IJARSCT
ISSN (Online) 2581-9429
International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
Impact Factor: 7.67
Volume 5, Issue 5, March 2025

Hand Written Character Recognition using Deep Neural Network

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Abstract: *Handwritten Character Recognition (HCR) is a critical application in the field of pattern recognition and artificial intelligence, enabling machines to interpret and understand human handwriting. This technology has significant applications in document digitization, automated data entry, postal services, bank check processing, and many other fields. We're working on creating a strong and efficient system to recognize handwritten characters. Our project will use a Deep Neural Network (DNN) and a Convolutional Neural Network (CNN) to make this happen.In this project, we leverage the powerful feature extraction capabilities of CNNs to create a highly accurate character recognition model. Neural Networks (CNNs) are great for handling images because they can automatically and flexibly figure out the important details within them. They learn to recognize different levels of features, starting from simple elements like edges and textures, and moving up to more complex shapes and patterns..The model architecture includes multiple convolutional layers, max-pooling layers, and fully connected layers, followed by a softmax classifier to categorize handwritten characters. The dataset used for this project comprises labeled images of handwritten characters, sourced from publicly available datasets like the Modified National Institute of Standards and Technology (MNIST) database for digits or similar datasets for alphabetic characters We'll test how well our proposed model works by using a separate dataset specifically for validation. We'll measure its performance based on how accurate it is, how precise its results are, how well it recalls information, and its overall F1-score.*

Keywords: Handwritten Character Recognition

I. INTRODUCTION

Recognizing handwritten characters has been a major focus of research in computer vision and pattern recognition for a long time. It's all about teaching computers to read and understand human handwriting, which has many important applications, like reading handwritten notes or digitizing old manuscripts. It aims at the automatic identification and classification of handwritten characters across varying styles and formats. With the rapid digital transformation across industries, HCR has become crucial in applications such as automated document processing, postal address recognition, form digitization, and cheque verification systems.

Convolutional layers act as feature detectors, identifying visual patterns such as lines, curves, and intersections essential for character formation. Pooling layers reduce the dimensionality of feature maps, enhancing computational efficiency and aiding in generalization by retaining dominant features while discarding minor variations. Fully connected layers integrate the learned features to produce class probabilities for character recognition. Training a CNN for handwritten character recognition involves using labeled datasets of character images. The training process involves optimizing the CNN using backpropagation and gradient descent algorithms, minimizing classification errors by adjusting the weights of the network.A notable strength of CNNs in HCR is their ability to handle noisy and distorted inputs. Handwritten documents often contain imperfections such as smudges, missing strokes, or skewed text. Modern CNN architectures, including MobileNet and ResNet, offer optimized designs with fewer parameters and reduced memory requirements, making them suitable for deployment on devices with limited computational resources.

II. PROBLEM STATEMENT

In today's digital world, advances in artificial intelligence (AI) and machine learning have significantly enhanced the way we interact with computers. This technology, especially when using deep neural networks (DNNs), has become crucial for automating data entry, improving accessibility tools, and enhancing how we interact with devices. Traditional methods of character recognition relied on extracting features and using classical machine learning algorithms. However, these methods struggled with the diversity of handwriting styles, different sizes, and noisy data. Additionally, factors like image quality, noise, and lighting conditions made the task more complex. For a system to accurately recognize handwritten characters, it needs to overcome these challenges to achieve high accuracy and reliability.

In the healthcare sector, automated recognition of handwritten prescriptions and medical records can help reduce errors and improve workflow efficiency. This makes HCR technology invaluable in various applications.

The wide range of applications highlights how important and valuable it is to develop an effective handwritten character recognition (HCR) solution for both society and businesses. Deep learning, especially Convolutional Neural Networks (CNNs), has transformed image recognition tasks. These networks can automatically learn and identify different levels of features in images.Unlike traditional methods, CNNs don't need manual feature engineering—they can learn directly from the input images. Building a CNN- based HCR system involves several key steps, beginning with collecting and preprocessing the data.

III. LITERATURE REVIEW

In their 2022 paper titled "Lexicon and Attention- Based Handwritten Text Recognition System," Lalitha Kumari, Sukhdeep Singh, and VVS Rathore present a new method to enhance the accuracy of recognizing handwritten text. They combine lexicon constraints (a list of words the system knows) with an attention mechanism that helps the model focus on the important parts of the text. This combination allows for better accuracy when decoding sequences of handwritten text. Their experiments show that this new approach significantly outperforms traditional methods, making it very promising for real-world applications, like digitizing handwritten documents.[1]

In their 2022 study titled "Transfer Learning Based Handwritten Character Recognition of Tamil Script Using InceptionV3 Model," Rajagopal Gayathri and R. Babitha Lincy explore using transfer learning to improve the recognition of handwritten Tamil characters with the Inception-V3 model. Their results show that this model outperforms traditional methods by addressing issues like overfitting and computational inefficiency. This study highlights the potential of transfer learning in recognizing handwritten characters, especially for scripts with unique features, leading to more efficient and accurate systems in various languages.

In their 2022 paper titled "Comparing Transformer- Based to RNN-Based Models in a Handwritten Text Recognition Task," L.R.B. Schomaker and M. Ameryan examine how well transformer-based models compare to recurrent neural networks (RNNs) for recognizing handwritten text. The study highlights the drawbacks of traditional RNNs, especially their difficulties with handling long-range dependencies and their inefficiencies in computation. This research helps us better understand how to choose models for handwritten text recognition and suggests that Transformers might be a more promising direction for future advancements in the field.[3]

In the 2022 paper "Comparing Transformer-Based to RNN-Based Models in a Handwritten Text Recognition Task" by L.R.B. Schomaker and M. Ameryan, the authors examine how transformer- based models stack up against recurrent neural networks (RNNs) for recognizing handwritten text. The study highlights the weaknesses of traditional RNNs, especially their struggles with long-range dependencies and inefficiencies in computation. This research helps us understand which models to choose for handwritten text recognition and suggests that Transformers might be a more promising option for future developments in this field.

In their 2022 paper titled "2D Self-Organized ONN Model for Handwritten Text Recognition," Hanadi Hassen Mohammed, Junaid Malik, Somaya Al-Madeed, and Serkan Kiranyaz present a new method using a 2D Self-Organized Neural Network (ONN) specifically designed for recognizing handwritten text. This model highlights how neural networks can self-organize and effectively learn the spatial and contextual features of handwritten characters.

In their 2022 paper titled "Training of Offline Handwritten Text Recognizers Using Computer-Generated Text," Evans Ehiorobo, Rukayat Koleoso, and Charles Uwadiaa present a new method to enhance the training of systems that

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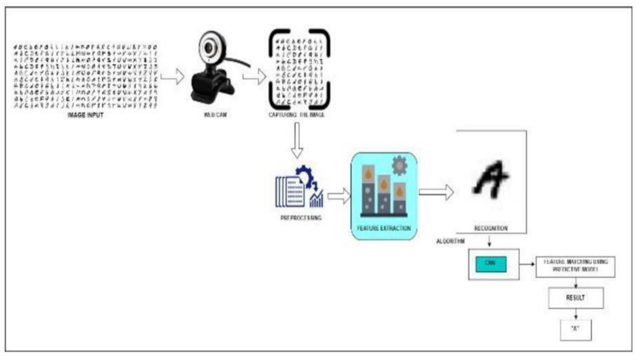
recognize offline handwritten text. They use computer-generated text datasets to improve the training process. This research emphasizes the importance of having diverse data for training, paving the way for creating systems that can effectively handle various handwriting styles.

In another 2022 paper titled "Incorporating Locally Linear Embedding and Multi-Layer Perceptron in Handwritten Digit Recognition," Ramin Barati introduces a new method that combines Locally Linear Embedding (LLE) with Multi-Layer Perceptron (MLP) to recognize handwritten digits.

The experiments show that this hybrid approach outperforms traditional methods, highlighting the effectiveness of using dimensionality reduction techniques along with neural networks. This research not only improves the performance of handwritten digit recognition systems but also demonstrates the potential of combining different methods to create robust and efficient solutions in pattern recognition.

IV. PROPOSED SYSTEM



A handwritten character recognition system using a Convolutional Neural Network (CNN) is built to process images of handwritten text and identify the characters. It begins with an image input layer where pictures of individual characters or sequences are fed into the system. Preprocessing steps, such as resizing images to a fixed size, normalizing pixel values, and data augmentation, help make the model more robust and ensure consistent input data.

After preprocessing, the input images pass through several convolutional layers in the CNN. Once enough features are extracted, the output is flattened into a 1D vector, getting it ready for further processing in fully connected layers. These layers work as classifiers, learning to match the extracted features to the corresponding character labels. The final fully connected layer connects to a softmax output layer, which calculates the probabilities for each possible character. The character with the highest probability is chosen as the model's predicted output.

Throughout the process, the system uses backpropagation to optimize the weights, reducing the error between predicted and actual outputs. Optimization algorithms like Adam or stochastic gradient descent (SGD) improve the learning process by minimizing the loss function. This CNN- based architecture is very effective for handwritten character recognition because it can automatically learn and extract relevant features from raw image data, leveraging its hierarchical structure and feature abstraction capabilities.

V. ALGORITHM USED FOR PROPOSED SYSTEM

The Convolutional Neural Network (CNN) algorithm for recognizing handwritten characters is a powerful deep learning model that automatically learns and extracts features from input images. It works by converting raw image data of handwritten text into structured output with recognized characters. The CNN architecture uses multiple layers, each specializing in different aspects of feature extraction and classification, making it perfect for handling complex variations in handwriting styles. These layers assign probabilities to each character class using a softmax function, which determines the most likely character that matches the input image. The model's performance is fine-tuned using backpropagation to adjust the network's weights and minimize errors. CNNs excel at handwritten character recognition because they effectively learn spatial hierarchies and manage variations in style, size, and orientation. This adaptability

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makes CNN-based systems highly accurate and robust for real-world applications, such asdocument digitization, automated form processing, and handwriting-based user interfaces..

VI. APPLICATION

a) Automated Data Entry: Handwritten character recognition can streamline data entry processes by automatically converting handwritten forms, invoices, and surveys into digital text, reducing human error and saving time in data management.

b) Postal Services: The technology is employed in postal and courier services for reading handwritten addresses on envelopes and packages, facilitating efficient sorting and delivery of mail based on automated recognition systems.

c) Banking and Finance: Banks utilize handwritten character recognition for processing checks and forms, enabling faster transaction processing and verification while enhancing customer service efficiency.

d) Document Digitization: Historical archives, libraries, and organizations can use handwritten character recognition to digitize handwritten manuscripts, notes, and records, preserving valuable information and making it accessible in digital formats.

e) Education: In educational settings, the technology can be used to grade handwritten exams or homework, providing instant feedback to students and teachers while minimizing manual grading efforts.

f) Healthcare: Handwritten character recognition can assist in digitizing patient records, prescriptions, and notes, improving data accessibility, accuracy, and efficiency in healthcare settings.

g) Assistive Technology: The technology can aid individuals with disabilities by converting handwritten input into digital text, facilitating easier communication and interaction with technology. h)Historical Research: Researchers and historians can use handwritten character recognition to analyze historical documents and letters, enabling advanced text analysis and research into historical contexts.

i) Legal Industry: Handwritten character recognition helps digitize legal documents, contracts, and case notes, enhancing document management and searchability for faster legal research and case preparation.

j) Personal Note-Taking Applications: Apps like note organizers and journals can convert handwritten notes into editable digital text for better storage and retrieval.

k) Customer Feedback and Surveys: Businesses use this technology to analyze handwritten feedback forms and surveys, gaining insights from customer responses without manual transcription

VII. CONCLUSION

In conclusion, using deep neural networks, especially Convolutional Neural Networks (CNNs), for recognizing handwritten characters is a major advancement in automating the reading of handwritten text. Training these models requires large labeled datasets and significant computational power, which can be quite resource-intensive. Achieving high performance across different languages and writing styles also demands extensive customization and refinement.

Looking ahead, ongoing research and innovation will continue to improve the capabilities and accessibility of handwritten character recognition technologies. As these systems become more efficient and versatile, their use in everyday tasks will greatly enhance productivity, accessibility, and user experience. From better personal note-taking apps to assistive technologies for people with disabilities, CNNs are poised to transform how we interact with handwritten content. These solutions offer a future where handwritten information can be processed just as easily as typed text, bridging the gap between traditional handwriting and digital systems.

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DOI: 10.48175/IJARSCT-24170