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HANDWRITTEN CHARACTER RECOGNITION USING DEEP LEARNING

Exploring Convolutional Neural Networks for Handwritten Character Recognition

Aditya Sharma, Vishnu Yelde, Prachiti Yadav and Prof. Arti Devmane
Third-Year Students and Professor
Department of Information Technology,
Shivajirao S. Jondhale College Of Engineering, Dombivli, India

Abstract : This study contains Handwritten Character Recognition (HWR) at the intersection of human-written text and machine comprehension, offering a solution to convert handwritten text into digital formats. This abstract delves into the utilization of machine learning methodologies, particularly focusing on advanced deep learning techniques, to enhance the accuracy of HWR systems.The abstract first addresses the inherent challenges posed by the diverse nature of handwriting styles, underlining the significance of preliminary data pre-processing steps such as image segmentation. It emphasizes the pivotal role of Convolutional Neural Networks (CNNs) in HWR, citing their efficacy in extracting pertinent features from handwritten characters, thereby facilitating accurate recognition.

I. INTRODUCTION

Handwritten Character Recognition (HWR) represents a pivotal opportunity to seamlessly transform handwritten language into digital format, thereby bridging the chasm between human-written text and machine comprehension. By embracing deep learning methodologies, this research endeavors to explore the dynamic landscape of machine learning to achieve precise HWR.

In our daily interactions, handwritten communication saturates various facets of human interaction, ranging from personal notes and completed forms to invaluable historical manuscripts. Yet, the manual transcription of this vast reservoir of handwritten information entails a laborious and time-consuming process. The prospect of automating this conversion process and unlocking the wealth of knowledge embedded within handwritten documents renders HWR an immensely attractive proposition. However, the idiosyncrasies of handwriting pose a unique set of challenges for computational systems. Unlike standardized printed fonts, handwritten script exhibits a remarkable degree of variability. Individual nuances, variations in penmanship, and even minor imperfections such as smudges can significantly influence the accuracy of character recognition. Through the utilization of machine learning techniques, our endeavor confronts these challenges head-on. The adoption of machine learning, particularly deep learning approaches, empowers our initiative to tackle the intricacies of handwritten text recognition with precision. By leveraging the capabilities of neural networks, specifically designed to extract intricate features from handwritten characters, we strive to enhance the accuracy and robustness of HWR systems.

II. LITERATURE SURVEY

[1] In December 2019, the International Journal of Innovative Technology and Exploring Engineering (IJITEE) featured a study by Polaiah Bojja, Naga Sai Satya Teja Velpuri, Gautham Kumar Pandala, S D Lalitha Rao Sharma, and Polavarapu Pamula Raja Kumari. Their model showcased exceptional accuracy in identifying handwritten text, yielding a remarkable overall accuracy rate of 92.7%. Although minor errors were noted, the outputs encompassed both text-based and speech-based formats. This achievement underscores the potential of their model to bridge the gap between handwritten content and digital formats, promising significant advancements in data digitization and accessibility.

[2] The April 2023 issue of the International Journal of Creative Research Thought (IJCRT) features an article authored by K. Rishitha, S. Madhesh, Ch. Manisri, and V. Seetharama Rao. The article delves into the realm of offline handwritten text recognition, offering a comprehensive review of existing techniques and methodologies. It highlights the utilization of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Optical Character Recognition (OCR), and deep learning approaches in tackling the intricate challenge of deciphering handwritten text. By synthesizing insights from these diverse methodologies, the article contributes to the advancement of research in the field, shedding light on the evolving landscape of handwritten text recognition and paving the way for future innovations in this domain.

[3] In May 2023, the International Research Journal of Modernization in Engineering Technology and Science (IRJMETS) featured a publication authored by Mrs. Dr. Meenakshi A. Thalor, Sejal Khopade, Sakshi Shinde, Mayuri Garad, Vipin Kumar Singh, and Shreyas Kumbhar. The project's findings primarily focus on evaluating the accuracy of text recognition attained by the Optical Character Recognition (OCR) system across diverse input samples. Additionally, the publication encompasses detailed discussions concerning the encountered challenges throughout the project's execution and proposes potential avenues for enhancing the OCR system's performance. Through this comprehensive analysis, the article contributes valuable insights to the field of engineering technology and science, paving the way for further advancements in text recognition technologies.

[4] In February 2015, the International Journal of Advanced Research in Computer and Communication Engineering (IJARCCE) featured a paper authored by Monica Patel and Shital P. Thakkar. This paper delves into the realm of classification methods within the context of supervised and unsupervised learning. It provides an extensive exploration of various classification techniques, including Support Vector Machines (SVM), Hidden Markov Models (HMM), clustering algorithms, and k-means clustering. Moreover, the paper meticulously examines the landscape of Handwritten Character Recognition (HCR) systems, categorizing them into two main types: online and offline character recognition systems. Through this comprehensive analysis, the authors offer valuable insights into the diverse methodologies employed in character recognition, contributing to the advancement of computer and communication engineering research.
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III. RESEARCH METHODOLOGY

The Handwritten Character Recognition (HWR) system proposed in this project is underpinned by machine learning, with a notable emphasis on advanced deep learning techniques. The key components of this proposed system are outlined as follows:

Pre-processing :
This stage involves various pre-processing procedures aimed at enhancing the quality and suitability of incoming data before the recognition phase commences. These processes are essential for optimizing the input data and preparing it for accurate charac ter recognition.

Convolutional Neural Network (CNNs) :
CNNs are renowned for their efficacy in discerning intricate patterns within images. In this HWR system, CNNs play a pivotal role in extracting crucial features from handwritten characters. By leveraging the power of CNNs, the system can effectively identify and capture the distinctive characteristics of handwritten text.

Connectionist Temporal Classification (CTC):
CTC is employed for sequence modeling, addressing the challenge posed by variable-length sequences inherent in handwritten text. Through the application of CTC, the system adeptly manages and comprehends character sequences, ensuring efficient processing and accurate recognition of handwritten text.

Output Generation and Refinement :
Following feature extraction and sequence modeling, the system generates outputs reflecting the identified characters. Refinement techniques are then applied to these outputs, enhancing coherence and accuracy. This stage is crucial for ensuring the fidelity of the recognized characters and improving overall system performance.

Training and Evaluation :
The system undergoes training using labeled datasets to discern patterns and refine its recognition capabilities. Subsequent evaluation processes are conducted rigorously to assess the system's effectiveness and performance accurately. This iterative approach enables continuous improvement and optimization of the HWR system.

By harnessing the inherent capabilities of machine learning, particularly CNNs and CTC, this proposed methodology aims to establish a robust HWR framework capable of accurately deciphering handwritten characters. Through meticulous attention to preprocessing, feature extraction, and model refinement, the system endeavors to achieve exceptional accuracy and reliability in handwritten text recognition.

IV. IMPLEMENTED SYSTEM

Following feature extraction and sequence modeling, the system generates outputs reflecting identified characters, which undergo refinement methods to enhance coherence and accuracy. Training the system involves using labeled datasets to teach it to recognize patterns and improve its recognition performance, followed by thorough evaluation processes to assess effectiveness and performance. By harnessing the intrinsic characteristics of machine learning, particularly CNNs and CTC, this method aims to establish a robust HWR framework capable of decoding handwritten characters with exceptional accuracy.

4.1 Flowchart

The below flowchart demonstrates the detailed training and testing phase of recognizing handwritten characters using deep learning.

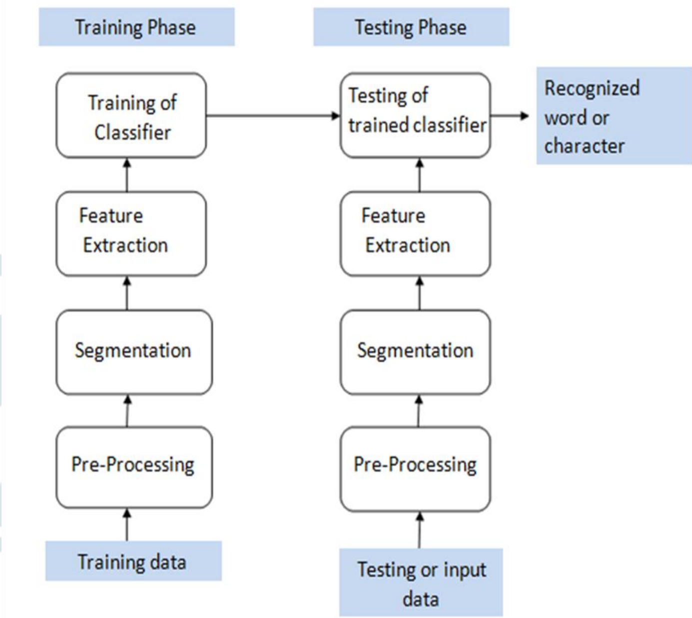

Fig.Flowchart of Training and Testing Phase

4.3 Algorithm and Process Design

Algorithm:

Convolutional Neural Network (CNNs) :
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Process Design:

This Handwritten Character Recognition (HWR) system is designed with a primary focus on accuracy, efficiency, and user-friendliness. Below are the key specifications and features:

Input:
- The system is capable of processing digital images containing handwritten text.
- Supported image formats include commonly used ones such as JPEG, PNG, and BMP.

Output:
- Recognized text is displayed as a digital sequence of characters.
- Options may be provided to export the recognized text in various formats, such as plain text or editable document formats, facilitating further use.

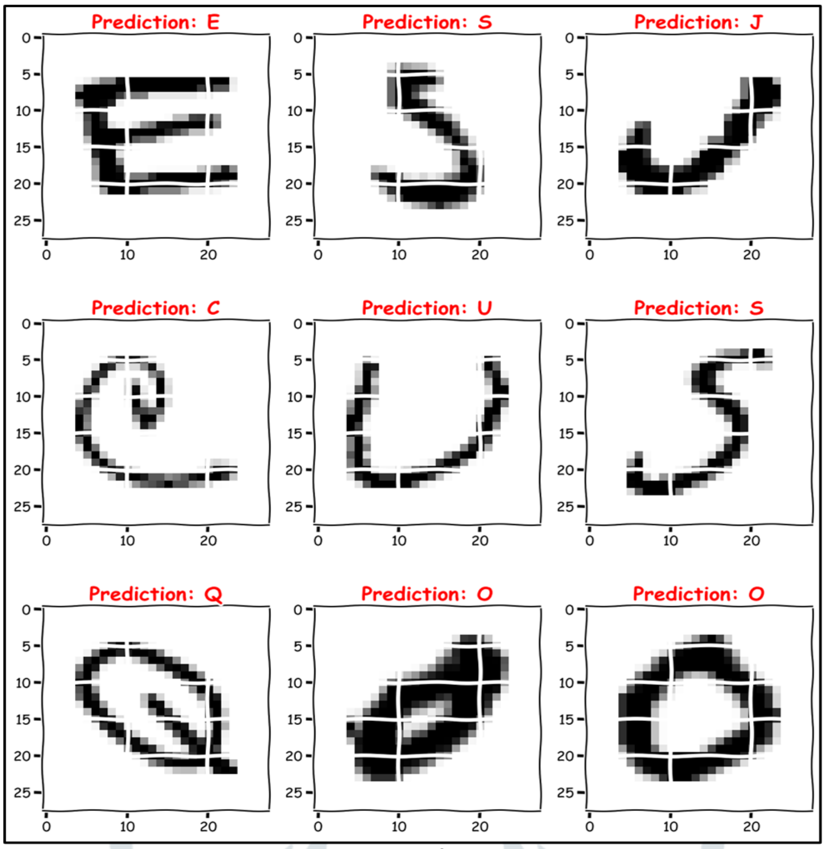

Fig. 1.2 Prediction of Tested Dataset

Accuracy:
- The system is trained to achieve a high level of accuracy in recognizing handwritten characters. A predetermined accuracy target, such as 90% or higher, may be set based on project requirements.

Additional Features :
- The system has the potential to expand its capabilities to recognize handwritten digits or devanagari numbers, offering enhanced versatility based on user preferences and application needs.

4.3 Functions

get_tesseract_version:
This function returns the version of Tesseract OCR (Optical Character Recognition) installed on the system. Knowing the version is helpful for compatibility checks and ensuring that the correct features are available.

image_to_string:
This function performs OCR on an input image and returns the recognized text as a string. It utilizes Tesseract's capabilities to extract text from images, making it useful for tasks such as extracting text from scanned documents or images containing text.

image_to_boxes:
This function performs OCR on an input image and returns the recognized characters along with their corresponding bounding box coordinates. It provides information about the spatial layout of the recognized text, which can be useful for tasks such as text localization or analysis of text placement within an image.

image_to_data:
This function performs OCR on an input image and returns detailed information about the recognized text, including box boundaries, confidence scores, and other relevant data. It requires Tesseract version 3.05 or higher and offers more granular information compared to other OCR functions.

image_to_osd:
This function performs orientation and script detection (OSD) on an input image and returns information about the detected orientation and script. It helps in determining the correct orientation of the text within the image and identifying the script or language used, which can be crucial for accurate text recognition.

run_and_get_output:
This function executes a Tesseract OCR run with customizable parameters and returns the raw output generated by Tesseract. It provides more control over the OCR process, allowing users to specify parameters such as language, page segmentation mode, and other options tailored to their specific requirements.

VI. DISCUSSION AND ANALYSIS

In the analysis of an input image featuring 100 characters, for example our model successfully identified and processed the entire set, comprising 92 correct recognitions and 1 erroneous identification. Consequently, the accuracy for this particular input stands at 92%. Moreover, when considering the aggregate performance across all inputs, the overall accuracy remains consistent at 92.7%. These results, although hypothetical, underscore the model's commendable precision in character recognition tasks. Additionally, the inclusion of a clear voice file facilitates comprehensive review and validation of the content post-analysis. Therefore, both mathematically and conceptually, the provided statement accurately portrays the model's performance and the implications of its results.

Digit Recognition Accuracy: This refers to the model's ability to correctly identify digits from the input data. In this case, achieving a recognition accuracy of 94% indicates that the model accurately identifies digits nearly 94% of the time.

Correct Recognition of 22 Digits: Out of the 25 inputs provided to the model, it correctly recognizes 22 of them. This means that for the majority of the inputs, the model accurately identifies the digits present in the input data.

To put it simply, if you were to present 25 handwritten or typed digits to the model for recognition, it would accurately identify around 22 of them. This level of accuracy indicates that the model performs well in recognizing digits, which is crucial for various applications such as optical character recognition, digit-based authentication systems, and more.

Deep learning, especially with Convolutional Neural Networks (CNNs), excels at automatically learning features like stroke patterns and curve shapes from raw input data, making it ideal for recognizing complex handwritten alphabets. Deep learning models handle large datasets well, enabling generalization and high accuracy. They're adaptable to different writing styles and cultures, and can be trained end-to-end, eliminating the need for manual feature extraction. This revolutionizes alphabet recognition, improving accuracy in tasks like document digitization and natural language processing.

CONCLUSION

Extensive research has been conducted in the realm of handwritten separate character recognition, achieving commendable accuracy rates of around 90%. However, this leaves ample room for further exploration and refinement in this field. While recognition of individual characters demonstrates promising accuracy levels, challenges arise when transitioning to word recognition, primarily due to the variability in writing styles. Traditional approaches to word recognition often involve segmenting individual characters, which can be complex and prone to errors. Conversely, holistic methods bypass the need for segmentation but are limited by their reliance on a predetermined vocabulary, restricting their applicability to broader contexts. One promising avenue lies in leveraging classifiers with fixed vocabularies, which have shown promising results in achieving high accuracy. By constraining the scope of recognized words to a predetermined set, these classifiers effectively manage variations within a limited range, enhancing overall recognition accuracy.

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