English alphabet and digit recognition. Moreover, the proposed CNN model gives above 99% recognition accuracy both in compact MNIST digit datasets and in extensive Kaggle datasets for alphabets.

➢ The distribution of the dataset is imbalanced. Hence, only the accuracy would be ineffectual in evaluating model performance, so advanced performances are analyzed to a great extent with a classification report for the best two proposed models for the Kaggle and MNIST datasets, respectively. Classification reports indicate the *F*1 score for each of the 10 classes for digits (0–9) and each of the 26 classes for alphabet (A–Z). In our case of multiclass classification, we examined averaging methods for the *F*1 score, resulting in different average scores, i.e., micro, macro, and weighted average, which is another novelty of this proposed project.

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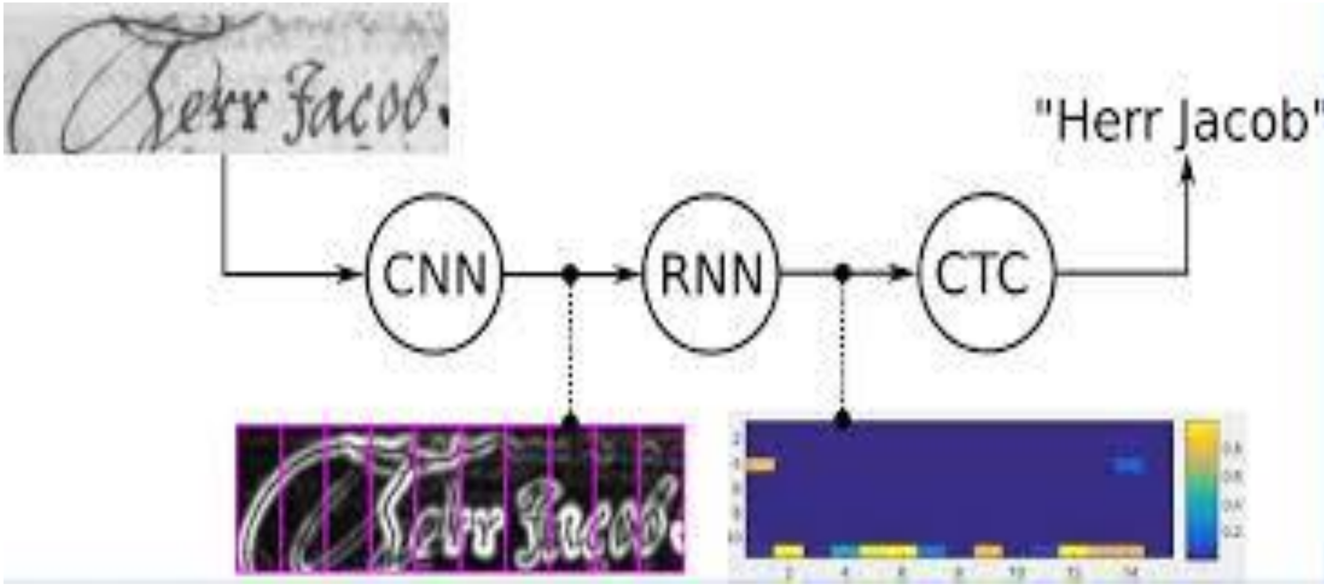
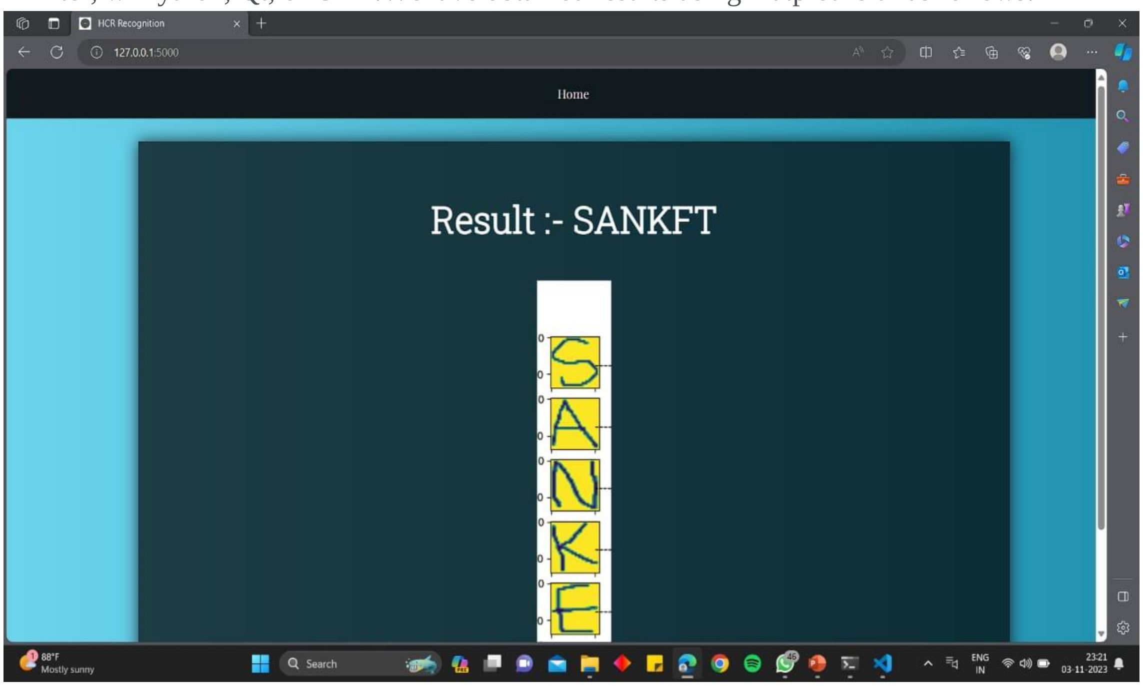


Matplotlib is a plotting library for the Python programming language and its numerical mathematics extension NumPy. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK.Wehave obtained results using matplotlib ar as follows:



C. Literature Review

1. Prof. Vaibhav. V. Mainkar.Et al, this paper deals with the various pre-processing techniques involved in the character recognition with different kinds of images ranging from simple handwritten form-based documents and documents containing colored and complex backgrounds and varied intensities. In this, different pre-processing techniques like skew detection and correction, image enhancement techniques of contrast stretching, binarization, noise removal techniques, normalization, and segmentation, and morphological processing techniques are discussed. 2. Venkata Prasanth Yanambaka Et al, In this paper author has proposed a system is to efficiently recognize the offline handwritten digits with higher accuracy than previous works are done. Also, previous handwritten number recognition systems are based on only recognizing single digits and they are not capable of recognizing multiple numbers at one time. So the author has focused on efficiently perform- ing segmentation for isolating the digits. 3. Yasir Babiker Hamdam Et al, In this paper they prove the the superiority to recognize the character with higher accuracy effectively among all types of OCR. This research article developed the framework to recognize various stylish characters inclusion provides better recognition rate and accuracy. Their proposed framework succeeds to achieve better accuracy with the inclusion of a stylish character recognition procedure. The writing style can depend on various handwriting characters with distorted strokes and variable thickness of italic characters. Their proposed SVM-based HCR method gives 94% accuracy and a good recognition rate while compared to existing methods. 4. Hongshuai Zhao1 Et al ,In this paper they uses deep learning theory into the character recognition technology for Shui characters in ancient books, with the objectives of overcoming the instability of the high-pixel ancient Shui characters generative model and the need for large scale handwritten text data annotation among other issues. By constructing a multilayer adversarial neural network with a Laplacian structure, a clear generative model is established for original image data of Shui characters and a stable adversarial network model with multiple mapping relationships from coarse to fine is formed. Based on the analysis of the feature distance of Shui character image samples, the minimum inter-class spacing value and the optimal number of clusters are calculated at 5. José Carlos Aradillas 1 Et al, In this paper they address the problem of offline handwritten text recognition (HTR) in historical documents when few labeled samples are available and some of them contain errors in the train set. Our three main contributions are: first, we analyze how to perform transfer learning (TL) from a massive database to a smaller historical database, analyzing which layers of the model need fine-tuning. Second, we analyze methods to efficiently combine TL and data augmentation (DA).

D. CONCLUSION

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 70%. This algorithm will provide both the efficient and effective results for the recognition. The project gives best accuracy for the text which has less noise. The accuracy completely depends 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.

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