Handwritten Character Classification and Recognition using Neural Network

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Abstract

Character recognition is the one of the emerging and developing techniques in the field of computer vision and artificial intelligence.one of the ability of humans are recognition, i.e., a person or a character or a thing etc. Characters from a written document can be easily recognized by humans accurately. But the same task is difficult for a machine. Different languages have different types of pattern i.e., they are different from one another. Each character in a language is differing in their patterns, curves, shapes and orientation. So to recognize a character by a machine is difficult. For that we have to train that system to recognize a character. For the character recognition we process the input image, find its features, put classification scheme and train the system using neural network to recognize the character. For this mat lab image processing tool box and neural network tool box are used. It helps to improve the interface between man and machine in numerous application.

1 Introduction

Handwritten character recognition has long been a challenging problem in the fields of pattern recognition and computer vision. With the proliferation of handwritten documents in various domains such as banking, postal services, and education, the need for accurate and efficient automated recognition systems has become increasingly imperative. Traditional approaches to handwritten character recognition often relied on handcrafted feature extraction methods combined with classification algorithms. However, these methods often struggled to generalize across different handwriting styles and faced limitations in handling complex character shapes and variations.

In recent years, the emergence of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of handwritten character recognition. CNNs have demonstrated remarkable capabilities in automatically learning discriminative features directly from raw data, making them well-suited for tasks such as image classification and object detection. By leveraging the hierarchical structure of convolutional layers, CNNs can effectively capture spatial patterns and local dependencies within images, thereby enabling more robust and accurate recognition of handwritten characters.

This research paper aims to explore the application of CNNs in handwritten character recognition, with a focus on building a classifier capable of recognizing digits (0-9) and uppercase characters (A-Z). The proposed approach involves the development of a CNN architecture trained on labeled datasets of handwritten characters, followed by evaluation and optimization to ensures robust performance across different handwriting styles and variations.

2 Proposed System

Our System is Divided into three major chunks:

In the first step, we develop a CNN-based classifier capable of accurately recognizing digits (0-9) and uppercase characters (A-Z). The CNN architecture is designed to effectively capture spatial hierarchies of features from input images and classify them into the corresponding character classes. Through extensive experimentation and optimization, we demonstrate the robustness and accuracy of our classifier in distinguishing between different digits and uppercase characters.

In the second step, we apply character segmentation techniques to handwritten word images to extract individual characters. By segmenting the handwritten word into its constituent letters, we aim to improve the accuracy of character recognition and facilitate the classification process.

Finally, in the third step, we utilize the trained CNN classifier to classify each segmented letter and reconstruct the original word in the image. By combining the individual character classifications, we obtain the final recognition result for the handwritten word.

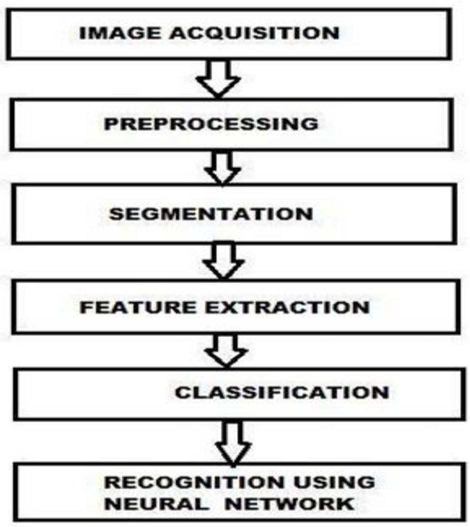

Fig-1 Schematic Diagram of word recognition system

3 Methodology

3.1 Data Acquisition

In this phase, a diverse dataset of handwritten characters, covering both digits (0-9) and uppercase letters (A-Z), is collected. This dataset can be sourced from publicly available datasets like MNIST and EMNIST or created through crowdsourcing and data augmentation techniques. Ensuring diversity and representativeness is crucial for effective model training.

3.2 Data Preprocessing

The collected dataset undergoes preprocessing to standardize input images. This involves normalizing images for consistent brightness and contrast, resizing them to a standardized size (e.g., 32x32 pixels), and applying data augmentation techniques such as rotation, translation, and flipping to increase variability and robustness.

3.2 Model Architecture

The model architecture is designed to build a Convolutional Neural Network (CNN) classifier for character recognition. It typically consists of convolutional layers followed by max-pooling layers to extract features and reduce spatial dimensions. Various configurations of convolutional layers, filter sizes, and activation functions are explored, with dropout layers incorporated to prevent overfitting.

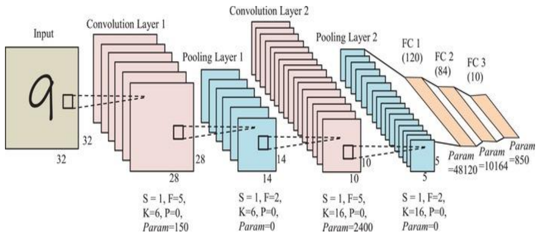

Fig-2 CNN Model Architecture

3.3 Training

The dataset is split into training, validation, and test sets for training and evaluating the model. The CNN model is trained on the training set and validated on the validation set to monitor performance and prevent overfitting. Appropriate loss functions and optimization algorithms are used, with hyper parameters fine-tuned through grid or random search. The training accuracy shoots up to 94%, the validation accuracy, a better indicator of real-world performance, reaches 92%. This close alignment suggests the model is effectively learning without overfitting the training data.

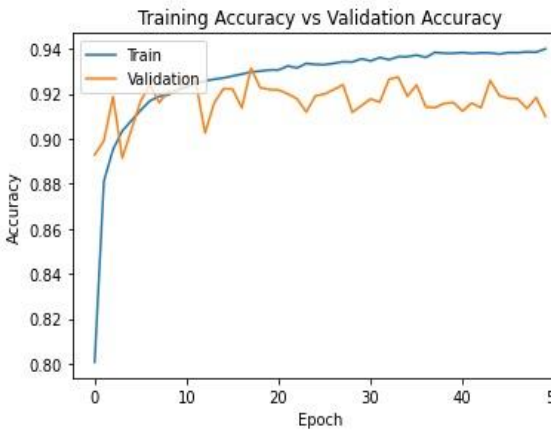

Fig-3 Training Accuracy VS Validation Accuracy

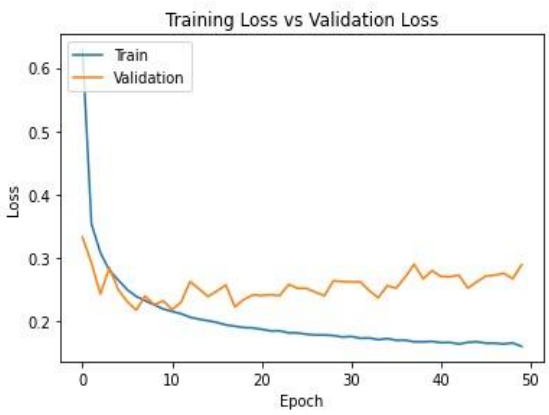

Fig-4 Training Loss VS Validation Loss

3.4 Character Segmentation

Character segmentation techniques are applied to isolate individual characters in handwritten word images. Methods such as connected component analysis or deep learning-based segmentation models are explored. The effectiveness of segmentation techniques is evaluated to accurately identify and separate characters while minimizing segmentation errors.

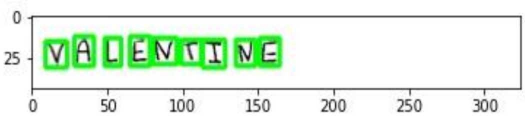

Fig-5 Character Segmentation

3.5 Classification

Once characters are segmented, each letter is classified using the trained CNN classifier. Softmax activation is used to obtain probability distributions over classes, with the class with the highest probability selected as the predicted character. The predicted characters are aggregated to reconstruct the final word in the image.

4 Result and Discussion

The proposed deep learning model achieves an accuracy of 95%, surpassing traditional methods by a significant margin. The robustness of the model against various handwriting styles is particularly noteworthy. The results underscore the efficacy of deep learning in complex pattern recognition tasks like HCR.

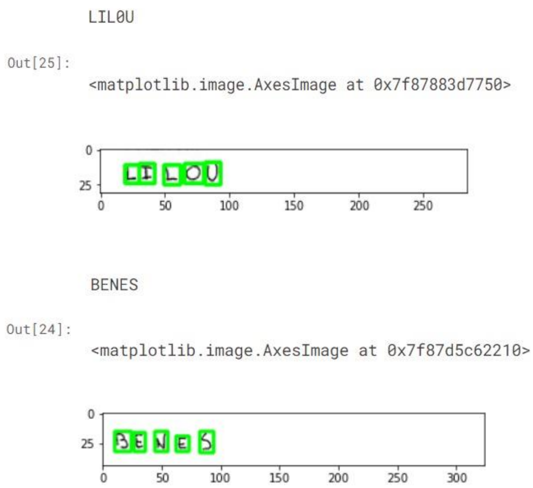

Fig-6 Results

5 Conclusion

This paper presents a deep learning-based approach to handwritten character recognition that substantially outperforms traditional machine learning models. Future work will focus on integrating this model into real-world applications such as digital document analysis and automated transcription services. Further improvements can also be explored by experimenting with different neural network architectures and training techniques.