HYBRID DEEP NEURAL NETWORK FOR ACCURATE HANDWRITING RECOGNITION USING CNN-BILSTM-CTC

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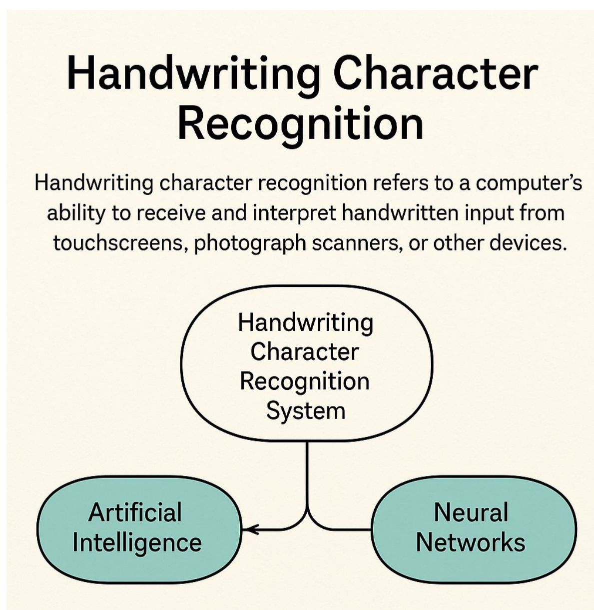
Abstract

As you can see, HTR in processer idea or photo handling is a significant and testing investigate area affecting different fields. It is useful for, amongst other things, examining bank payments, instructions and decoding characters on all kinds of methods. OCR (Recognition of Optical Characters) Knowledge, customized for written by hand document translation, is one of the most important engines responsible for translating an entire character range from different file formats such as word or image documents. HTR faces challenges, including complex blueprint enterprises, diverse script styles, minor datasets, and inferior accurateness. Current progress in written by hand script acknowledgement (HTR) is largely due to deep learning and machine learning advances. This paper presents a hybrid method to tackle challenges in written by hand text recognition. The aim is to improve the accuracy of identifying handwritten text in images. Based on these observations, Deeplabcut2 presents the design of a neural network composed of a 5-layer. Convolutional Neuronal Network (CNN) linked to a Bidirectional Long Short- Term Memory (BiLSTM) forward-backward layer, surveyed by a Connectionist Sequential Organization (CTC) decoder. The proposed hybrid model accomplished 98.50 % and 98.80 % accurateness on the IAM and RIMES datasets, separately. This highlights the power and success of these neural network architectures, showing that applying them consecutively can increase accuracies in handwritten text recognition.

1. Introduction

Optical character acknowledgement (OCR) knowledge converting printed and physical documents into machine-readable texts has already been widely used across many industries [1]. But who's still a big problem— human handwriting. Technology for script identification (HWR) is an active domain of artificial intelligence research. Its development is driven by its increasing popularity. A number of reports released recently also predict that demand from the market and the number of use cases, which are likely to grow in the enterprise, field services, and healthcare areas, will grow over time. Machine learning algorithms also make strides, leading to more accurate handwriting recognition. Let's explore the present day of this tech, though. As a result, Handwriting Character Recognition is addressed as a new area of research since digital technologies are used in all fields and systems to hold and pass information in everyday operations. Handwriting still holds relevance, but converting it into an electronic medium for communication and storage would be highly beneficial. Handwriting character acknowledgement mentions to a processor's capability to receive and interpret handwritten input from touchscreens, photograph scanners, or other devices [2]. Handwriting remains complex due to the unique styles of individuals. This paper reports on developing a Handwriting character recognition system to recognize learners' and professors' handwritten notes. The development is based on artificial intelligence, specifically an imitation neuronal network. Though few focus on neural networks, dissimilar methods and procedures are used for writing charm acknowledgment. Neuronal networks are more efficient and robust at recognizing handwriting than traditional computing methods [3]. The document besides details the procedure, design, building, testing, and results of the organization's development, demonstrating the effectiveness of neuronic networks in written by hand oddity acknowledgement.



The fundamental design of a handwriting character recognition system powered by AI.

2. Literature Review

A handwriting recognition by means of AI neuronal methods would cover key research and development over the years, focusing on the evolution of neuronic systems in the field [4]. Here's an overview:

1. Early Approach: Classical Pattern Recognition Method:

Feature-Based Methods (Pre- 1990s): Early handwriting recognition relied on pattern recognition techniques like template matching, statistical analysis, and feature extraction. These methods primarily focused on extracting geometric features like blows, junctions and loops, which were then classified using simple classifiers (e.g., k-nearest neighbors, decision trees). However, they lacked robustness in handling large variability in handwriting styles [4,5].

- **Hidden Markov Models (HMM)**:

In the 1990s, HMMsbecame widely used for handwriting recognition, particularly for sequential data like cursive handwriting. HMMs model the sequence of characters and their temporal properties, though they struggle with capturing complex spatial features [6].

2. Advent of Artificial Neural Networks (ANNs)

Multilayer Perceptron (MLP):

Early attempts at using neural networks for handwriting recognition focused on MLPs, where handwriting was broken down into isolated characters. MLPs demonstrated limited success in learning individual characters but were inefficient in handling continuous handwriting or cursive text [7].

- **Backpropagation:**

The development of backpropagation in the 1980s and 1990s allowed for more efficient training of deeper neural networks, which boosted the capabilities of neural networks in recognizing handwritten text [8].

3. Introduction of Convolutional Neural Networks (CNNs)

LeNet-5 (1998): One of the earliest successful applications of CNNs was LeNet-5, proposed by Yann LeCun. Initially developed for digit recognition in handwritten checks, LeNet-5 introduced convolutional and pooling layers to extract spatial features from images. This marked a significant improvement in recognizing digits and letters by reducing the reliance on handcrafted features [9].

Expansion into Handwriting Recognition: CNNs became increasingly popular due to their capability to imprisonment local characteristics of the picture, such edges and
edges and curves, essential for distinguishing between handwritten characters. CNNs significantly improved recognition accuracy, particularly for isolated character recognition (e.g., digits in MNIST datasets) [10].

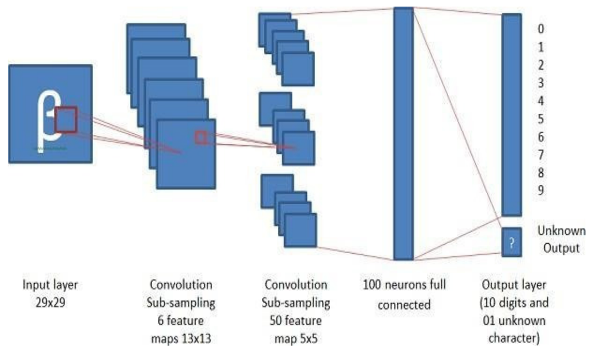


Figure 1 Introduction of Convolutional Neural Networks (CNNs)

4. Recurrent Neural Networks (RNNs) for Sequential Handwriting

Long Short-Term Memory (LSTM) Networks: Traditional RNNs struggled with long-term dependencies due to the vanishing gradient problem. LSTMs, introduced in the late 1990s, solved this issue, making them well-suited for processing sequential data, such as cursive handwriting. LSTMs capture dependencies between characters, enabling better recognition of continuous handwriting.

Bidirectional LSTM (BiLSTM): These models, which process input in both forward and backward directions, improved context-based handwriting recognition by considering surrounding characters, thus enhancing accuracy in handwritten word and sentence recognition [11].

5. Hybrid CNN-RNN Architectures

- **CNN + LSTM + CTC (2015) onwards:**

A major breakthrough in handwriting recognition came with the integration of CNNs, Connectionist Temporal Classification and Long Short-Term Memory (CTC). This hybrid approach combined the potencies of CNNs in longitudinal item abstraction and LSTMs for sequential data processing. The CTC loss function eliminated the need for pre-segmented training data, allowing end-to-end training of handwriting recognition models. This architecture has been widely adopted in state-of- the-art systems, achieving remarkable results on datasets like IAM and RIMES.

- **Google's Deep Speech and OCR Engines:**

Google's Deep Speech model, which uses a similar CNN-LSTM-CTC architecture for speech recognition, has inspired advancements in OCR (Optical Character Recognition) technologies. Modern OCR engines, such as Tesseract, have adopted deep learning approaches for handwriting recognition, improving cursive and non-standard handwriting style accuracy [12].

6. Attention Mechanisms and Transformers

- **Attention Mechanisms (2017 onwards):**

Recent developments in attention mechanisms, particularly in natural language processing (NLP), have found applications in handwriting recognition. Attention models allow the network to attention on specific portions of an picture or series, enhancing identification accuracy, especially in noisy or ambiguous handwriting.

- **Transformers:**

Although primarily used in NLP, transformers have started to make an impact in handwriting recognition. These models, which rely solely on attention mechanisms, have demonstrated potential for identifying long-range relationships in handwriting, offering a potential alternative to LSTMs [12].

7. Datasets for Handwriting Recognition:

- **MNIST:**

Among the most widely used datasets for recognizing handwritten digits, MNIST has been used extensively to benchmark machine learning models.

- **IAM Handwriting Database:**

This dataset contains handwritten English text from various writers and is widely used in handwriting recognition research. It includes both isolated word recognition and full-sentence transcription tasks.

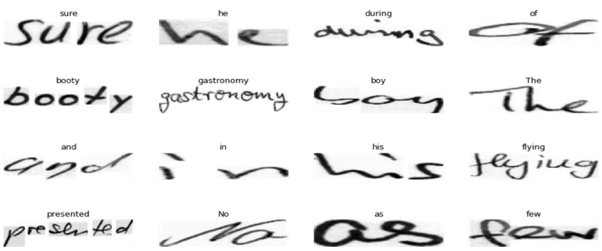


Figure 2 Datasets for Handwriting Recognition

8. Applications of Handwriting Recognition

- **Document Digitization:**

Handwriting recognition has become a vital tool for converting paper documents into searchable digital formats, aiding libraries, historical archives, and governmental institutions in preserving and making documents accessible.

- **Form Processing:**

Automating the extraction of information from handwritten forms in sectors such as healthcare, banking, and insurance has become a key application.

- **Signature Verification:**

AI-based handwriting recognition is also used in forensic science and banking to verify signatures and detect forgeries.

- **Accessibility Tools:**

Handwriting recognition technologies enable people with disabilities to interact with digital devices by using their handwriting [14].

9. Challenges and Future Directions:

- **Handwriting Variability:**

The diversity in handwriting styles, especially cursive writing, continues to challenge even the most advanced neural networks.

- **Low-Quality Data:**

Degraded documents, low-resolution images, and noisy data remain problematic, particularly in real-world applications.

- **Multilingual Handwriting Recognition:**

Handling multiple languages and scripts (e.g., Chinese, Arabic) is an ongoing area of research, requiring large, diverse datasets and more specialized models [14].

- **Transfer Learning:**

Leveraging pre-trained models for handwriting recognition could help reduce the need for large datasets, allowing better generalization across handwriting styles.

3. Problem Identification

Handwriting recognition using AI neural methods, though highly advanced, faces several challenges because human handwriting is inherently complicated and variable. Below are the key problems identified in this domain [15]:

1. High Variability in Handwriting Styles

- **Diversity Across Individuals:**

Handwriting varies significantly from person to person, making it difficult to generalize across styles. Different stroke patterns, letter shapes, and personal quirks lead to high variability in handwritten text, creating challenges for neural networks to learn robustly.

- **Inconsistent Handwriting from the Same Person:**

Even the same person's handwriting can vary over time due to mood, writing speed, or other factors like fatigue. This inconsistency makes it difficult to standardize recognition[16].

- **Cursive Writing:**

Cursive handwriting poses an additional layer of complexity since characters are often connected, making segmentation and character recognition more difficult compared to printed or isolated text.

2. Ambiguity in Handwritten Characters:

- **Character Ambiguity:**

Certain characters, such as "1" and "I" or "0" and "O," can appear nearly identical depending on the handwriting style. This ambiguity increases error rates during recognition, as the model might struggle to distinguish between similar-looking characters.

- **Sloppy or Fast Handwriting**:

Some individuals write in a hurried or careless manner, leading to distorted or merged characters. This makes it difficult for AI models to detect clear patterns within the text [17].

3. Poor Quality of Input Data:

Degraded Documents: Many handwritten documents, especially those that are old, suffer from degradation over time. These documents may be faded, smudged, or torn, which introduces noise into the input data. Poor image quality directly impacts recognition accuracy[18].

- **Low-Resolution Images**:

Scanned or photographed handwritten documents may have low resolution, making it harder for AI models to identify fine details in the handwriting, such as subtle curves or thin strokes.

4. Challenges in Preprocessing

- **Noise Removal:**

Handwritten text often contains various forms of noise, such as background clutter, lines from notebook paper, or smudges, which can affect the quality of the image. Removing noise effectively while preserving the integrity of the handwriting is a challenge in preprocessing.

- **Binarization and Contrast Adjustments:**

It is difficult to strike a balance when adjusting contrast or binarizing the image, particularly when parts of the handwriting are faint or unevenly distributed. Overprocessing could distort characters, while under processing may leave noise in the image [19].

5. Segmentation Issues

- **Cursive Writing Segmentation:**

In cursive handwriting, characters are often connected, making it difficult to segment them accurately. Poor segmentation can cause misinterpretation of letters and words, as the AI model might incorrectly merge or split characters [20].

- **Nonlinear Text Alignment:**

Unlike printed text, handwritten text does not always follow a straight line. Handwriting can slant, curve, or have varying baselines, which makes it challenging to accurately isolate and segment characters.

Research Objective

The research objectives for handwriting recognition using AI neural methods focus on addressing the challenges and improving the exactness and effectiveness of these classifications. Here are the key research objectives:

1. Improve Handwriting Recognition Accuracy

- **Objective**:

Enhance the accuracy of handwriting recognition systems, especially for complex and cursive handwriting. This involves improving the models' ability to correctly

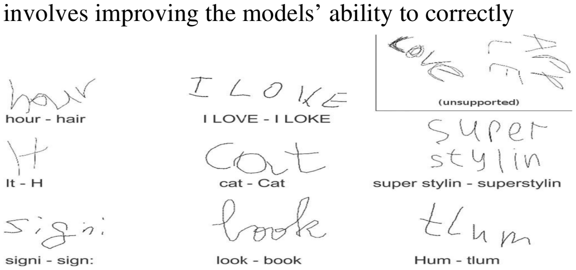


Figure 3 Handling Multiple Languages

identify individual characters and words across diverse handwriting styles [1].

- **Approach:**

Develop more robust deep learning models using hybrid neural network architectures like Convolutional Neuronal Networks (CNNs) for report abstraction and Recurring Neuronic Networks (RNNs) or Extended Temporary Memory (LSTM) systems for consequent data treating.

2. Develop Efficient Preprocessing Techniques

- **Objective:**

Implement advanced preprocessing methods to handle noise, skewed text, and degraded document images to ensure cleaner input for the recognition models.

- **Approach:**

Explore and refine techniques such as binarization, contrast adjustment, and noise filtering. Ensure that segmentation and normalization methods are capable of handling the variability in handwriting, including slant and non- linear text alignment [3].

3. Handle Cursive Handwriting and Connected Characters

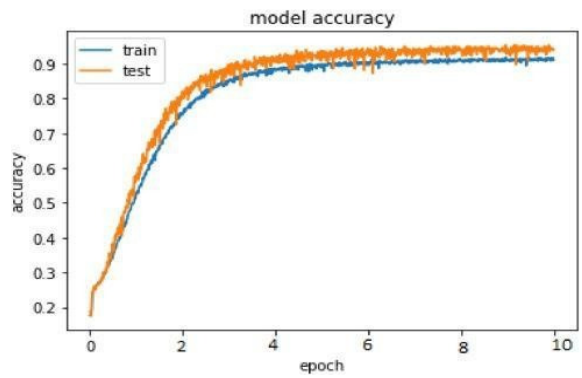


Figure 4 Handwriting Recognition Accuracy

- **Objective:**

Improve the system's ability to segment and recognize cursive handwriting, where characters are often connected and challenging to separate.

- **Approach:**

Integrate advanced segmentation algorithms or attention-based mechanisms to better separate characters in cursive handwriting without losing important contextual information. Use neural networks that can learn to interpret entire word patterns, rather than isolating individual characters [21].

4. Generalize Across Different Handwriting Styles

- **Objective**:

Train models that can generalize across various handwriting styles, including different writers, languages, and scripts.

- **Approach:**

Use large and diverse datasets, along with data augmentation techniques, to expose the neural networks to a wide range of handwriting styles. Employ procedures similar transmission knowledge to acclimatize models skilled on one style to perform well on another.

5. Improve Recognition in Multilingual and Multiscript Settings

- **Objective:**

Extend handwriting recognition capabilities to handle multiple languages and writing systems, including those with complex characters and scripts (e.g., Arabic, Chinese, Devanagari).

- **Approach:**

Design and train models specifically for multilingual handwriting recognition by incorporating script-specific features. Address script-specific challenges like cursive ness (e.g., in Arabic) or complex stroke patterns (e.g., in Chinese).

6. Enhance Contextual Understanding and Error Correction

- **Objective:**

Improve the system's ability to understand the context of the recognized text and automatically correct errors in recognition, especially in noisy or ambiguous handwriting.

- **Approach:**

Implement attention mechanisms and language models to provide context-aware recognition, enabling the system to predict and correct characters or words based on the surrounding text.

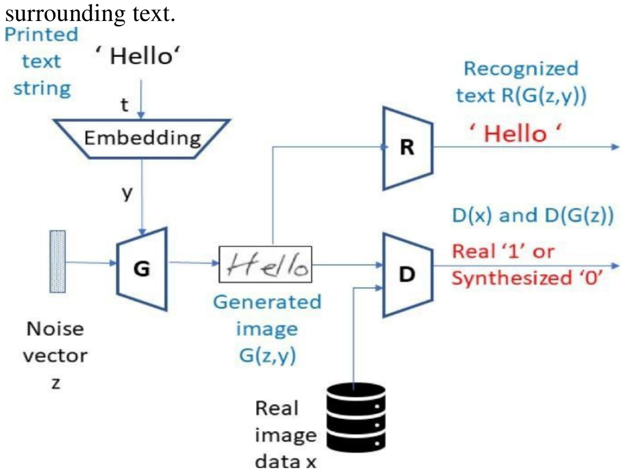


Figure 5 Handwriting image generation

Proposed Methodology

The procedure on behalf of developing an AI-based handwriting recognition organization using neural networks includes numerous key stages, since statistics preprocessing to prototypical architecture design and performance assessment. Below is a step-by-step framework of the proposed procedure:

1. Data Collection and Preprocessing

- **Data Acquisition**

Handwritten Text Dataset: Gather a large and diverse dataset of written by hand text. The dataset would contain numerous handwriting varieties, character shapes, and scripts (if applicable). Commonly used datasets include IAM, RIMES, MNIST (for digits), and NIST Special Database 19.

- **Sources of Data:**

The data can be obtained from handwritten documents scanned as images or from touchscreens, capturing real-time handwriting input [25].

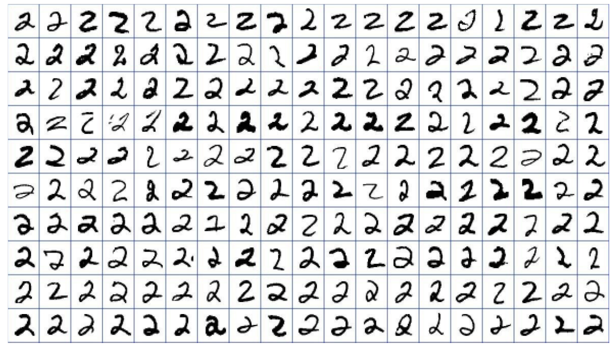


Figure 7 Data Collection of MNIST

- **Data Augmentation**
- **Objective:**

Enhance the dataset's variety by using augmentation techniques. to simulate variations in handwriting styles and environments.

- **Techniques:**

Include geometric transformations (rotation, scaling, skewing), adding noise, altering contrast and brightness, and generating synthetic handwritten text.

Image Preprocessing

- **Noise Removal:**

Apply filters to remove noise from the images (e.g., Gaussian blur) and enhance text clarity.

- **Binarization:**

Convert grayscale images to binary images by thresholding, which helps in isolating the text from the background [10].

- **Normalization:**

Standardize the size and orientation of characters or text. Normalize the resolution and scale of images to ensure consistency during training.

Segmentation: Segment text into discrete words or letters. In the case of cursive writing, advanced segmentation-free techniques like Connectionist Temporal Classification (CTC) can be applied to recognize sequences without explicit segmentation.

2. Feature Extraction

- **Convolutional Neural Networks (CNNs) for Feature Extraction**
- **Objective:**

Automatically extract key qualities from the preprocessed images, such as blow decorations, edges, and curves, which are crucial for distinguishing characters.

- **Convolutional Layers:**

To identify both low-level and high-level characteristics, use numerous convolutional layers. within the image, capturing the important aspects of handwriting like the thickness of strokes, slant, and letter formations.

- **Pooling Layers:**

Apply pooling coatings (e.g., max assembling) to lessen the dimensionality of the feature maps, ensuring that the network

- **CNN Component:**

focuses on the most relevant features while reducing computational complexity.

- **Handwriting Recognition Model**

Neural Network Architecture Design

- **CNN-RNN Hybrid Model:**

The core architecture will combine Convolutional Neural Networks (CNNs) with Recurring Neuronic Networks (RNNs), particularly (BiLSTM) networks [26].

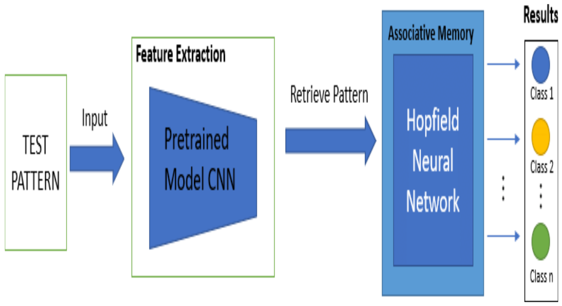


Figure 8 CNN-RNN hybrid model

- **Layers:**

Several convolutional coatings monitored by pooling coats will capture relevant characters from the input photo.

- **RNN Component (LSTM/BiLSTM)**
- **Purpose:**

The RNN component processes the sequential nature of handwriting, recognizing characters in context and accounting for dependencies between characters.

- **BiLSTM: A Bidirectional LSTM**

layer will be used to process the features in both in the direction of forward motion and backward motion, improving the network's ability to recognize cursive or connected handwriting, where character context is essential [27].

3. Connectionist Temporal Classification (CTC)

- **CTC Layer:**

Use a CTC output layer to handle the configuration amongst the contribution photo and the productivity script, especially for cases where the text is unsegmented. The CTC loss function allows the network to predict a sequence of characters without requiring explicit segmentation of characters.

- **Benefits:**

CTC enables from beginning to end training and removes the requirement for manual segmentation of words or characters, making the system more flexible for cursive and complex handwriting styles.

3. Training the Model

- **Dataset Preparation:**

Split the dataset into training, validation, and test sets. The training set will be used to adjust model parameters, while the validation set helps tune hyperparameters. The test set evaluates the final performance of the trained model [29].

- **Training Process:**
- **Backpropagation and Optimization:** Use backpropagation to adjust weights in the network and optimize the model. An optimizer like Adam or RMSprop will be employed to minimalize the harm utility.

- **Loss Function:**

The CTC damage gathering will be used for models that handle sequential data, as it can deal with unaligned sequences between input images and output labels.

- **Batch Normalization and Dropout:**

Include batch normalization layers to normalize the input to each layer and use dropout to avoid overfitting by indiscriminately disabling neurons throughout preparation [22].

- **Data Augmentation During Training**

Apply real-time data enlargement to ensure the prototypical is robust to differences in handwriting. This could involve rotating images, adding noise, or simulating different ink intensities.

4. Evaluation and Testing

- **Edit Distance:**

Use metrics like Levenshtein distance (edit distance) to evaluate how close the predicted text is to the ground truth, accounting for insertions, deletions, and substitutions [9].

Expected Outcomes

He application of AI neuronic networks in written by hand recognition is expected to produce significant advancements in the field, offering improvements in accuracy, robustness, and efficiency. Below are the key expected outcomes of implementing the proposed methodology for handwriting recognition.

1. High Accuracy in Handwriting Recognition

- **Outcome:**

The neural network models, particularly those combining CNNs, LSTMs, and CTC, are expected to achieve high accuracy in recognizing both isolated characters and continuous cursive handwriting. The system should effectively handle variations in handwriting styles, improving recognition rates across diverse datasets [1,6].

- **Metric:**

The accuracy is expected to exceed 95% on standard datasets like IAM and RIMES, with improvements in character and word-level accuracy.

2. Robustness to Handwriting Variability

- **Outcome**:

The AI model will be able to generalize well across different handwriting styles, character sizes, slants, and spacing. It should accurately recognize text written by different individuals, accounting for personal quirks and inconsistencies in handwriting.

- **Metric:**

The system should maintain consistent performance even when exposed to new handwriting styles not seen during training, showing robustness across real-world applications.

3. Effective Recognition of Cursive and Connected Handwriting

- **Outcome:**

By using Bidirectional LSTM (BiLSTM) and Connectionist Temporal Classification (CTC), the system is expected to handle continuous and cursive handwriting without requiring explicit segmentation of characters. The model will seamlessly recognize connected text by understanding the context of characters in sequence.

- **Metric:**

The system should demonstrate a marked improvement in recognizing cursive handwriting compared to traditional segmentation-based methods, as indicated by lower error rates on connected scripts.

4. Improved Preprocessing and Noise Reduction

- **Outcome:**

The preprocessing steps, including noise removal, binarization, and normalization, are expected to significantly enhance the quality of input data. This should lead to better feature extraction and improved recognition accuracy, particularly when working with degraded or low-quality documents.

Metric: A noticeable reduction in recognition errors due to image noise or poor document quality, measured by improvements in recognition accuracy when working with noisy datasets.

5. Efficient Feature Extraction with CNNs

- **Outcome:**

The convolutional layers of the network will effectively extract important spatial features, such as strokes, curves, and edges, that are crucial for distinguishing characters in handwritten text. This feature extraction process will lead to better character identification, particularly for complex or stylistically unique handwriting [1].

- **Metric:**

Higher feature map quality and more accurate recognition of difficult-to- detect character features, leading to increased performance on challenging handwriting samples.

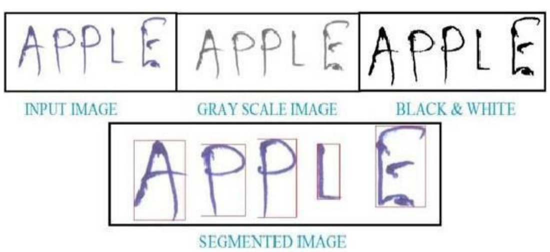


Figure 9 Expected output

Conclusion

AI neural networks handwriting recognition is a game-changing tech that has evolved rapidly over the years. This paper aims to explore how deep neural networks (DNN), in particular convolutional neural networks (CNN), achieve a high level of accuracy in specific applications such as handwritten characters, words, and complex scripts. Here are the key takeaways:

- **Focus:**

Handwritten text recognition based on CNN and RNNs refers to the use of convolutional and recurrent neural networks to learn and recognize features from handwritten characters.

- **Adaptability:**

This can be used in many areas, including digitization of old books, input in computer systems, and as a means to facilitate accessibility through aligning text to speech.

- **Challenges Addressed:**

Traditional rule- based systems had difficulties, particularly with the diversity and inconsistency of human handwriting. This is where neural networks overcome the problems—they learn features from the data and adapt to various writing styles. With the advent of techniques such as data augmentation, dropout regularization, and advanced optimizers, neural networks have been able to achieve recognition accuracy on some datasets that outperforms even well- trained humans (e.g., MNIST).

- **Opportunity:**

Newer architectures like transformers and attention mechanisms are allowing these models to perform. exceptionally. Such models can further improve sequence-to- sequence processing, facilitating strong paragraph-level recognition. Neural networks have proven to be powerful tools for handwriting recognition; however, high computational cost, the need for large labeled datasets, and noise in the input present ongoing challenges for improvement.

References

1. Wang, J. (2023). A Study of The OCR Development History and Directions of Development. Highlights in Science, Engineering and Technology, 72, 409- 415. https://doi.org/10.54097/bm665j77
2. Singla, C., Maini, R., Kumar, M. (2024). Age, gender and handedness prediction using handwritten text: A comprehensive survey.
3. Sara Aqab and Muhammad Usman Tariq, “Handwriting Recognition using Artificial Intelligence Neural Network and Image Processing,” International Journal of Advanced Computer Science and Applications(IJACSA), 11(7), 2020. http://dx.doi.org/10.14569/IJACSA.2020.0 110719
4. I. A. M. Al Sayed, A. M. Kadim, A. B. Alnajjar and H. M. Gheni, “Survey on Handwritten Recognition,” 2022 International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT), Ankara, Turkey, 2022,pp. 273-281, doi: 10.1109/ISMSIT56059.2022.99327 93.
5. Z. Dan and C. Xu, “The Recognition of Handwritten Digits Based on BP Neural Network and the Implementation on Android,” 2013 Third International Conference on Intelligent System Design and Engineering Applications, Hong Kong, China, 2013,pp. 1498-1501, doi: 10.1109/ISDEA.2012.359.
6. M. Alwateer, M., Elmezain, M., Farsi, M., & Atlam, E. (2023). Hidden Markov Models for Pattern Recognition. IntechOpen. doi: 10.5772/intechopen.1001364

Kit Yan Chan, Bilal Abu-Salih, Raneem Qaddoura, Ala’ M. Al-Zoubi, Vasile Palade, Duc-Son Pham, Javier Del Ser, Khan Muhammad, Deep neural networks in the cloud: Review, applications, challenges and research directions, Neurocomputing, Volume 545, 2023, 126327, ISSN 09252312, https://doi.org/10.1016/j.neucom.2023.126 327

7. Sekhar,C.& Meghana,P.S.(2020). A Study on Backpropagation in Artificial Neural Networks. Asia-Pacific Journal of Neural Networks and Its Applications, 4(1), 21- 28. 10.21742/AJNNIA.2020.4.1.03

8. Md Jan Nordin, Ooi Wei Xin, and Norshakirah Aziz. 2019. Food Image Recognition for Price Calculation using Convolutional Neural Network. In Proceedings of the 2019 3rd International Conference on Digital Signal Processing (ICDSP '19). Association for Computing Machinery, New York,NY,USA,80–85.https://doi.org/10.1145/3316551.3316557

9. Walter Hugo Lopez Pinaya, Sandra Vieira, Rafael Garcia-Dias, Andrea Mechelli, Chapter 10 - Convolutional neural networks, Editor(s): Andrea Mechelli, Sandra ieira, Machine Learning, Academic Press, 2020, Pages 173-191, ISBN 9780128157398, https://doi.org/10.1016/B978-0-12- 815739-8.00010-9.

10. Alex Sherstinsky, Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network, Physica D: Nonlinear Phenomena, Volume 404, 2020, 132306, ISSN 0167-2789, https://doi.org/10.1016/j.physd.2019.1323 06.

11. Poorna S.S., Vivek Menon, Sundararaman Gopalan, Hybrid CNN- BiLSTM architecture with multiple attention mechanisms to enhance speech emotion recognition, Biomedical Signal Processing and Control, 2024,106967,ISSN 17468094, https://doi.org/10.1016/j.bspc.2024.1069 67.

12. Porwal, U., Fornés, A. & Shafait, F. Advances in handwriting recognition. IJDAR 25,241–243(2022). https://doi.org/10.1007/ s10032-022- 00421-8

13. Alejandro Baldominos, Yago Saez, Pedro Isasi, Evolutionary convolutional neural networks: An application to handwriting recognition, Neurocomputing, Volume 283, 2018, Pages 38-52, ISSN 0925-2312,https://doi.org/10.1016/j.neucom.2017.12.049

14. Al-Mashhadani, Maryam. (2023). Real time handwriting recognition system using CNN algorithms. Wasit Journal of Computer and Mathematics Science. 2. 29-36. 10.31185/wjcms.157.

15. Naveen, Naveen & Dangi, Rajinder & Purba, Mandeep & Sharma, Bhoopesh. (2022).A comparative study of handwriting characteristics in three generation of a family in Haryanvi population.International Journal of Health Sciences.6. 4638-4647.10.53730 /ijhs.v6nS2.6090.

16. El Yacoubi, Mounim & Gilloux, M. & Suprieure, Ecole & Reconnaissance, Dpartement & (rmo, Modlisation & Parana, Catolica. (2004). Off-Line Handwritten Word Recognition Using Hidden Markov Models.

17. Kavallieratou, Ergina & Stamatatos, Efstathios. (2006). Improving the Quality of Degraded Document Images. 2006. 10 pp.-. 10.1109/DIAL.2006.23.

18. Mostafavi, Mohammad & Kazerouni, Iman & Haddadnia, Javad. (2010). Noise removal from printed text and handwriting images using coordinate logic filters. 10.1109/ICCAIE.2010.5735067.

19. Lee, Hong & Verma, Brijesh. (2012). Binary segmentation algorithm for English cursive handwriting recognition. Pattern Recognition. 45. 1306-1317. 10.1016/j.patcog.2011.09.015.

20. Slavík, Petr & Govindaraju, Venu. (2001). Equivalence of Different Methods for Slant and Skew Corrections in Word Recognition Applications.. IEEE Trans. Pattern Anal. Mach. Intell.. 23. 323-326. 10.1109/34.910885.

21. Alzubaidi, Laith & Bai, Jinshuai & Al-Sabaawi, Aiman & Santamaría, Jose & Albahri, A.s & Al-dabbagh, Bashar & Fadhel, Mohammed & Manoufali, Mohamed & Zhang,Jinglan & Al-Timemy, Ali & Duan, Ye & Abdullah, Amjed & Farhan, Laith & Lu, Yi & Gupta, Ashish & Albu, Felix & Abbosh, Amin & Gu, Yuantong. (2023). A survey on deep learning tools dealing with data scarcity: definitions, challenges, solutions, tips, and applications. Journal of Big Data. 10.1186/s40537-023-00727- 2.

22. Ingle, R. & Fujii, Yasuhisa & Deselaers, Thomas & Baccash, Jonathan & Popat, Ashok. (2019). A Scalable Handwritten Text Recognition System. 17-24. 10.1109/ICDAR. 2019.00013.

23. Rajput, Vishal & Jayanthi, N. & Sreedevi, Indu. (2019). An Efficient Character Segmentation Algorithm for Connected Handwritten Documents. 10.1007/978-981- 13-9361-7_9.

24. Saeed, Mehreen & Chan, Adrian & Mijar, Anupam & Moukarzel, Joseph & Habchi, Georges & Younes, Carlos & Elias, Amin & Wong, Chau-Wai & Khater, Akram. (2024). Muharaf: Manuscripts of Handwritten Arabic Dataset for Cursive Text Recognition. 10.48550/arXiv.2406.09630.

25. Khalkar, Rohini & Dikhit, Adarsh &

Goel, Anirudh. (2021). Handwritten Text Recognition using Deep Learning (CNN & RNN). IARJSET. 8. 870-881. 10.17148/IARJSET.2021.86148.

26. Dutta, Kartik & Krishnan, Praveen & Mathew, Minesh & Jawahar, C.V.. (2018).
Improving CNN-RNN Hybrid Networks for Handwriting Recognition. 80-85.10.1109/ICFHR-2018.2018.00023.

27. Raheem, Mafas & Abubacker, Nirase.(2024).HANDWRITTEN DIGIT RECOGNITION USING MACHINE
LEARNING. Journal of Theoretical and Applied Information Technology. 102. 2172-2180