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SURVEY ON HANDWRITTEN CHARACTER RECOGNITION USING RNN-GRU ALGORITHM

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Abstract: This survey paper navigates the realm of handwritten character recognition, converging pattern recognition and computer vision. Current RNN-CNN hybrid methods achieve a commendable 91.5% accuracy in predicting characters but exhibit limitations in recognizing entire lines of text. Our innovative system introduces a paradigm shift by adopting a line-by-line recognition approach, enhancing context awareness through integrating the GRU algorithm. A strategic collaboration with the IAM dataset facilitates robust training and enables error detection and correction, elevating the accuracy and reliability of handwritten text recognition. This holistic approach signifies a commitment to advancing recognition systems beyond isolated characters, ushering in a new era of context-aware text recognition.

Keywords - Handwriting Recognition, Recurrent Neural Network, Gated Recurrent Unit, IAM Dataset.

I. INTRODUCTION

Handwriting recognition is a challenging task that has been the subject of much research in recent years. The ability to recognize handwritten text has a wide range of applications, such as digitizing handwritten documents, enabling input for tablet devices, and developing accessible tools for people with disabilities. Traditional handwriting recognition methods involve template matching or statistical approaches. These methods are often limited in their ability to recognize a wide range of handwriting styles and can be sensitive to noise in the input image.

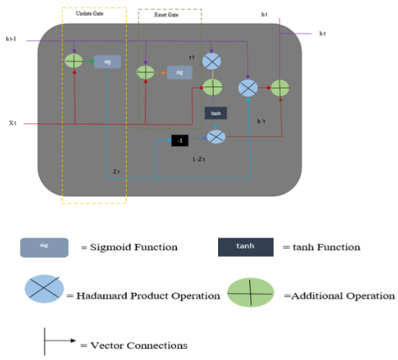
Optical Character Recognition (OCR) is the mainstream practice for handwriting recognition. It involves a glance at a handwritten document and changing it into a simple text document. Additionally, OCR can work by capturing a picture of handwritten text. However, there are numerous variations in handwriting quality, making it difficult to provide sufficient examples of how each character may appear. Furthermore, some characters are quite similar in appearance, making accurate recognition by a computer challenging. Handwriting can be classified into manuscript form and cursive form. Manuscript handwriting, which involves writing individual block letters, is easier for computers to recognize. Conversely, cursive handwriting requires recognition tools to correctly identify each character, which are often joined. Thus, accurately recognizing and identifying each character in cursive handwriting remains a challenging task for handwriting recognition tools.

In recent years, machine learning approaches have been more effective for handwriting recognition. These approaches use neural networks to learn the features of handwritten characters and to classify them into different categories. Convolutional neural networks (CNNs) have been particularly successful for handwriting recognition, as they can extract features from images that are relevant to the task. Despite the progress that has been made in handwriting recognition, there are still many challenges that remain. One challenge is that handwriting styles can vary widely, even among the same person. Another challenge is that handwritten characters can be noisy and difficult to read.

In this paper, we survey the state-of-the-art in handwriting recognition. We discuss the different approaches that have been used for handwriting recognition, and we present a summary of the latest results. We also discuss the challenges that remain in handwriting recognition, and we propose directions for future research.

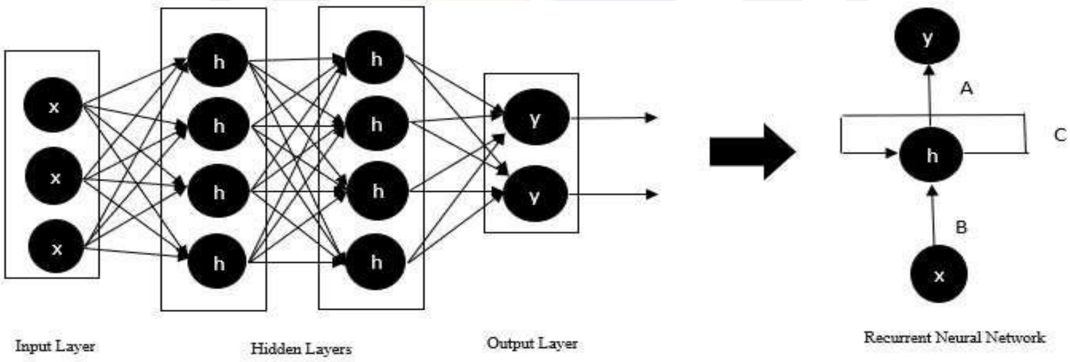
1.1 GRU Algorithm

Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) that was introduced by Cho et al. in 2014 as a simpler alternative to Long Short-Term Memory (LSTM) networks. Like LSTM, GRU can process sequential data such as text, speech, and time-series data. The basic idea behind GRU is to use gating mechanisms to selectively update the hidden state of the network at each time step. The gating mechanisms are used to control the flow of information in and out of the network. The GRU has two gating mechanisms, called the reset gate and the update gate. The reset gate determines how much of the previous hidden state should be forgotten, while the update gate determines how much of the new input should be used to update the hidden state. The output of the GRU is calculated based on the updated hidden state.
In summary, GRU networks are a type of RNN that use gating mechanisms to selectively update the hidden state at each time step, allowing them to effectively model sequential data. They are effective in various natural language processing tasks, such as language modelling, machine translation, and speech recognition.



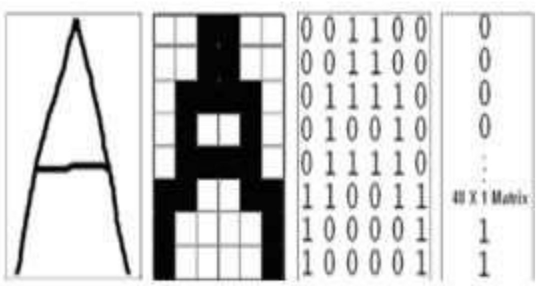
1.2 Recurrent Neural Network

Recurrent Neural Networks (RNNs) are a type of neural network that can be used for handwritten character recognition. RNNs are designed to process sequential data, where each input in the sequence depends on the previous inputs in the sequence. Handwritten characters can be represented as a sequence of pixel values, making them a good fit for RNNs. To use an RNN for handwritten character recognition, the first step is to preprocess the input images. This typically involves converting the images to grayscale and scaling them to a fixed size. The resulting images can then be treated as a sequence of pixel values and fed into the RNN. During training, the RNN learns to predict the correct label for each image by processing the image as a sequence of pixel values and adjusting its internal state at each time step. The network can be trained using backpropagation and a variety of optimization algorithms, such as stochastic gradient descent or Adam optimization.



1.3 Image Processing

Image processing is a method to perform some operations on an image, to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which the input is an image and the output may be an image or characteristics/features associated with that image.



Fundamental Image Processing steps are mentioned below:

A. Image Acquisition: Image acquisition is the first step in image processing. This step is also known as pre-processing in image processing. It involves retrieving the image from a source, usually a hardware-based source.

B. Image Enhancement: Image enhancement is the process of bringing out and highlighting certain features of interest in an image that has been obscured. This can involve changing the brightness, contrast, etc.
C. Image Restoration: Image restoration is the process of improving the appearance of an image. However, unlike image enhancement, image restoration is done using certain mathematical or probabilistic models.
D. Segmentation: Segmentation is one of the most difficult steps of image processing. It involves partitioning an image into its constituent parts or objects.
E. Recognition: Recognition assigns a label to an object based on its description. The types of recognition are as follows:
a. Printed Character Recognition: Printed Character Recognition is the most popular document-capturing system at present. It is a process to perform electronic conversion of the text on a physical paper.
b. Handwritten Character Recognition: Handwriting recognition systems use pattern matching to convert handwritten letters into corresponding computer text or commands in real-time. Handwritten Character recognition is further classified into two types A. Online Character Recognition and B. Offline Character Recognition

II. REVIEW OF LITERATURE

[1] Automated bank cheque verification using image processing and deep learning methods.
Author: Agrawal, P., Chaudhary, D., Madaan

The purpose of this research is to improve the accuracy of handwritten text recognition (HTR) systems using deep learning algorithms. Existing research methods for HTR have some limitations, so the researchers collected data, extracted features, and trained a deep learning model using a 2D LSTM approach to address these limitations. They also employed a word recognition strategy to enhance accuracy. The resulting approach was integrated into an OCR system, and its performance was compared with another approach on the IAM handwritten dataset. The study found that the 2D LSTM-based outperformed the other approach. However, it should be noted that the experiments were limited to the IAM dataset, and more research is needed to evaluate the generalizability of the findings to other datasets. Moreover, the paper does not provide a comprehensive comparison with other state-of-the-art methods for HTR.

[2] A search method for online handwritten text employing writing-box-free handwriting recognition
Author: H.Oda, Akihito Kitadai, M.Onuma

Handwriting recognition without writing boxes was discovered by H. Oda et al. in an online search of handwritten text. This paper presents a novel approach for searching online handwritten text without requiring a writing box, by searching for a specific keyword in a lattice consisting of potential character segmentations. The paper also briefly surveys related work in the field of online handwritten text recognition and search. To estimate the proposed method, experiments were conducted. The result is that the method achieved a recall percentage of 89.4%, a precision rate of 90.2%, and an F-measure of 0.912 when searching for three-character keywords, demonstrating its effectiveness in reducing noise and improving search accuracy. However, the paper lacks a comprehensive analysis of the proposed method's performance and a comparison with existing methods. It also fails to discuss the potential limitations or drawbacks of the approach.

[3] Text-line Detection and Recognition in Answer Sheet Composition with Few Labeled Data
Author: Kunnan Wu, Huiyuan Fu, Wensheng Li.

This paper confirmed the detection and recognition of handwritten text lines on answer sheets with small amounts of tag data. This paper describes a novel approach to detect and recognize handwriting text lines in scanned answer sheet images, with a focus on addressing the challenges of automatic location and recognition of handwritten text in the education industry, using a few labelled data. In particular, to improve recognition accuracy, a dataset synthesis method is used that finds written text in scanned answer sheet images and an advanced handwritten text recognizer based on CRNN. The proposed method focuses on the depth of the network and each of the MLC modules, showing that both can contribute to handwritten text line recognition. Experimental results show that the proposed method has better detection and recognition accuracy than the existing methods. However, the proposed dataset synthesis method may not be generalizable to other types of handwritten text or languages, and the proposed handwritten text-line recognition method may not perform well on highly cursive or illegible handwriting.

[4] Offline Handwritten Quranic Text Recognition: A Research Perspective
Author: Arshad Iqbal, Aasim Zafar.

The authors encountered several difficulties in recognizing non-digital handwritten Quranic Arabic text, which include distinct writing styles, the usage of diacritics, overlaps and ligatures. Their paper delves into the recognition system for Quranic handwritten text and details the associated challenges, such as the similar appearances of certain letters that hinder Quranic handwriting recognition. Furthermore, the paper distinguishes between non-digital and digital text-recognizing systems, highlighting that online recognition has a higher recognition rate than offline recognition due to the temporal nature of writing, where the characters can be distinguished based on the order in which they are stroked. Although the paper does not provide any specific findings as it offers an overview of the challenges and recognition system for non-digital Quranic-handwritten text, it examines the unique attributes of Arabic linguistics and the issues related to non-digital Quranic-handwritten text, providing examples. However, this paper does not discuss any new or novel techniques for the recognition of handwritten Quranic text, and it does not provide a detailed analysis or evaluation of any specific recognition system. The paper's limitations are not explicitly stated.

[5] Adversarial Feature Enhancing Network for End-to-End Handwritten Paragraph Recognition
Author: Yaoxiong Huang, Zecheng Xie, Lianwen Jin.

This proposed system introduces an Adversarial Feature Enhancing Network for quick recognition of handwritten phrases offline. The proposed AFEN work consists of 5 main components: common feature extractor, branch search, RoIRotate for feature extraction, disputed feature learning network, and text. Compared to previous methods, it has been suggested in the literature that the AFEN method is effective with controlled testing of two popular sentence registers, IAM and Rimes. However, this article has some limitations. For example, the recognition model evaluates the performance of the proposed AFEN system with only two documents together and against other unknown documents. Also, this article does not provide detailed information about the computational complexity of the proposed method, which may be problematic for real-time applications. Finally, this paper does not compare the proposed AFEN system with state-of-the-art handwritten deep learning models to better understand its performance.

[6] Framewise phoneme classification with bidirectional LSTM and other neural network architectures
Author: Alex Graves, Jürgen Schmidhuber

This paper introduces bidirectional Long Short-Term Memory (LSTM) networks with a modified, full gradient learning algorithm. The study evaluates various network architectures, emphasizing the superiority of bidirectional over unidirectional networks. Assessing framewise phoneme classification on the TIMIT database, the results highlight the efficiency and accuracy of Long Short-Term Memory (LSTM) compared to standard Recurrent Neural Nets (RNNs) and time-windowed Multilayer Perceptrons (MLPs). The findings underscore the importance of contextual information in speech processing, endorsing Bidirectional LSTM (BLSTM) as an effective architecture for exploiting this crucial aspect.

[7] Recognition of Handwritten Digit using Convolutional Neural Network in Python with Tensorflow and Comparison of Performance for Various Hidden Layers
Author: Fathma Siddique, Shadman Sakib, Md. Abu Bakr Siddique

Recent advancements in machine learning, particularly with the rise of Artificial Neural Networks (ANNs) and deep learning, have revolutionized various fields. Convolutional Neural Networks (CNNs) play a central role in these advancements, contributing to applications in surveillance, health, sports, and more. This paper focuses on assessing CNN's accuracy in classifying handwritten digits and exploring variations with different hidden layers and epochs. The evaluation utilizes the Modified National Institute of Standards and Technology (MNIST) dataset, training the network through stochastic gradient descent and the backpropagation algorithm. The study aims to compare CNN accuracies under different configurations, providing insights into optimal model settings.

[8] Handwritten Text Recognition Using Convolutional Neural Network
Author: Atman Mishra, A. Sharath Ram, Kavyashree C

Optical Character Recognition (OCR) is a technology that rapidly scans documents, recognizing both handwritten and printed alphanumeric characters. OCR involves using electronic devices to convert 2D textual information into machine-encoded text, applicable to both handwritten and machine-written text. This paper focuses on presenting the outcomes of a Convolutional Neural Network (CNN) model trained on the National Institute of Science and Technology (NIST) dataset, comprising over 100,000 images. The CNN learns from extracted features to generate probabilities for each class, achieving an impressive 90.54% accuracy with a 2.53% loss. The results highlight the efficacy of the CNN model in advancing OCR and ICR capabilities for diverse applications.

[9] A new normalization technique for cursive handwritten words
Author: Alessandro Vinciarelli, Juergen Luettin

This survey paper introduces novel techniques for slant and slope removal in cursive handwritten words without the need for heuristics or parameter tuning. A comparison with Bozinovic and Srihari's method is conducted, measuring their performance within a word recognition system on various databases. The proposed technique demonstrates a significant improvement, yielding a 10.8% relative increase in the recognition rate compared to traditional normalization methods. Notably, the approach eliminates the need for extensive parameter exploration, streamlining the deslanting process.

[10] ResneSt-Transformer: Joint attention segmentation-free for end-to-end handwriting paragraph recognition model
Author: Mohammed Hamdan, Mohamed Cheriet

This paper introduces a novel one-stage, segmentation-free pipeline, named ResneSt-Transformer, for end-to-end recognition of handwritten paragraphs. The approach leverages joint attention mechanisms, integrating vision and language models, with a split attention CNN (ResneSt50) for feature extraction, followed by encoder and decoder modules utilizing multi-head self-attention. This segmentation-free strategy enables implicit line segmentation, significantly advancing paragraph-level transcription. Experimental results on benchmark datasets (RIMES, IAM, READ 2016) demonstrate competitive performance compared to recent models, emphasizing reduced complexity and improved efficiency in offline handwritten text recognition.

[11] AttentionHTR: Handwritten Text Recognition Based on Attention Encoder-Decoder Networks
Author: Dmitrijs Kass, Ekta Vats

This work presents an attention-based sequence-to-sequence model for handwritten word recognition, employing transfer learning for data-efficient training. Utilizing models pre-trained on scene text images, the approach mitigates data scarcity in training. The encoder combines ResNet feature extraction with bidirectional LSTM-based sequence modelling, while the prediction stage features a decoder with a content-based attention mechanism. Empirical evaluation of the Imgur5K and IAM datasets showcases the effectiveness of the proposed end-to-end Handwritten Text Recognition (HTR) system. Experimental results and detailed error analysis contribute insights into the system's performance, offering a valuable contribution to the field of HTR.

[12] Hybrid CNN-GRU model for high efficient handwritten digit recognition
Author: Vantruong Nguyen, Jueping Cai, Jie Chu

In this paper, a hybrid model combining convolutional neural network (CNN) and gate recurrent units (GRU) is proposed, wherein the CNN fully connected layer portion is replaced with GRU to obtain excellent identification accuracy with shorter running times. In this model, the CNN extracts the original image's features first, then the GRU classifies them dynamically. The results of an experiment using the MNIST handwritten digit dataset indicate a 99.21% recognition accuracy with 57.91 seconds for training and 3.54 seconds for testing. The limitations of this paper arise from the RNN being better suited for analyzing long series of characters and this paper only emphasizes digit recognition.

III. EXISTING SYSTEM

The current system employs a hybrid architecture combining Recurrent Neural Networks (RNN) and Convolutional Neural

Networks (CNN) to achieve a commendable accuracy rate of 91.5% in predicting individual handwritten characters within images. However, a significant limitation lies in its character-by-character and word-by-word recognition methodology, restricting its ability to recognize entire lines of text and comprehend the contextual flow of complete sentences.

3.1 Issues with the Existing System:

3.1.1 Character-by-character and word-by-word approach:

The existing system adopts a character-by-character and word-by-word recognition approach. Recognition is performed at the level of individual characters, and these characters are subsequently assembled into words. This approach may lead to efficiency limitations, especially when dealing with larger units of text such as entire lines or paragraphs. Processing character by character and word by word might not be optimal for recognizing longer sequences efficiently.

3.1.2 Limited context awareness:

The system primarily focuses on isolated characters and individual words within the handwritten text. Context awareness, or the understanding of the sequential flow and semantic meaning of complete sentences, is limited. Semantic Understanding: The system may struggle to comprehend the semantic nuances and contextual relationships in sentences. Understanding the meaning of words in the context of surrounding words may be challenging.

IV. PROBLEM IDENTIFICATION

The character-by-character and word-by-word approach adopted by the existing system poses efficiency challenges when dealing with larger units of text, such as entire lines or paragraphs. Processing each character and word individually may not be optimal for recognizing longer sequences efficiently. This limitation suggests the need for a more holistic approach that can capture the structure and flow of complete sentences.

The existing system lacks sufficient context awareness, primarily focusing on isolated characters and individual words within handwritten text. This limitation results in a lack of semantic understanding, making it challenging for the system to comprehend the nuanced relationships between words in the context of complete sentences. This deficiency hinders the system's ability to provide a holistic and meaningful interpretation of handwritten content.

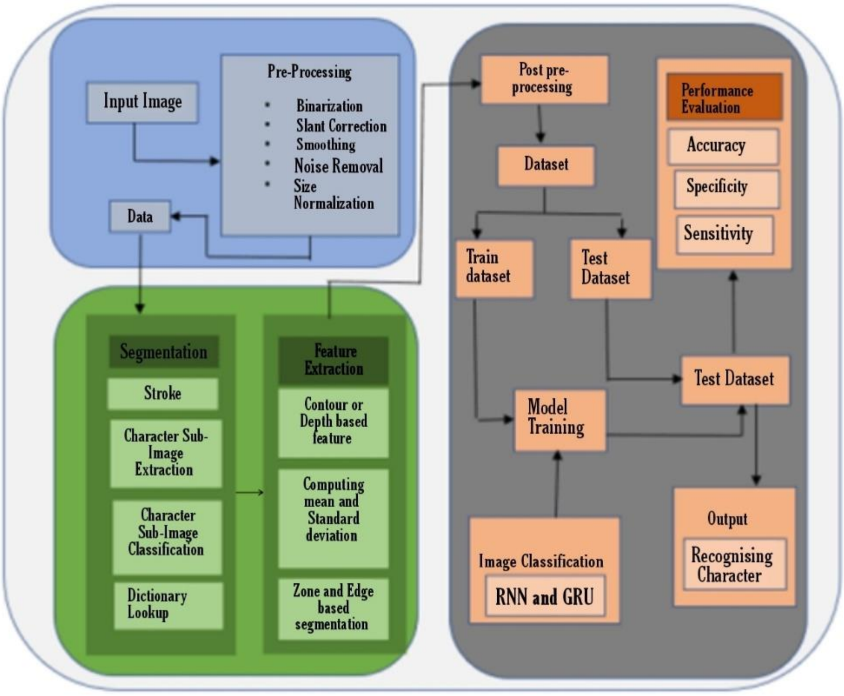
The inability to recognize entire lines of text is a critical issue. The current character-centric approach makes it challenging to interpret the structure of complete lines of handwritten text accurately. This limitation can impact the system's ability to process and interpret the entirety of handwritten content, particularly when context and meaning are conveyed through the arrangement of words within a sentence.

V. PROBLEM DEFINITION

In response to the limitations of the existing system, the proposed system introduces a combination of Recurrent Neural Network (RNN) and Gated Recurrent Unit (GRU) algorithms. While RNNs excel in processing sequential data, the traditional RNN architecture faces challenges in capturing long-range dependencies due to the vanishing gradient problem. The proposed GRU algorithm serves as an enhancement to address this limitation.

The identified problem revolves around the inefficiency of the existing system's character-by-character and word-by-word recognition approach, particularly when applied to longer sequences of handwritten text. The proposed system aims to improve the processing of sequential data by integrating RNN and GRU algorithms, addressing challenges related to long-range dependencies and enhancing the system's ability to recognize entire lines or paragraphs.

The existing system lacks sufficient context awareness, leading to challenges in semantic understanding within the handwritten text. The proposed system seeks to rectify this limitation by employing the GRU algorithm, enhancing the model's capacity to predict the next letter in incomplete words. This enhancement contributes to a more context-aware analysis, enabling the system to understand and predict the structure of complete sentences, thus achieving more comprehensive and contextually aware character recognition. The problem is defined as the need for an improved system that can overcome the limitations of the existing character-by-character and word-by-word recognition methodology, facilitating a more holistic understanding of handwritten content.



Architecture Diagram

VI. ANALYSIS

6.1 Data Collection:

The IAM Handwritten Database is a large and diverse collection of handwritten text images and their corresponding labels. It is a valuable resource for research on handwriting recognition, writer identification, and text-to-image synthesis. The database contains over 13,000 images of handwritten text lines, including both isolated and context-dependent lines. The text is written by 657 different writers, making the dataset representative of a wide range of handwriting styles.

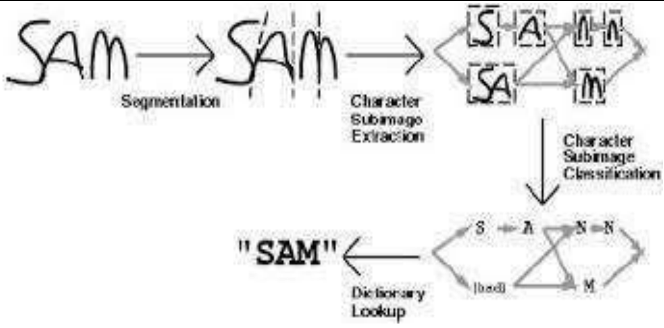
6.2 Pre-Processing

Pre-processing is an essential step in preparing data for future analysis. It involves several techniques to format the input image, such as reducing Noise, Normalization, Smoothing, and other methods used in the Recognition Process. The primary purpose of Preprocessing is to enhance the quality of the image and analyze it more accurately. Image pre-processing involves operations at the lowest level of image abstraction, and these operations do not increase image information. However, they can decrease the image information if necessary. The ultimate purpose of pre-processing is to enhance visual attributes that are important for the processing and analysis task, improve the image data, and suppress unwanted distortions.
The pre-processing steps to be performed in this project are:

A. Binarization: Conversion of an image into a binary format, typically black and white, by thresholding pixel values to enhance contrast and simplify subsequent processing.
B. Slant Correction: Adjustment of text or object orientation to eliminate slant or tilt, ensuring proper alignment for improved recognition accuracy.
C. Smoothing: Reduction of image noise and fine details through techniques like blurring, to create a more regular and simplified representation.
D. Noise Removal: Elimination or reduction of unwanted artefacts or irregularities in the image, enhancing the clarity of relevant features.
E. Size Normalization: Resizing or scaling images to a standardized size, ensuring consistent input dimensions for recognition systems and improving robustness.

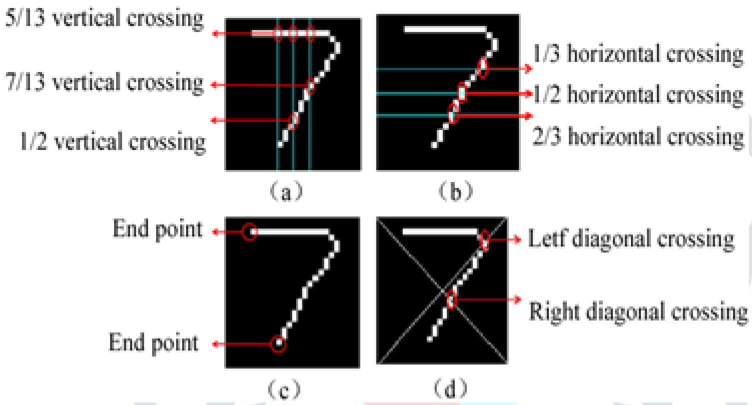
6.3 Image Segmentation

Segmentation is a crucial step in any Recognition method as it involves separating lines, words, or characters from a handwritten document. This process involves breaking down the input image into various sub-groups called segments of the image. Image segmentation is a method utilized to partition a digital image into subgroups, thereby simplifying the image and allowing for subsequent processing or analysis of each image segment. Segmentation entails labelling pixels to distinguish between objects, persons, or other significant aspects in the image. Image segmentation is frequently used for object detection. The object detector functions on a bounding box that has already been defined by the segmentation algorithm, which results in an improvement in accuracy and a reduction in inference time.



6.4 Feature Extraction

Feature extraction is the process of obtaining important data or information from an independent format image. This stage is crucial in extracting the most relevant information from the text image, which aids in character recognition. Selecting a stable and representative set of features is essential in designing a pattern recognition system. The process of manually extracting features includes identifying, characterizing, and devising a method for extracting the features that are pertinent to a particular issue. Making conclusions about whether characteristics might be valuable often requires having a solid understanding of the context or domain.



6.5 Model Generation

The post-processing stage involves printing the corresponding recognized characters in a structured text form, which is achieved using OCR. However, recognition errors are common in system results due to character classification and segmentation problems. To correct these errors, contextual post-processing techniques are employed by CR systems. The statistical approach is commonly used in this context due to its computational time and memory utilization advantages. Also, the pre-processed features are used to train the GRU algorithm. During training, the algorithm learns to recognize patterns in the input data and make predictions about the corresponding output label. The trained model is then validated using a separate set of validation data to evaluate its performance. Finally, the model is tested using a set of test data to evaluate its accuracy in recognizing new handwritten characters.

6.6 Model Training

The preprocessed features extracted from the handwritten images are utilized to train the Gated Recurrent Unit (GRU) algorithm. During the training process, the algorithm learns to recognize intricate patterns in the input data and makes predictions about the corresponding output label. The GRU's ability to capture dependencies in sequential data is harnessed in this phase, ensuring the model comprehensively understands the contextual flow of handwritten characters. Following the training phase, the model is validated using a separate set of validation data. Here the evaluation of the performance of the trained model on data it has not seen during training, ensuring its ability to generalize to new instances. Subsequently, the model undergoes testing using a distinct set of test data to assess its accuracy in recognizing new handwritten characters.

6.7 Prediction

The recognition system, equipped with the trained model, transitions into the image classification stage. This is the decision-making component where the system analyses the features extracted from the input image and determines the most likely character class. The classification process involves matching the extracted features with the learned patterns stored in the model, facilitating the assignment of characters to their respective classes. The outcome of the image classification stage is the successful recognition of handwritten characters. The system, having analyzed the input image through a series of pre-processing, segmentation, feature extraction, and model training steps, leverages its learned patterns to accurately identify and classify characters within the handwritten content.

VII. CONCLUSION

Handwritten character recognition has seen a rise in popularity in recent years., particularly in creating paperless environments through the digitization and processing of existing paper documents. To this goal, several methods for reading handwriting have been put forth. Among these, the RNN with a Gated Recurent Unit network on a series-to-sequence approach has become a popular architecture of a neural network for the recognition of characters. We experimented with this strategy on the IAM dataset while contrasting the outcome to that of other models to assess its efficacy. Our findings show that the suggested model produced the maximum letter accuracy and word accuracy, making it the best-performing model for recognizing handwritten characters. In conclusion, the use of RNNs with GRUs on a sequence-to-sequence method has the potential to enhance the precision and effectiveness of automatic text recognition systems.

VIII. FUTURE IMPLEMENTATION

In advancing the handwritten text recognition project, consider implementing bidirectional GRU for comprehensive context understanding, integrating attention mechanisms to focus on key areas, exploring data augmentation for improved model robustness, and leveraging transfer learning with pre-trained models for enhanced performance. Additionally, hybrid architectures combining CNNs and RNNs, end-to-end models like Transformers, and multimodal approaches can offer diverse perspectives. Incorporate interactive training for real-time user feedback, optimize for edge device deployment, ensure robustness to noisy data, and continually fine-tune parameters to achieve optimal results. This holistic approach aims to elevate the system's accuracy, context awareness, and overall effectiveness in recognizing entire lines of handwritten text, pushing the boundaries of OCR capabilities.

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