Handwritten Text Recognition

Aryaman Surya
Department of Information Technology
National Institute of Technology Karnataka, Mangalore, India
aryamansurya.211it011@nitk.edu.in

Anshuman
Department of Information Technology
National Institute of Technology Karnataka, Mangalore, India
anshumansingh.211it009@nitk.edu.in

Vaidaant Thakur
Department of Information Technology
National Institute of Technology Karnataka, Mangalore, India
vaidaantthakur.211it075@nitk.edu.in

Vivek Nair
Department of Information Technology
National Institute of Technology Karnataka, Mangalore, India
vivekpremnair.211it084@nitk.edu.in

***Abstract*—This paper presents a comprehensive study on Handwritten Text Recognition (HTR) using the IAM dataset. HTR is a critical task in various domains, including document digitization, optical character recognition, and natural language processing. The dataset is split into training, testing, and validation sets, and robust preprocessing steps are applied to handle handwritten text samples. A data input pipeline is established, including building a character vocabulary and resizing images without distortion. The study explores different models, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and their hybrid, the CRNN architecture, for HTR. Performance is evaluated using the edit distance metric, and the CRNN architecture emerges as the most accurate for handwritten text recognition. The paper concludes with a demonstration of the models' practical application in predicting text from input images, thereby contributing to advancements in HTR technologies.**

***Index Terms*—Handwritten text recognition, model, CTC Loss, CNN, RNN, edit distance, CRNN**

I. Introduction

Handwritten Text Recognition (HTR) is a fundamental task in the field of pattern recognition and artificial intelligence. The applications range from document digitization to automated transcription systems. Despite advancements in optical character recognition (OCR) technology, it is still difficult to accurately decipher handwritten text due to variations in handwriting styles. HTR systems utilize machine learning and deep learning techniques to automatically transcribe handwritten text into machine-readable formats.

The IAM (IAM Handwriting Database) dataset serves as a benchmark dataset for HTR research. It provides a diverse collection of handwritten text samples captured from various sources, including historical documents, forms, and manuscripts. This dataset presents a unique set of challenges, such as variability in writing styles, word segmentation, and alignment issues. These factors makes it the ideal dataset for evaluating the robustness and accuracy of HTR models.

In this paper, we try to create a HTR using the IAM dataset. The goal is to develop and evaluate models capable of accurately recognizing handwritten text. We explore different architectures, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Convolutional Recurrent Neural Networks and determine which one is most efficient. These models are required to capture the spatial and temporal dependencies within the handwritten text data. We determine the superior model using metrics such as accuracy, loss, and edit distance. Additionally, we demonstrate the practical application of the trained models in real-world scenarios, showcasing their potential to streamline tasks such as document transcription and archival. Through this study, we contribute to the advancement of HTR technologies and provide insights into the challenges and opportunities in the field.

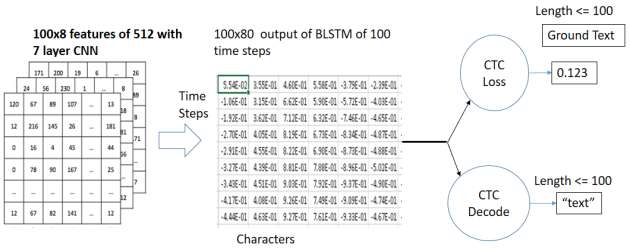

Fig. 1. CRNN model

II. Literature Survey

In our research paper, we delved into various neural network architectures and optimization techniques [1] introduced a Convolutional Neural Network (CNN)-based approach, demonstrating its efficacy in capturing spatial features within handwritten text images, leading to significant improvements in recognition accuracy. Subsequently, [2] proposed an enhanced methodology utilizing Recurrent Neural Networks (RNNs), showcasing the effectiveness of RNN-based models in capturing sequential dependencies inherent in handwritten text data. Building upon these foundations, [3] we've encountered a rich array of techniques [4] provided us with a comprehensive review of evaluation metrics, shedding light on the strengths and limitations of various approaches. Building upon this understanding, [5] introduced Adam, an optimization algorithm that enhances the training of neural networks by

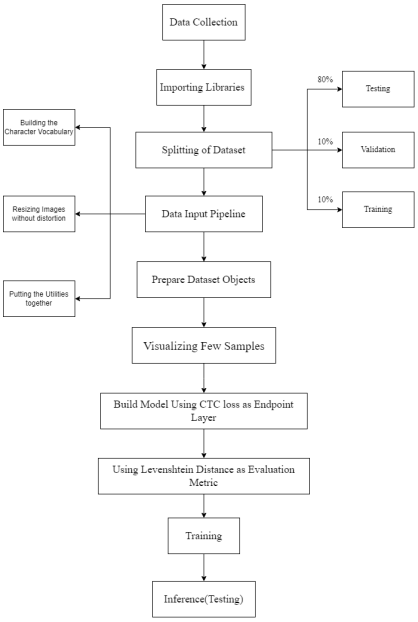

Fig. 2. Flowchart

adapting learning rates and momentum. Their work underscores the importance of effective optimization techniques in achieving robust performance. Additionally, we've explored the efficacy of different loss functions, including hinge loss as discussed in [6], which contributes to the construction of robust decision boundaries in classification tasks. These foundational concepts, coupled with advancements in neural network architectures, have propelled the field of handwritten text recognition forward, promising continued innovation and improvement, and offered theoretical insights into constructing robust decision boundaries, complementing the advancements in neural network architectures. Moreover, seminal works such as Connectionist Temporal Classification (CTC) in [7] and recent innovations like attention mechanisms [8] and Transformer-based models [9] have further propelled the field forward, enabling state-of-the-art performance in handwritten text recognition tasks. Finally, domain adaptation techniques surveyed in [10] provide valuable insights into addressing challenges related to varying handwriting styles and languages, promising continued advancements in the domain.

III. Methodology

Our methodology focuses on evaluating three key neural network architectures for Handwritten Text Recognition (HTR): Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Convolutional Recurrent Neural Network (CRNN). We begin by preprocessing the IAM dataset and splitting it into training, testing, and validation sets. Our robust data input pipeline ensures consistency, while our model architectures leverage spatial and temporal information to extract meaningful features from handwritten text data. Through rigorous evaluation using metrics like edit distance, we aim to provide insights into the effectiveness and comparative performance of these architectures in HTR.

A. Data Collection and Preparation

The IAM dataset, widely recognized in the field of Handwritten Text Recognition (HTR), is obtained for this study. This dataset comprises a diverse collection of handwritten text samples captured from various sources, including historical documents, forms, and manuscripts. It provides a rich repository of handwritten text data annotated with word-level labels and bounding boxes for individual characters.

1) Data Preprocessing: The acquired dataset undergoes extensive preprocessing to ensure its suitability for model training and evaluation. This preprocessing includes:
Noise Removal: Any artifacts or noise present in the images are removed to enhance data quality and clarity.
Standardization of Image Sizes: Images within the dataset are resized to a uniform dimension to ensure consistency across samples. This step is crucial for compatibility with the chosen model architectures.
Formatting Consistency: Ensuring uniformity in formatting across handwritten text samples, such as alignment and orientation, to facilitate accurate transcription and interpretation.

B. Dataset Splitting

To ensure the robustness and generalization of the Handwritten Text Recognition (HTR) model, the dataset is partitioned into three distinct subsets: training, testing, and validation sets.

1) Training Set: The training set constitutes the largest portion of the dataset, typically encompassing around 80% of the total samples. This subset is utilized for training the HTR model, allowing it to learn patterns and features from the handwritten text data.

2) Testing Set: The testing set comprises approximately 10% of the dataset and serves as an independent dataset for evaluating the performance of the trained model. It contains unseen samples that the model has not encountered during training, providing an unbiased assessment of its generalization ability.

3) Validation Set: The validation set, similar in size to the testing set, consists of around 10% of the dataset. It is used to fine-tune model hyperparameters and monitor its performance during training. The validation set helps prevent overfitting by providing an additional evaluation metric for model optimization.

C. Data Input Pipeline

1) Preprocessing: Before feeding the data into the Handwritten Text Recognition (HTR) model, a series of preprocessing steps are applied to ensure the data is in a suitable format for training:
Image Decoding: Raw image files are decoded into a format that can be processed by the model, such as NumPy arrays or TensorFlow tensors.
Normalization: Image pixel values are often normalized to a range between 0 and 1 to improve model convergence and

stability during training.
Resize and Reshape: Images are resized to a fixed dimension to ensure uniformity across samples. Additionally, images may be reshaped or padded to match the input dimensions expected by the model architecture

2) Building the Character Vocabulary: A character vocabulary is constructed by extracting unique characters from the training data. This vocabulary serves as a mapping between characters and their corresponding integer indices, enabling the model to process textual data in a numerical format. Special tokens, such as padding and end-of-sequence tokens, may be added to the vocabulary to handle variable-length sequences and assist in model training and inference.

3) Resizing Images without Distortion: Handwritten text samples often vary in size and aspect ratio, requiring standardization for compatibility with the model architecture. Images are resized to a uniform dimension without introducing distortion or altering the aspect ratio. Common resizing techniques include maintaining the original aspect ratio and padding or cropping the images to fit the desired dimensions. Resized images ensure consistency in input sizes across samples, facilitating effective feature extraction by the model.

4) Putting the Utilities Together: Once the character vocabulary is established, and images are resized, the utilities are combined to create a cohesive data input pipeline. This pipeline encompasses all preprocessing steps required to transform raw data into a format suitable for model training and evaluation. Images are decoded, normalized, resized, and paired with their corresponding encoded labels, forming input-output pairs ready for consumption by the model. The data input pipeline ensures that the model receives properly formatted data batches during training and inference, streamlining the overall workflow and enhancing training efficiency.

D. Model Architectures

1) CNN: The Convolutional Neural Network (CNN) architecture is employed for feature extraction from input images in the Handwritten Text Recognition (HTR) task. CNNs consist of multiple convolutional layers followed by activation functions, pooling layers, and optionally, fully connected layers. Convolutional layers apply learnable filters to input images, extracting local features such as edges, corners, and textures. Activation functions introduce non-linearity to the model, enabling it to capture complex patterns and relationships within the data.
Pooling layers downsample feature maps, reducing spatial dimensions while retaining essential information. Max-pooling is commonly used to extract the most significant features from each feature map. Fully connected layers aggregate extracted features and perform classification or regression tasks. However, in the HTR context, fully connected layers are often omitted or replaced with recurrent layers to model sequential data more effectively.

2) RNN: Recurrent Neural Networks (RNNs) are well-suited for processing sequential data, making them an ideal choice for modeling handwriting recognition tasks. RNNs incorporate feedback loops that allow information to persist over time, enabling them to capture temporal dependencies in sequential data. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are popular variants of RNNs commonly used in HTR models. These architectures address the vanishing gradient problem and facilitate the modeling of long-range dependencies in handwritten text sequences.
Bidirectional RNNs enhance model performance by processing input sequences in both forward and backward directions, capturing context from preceding and succeeding characters simultaneously. This bidirectional processing improves the model's ability to interpret and transcribe handwritten text accurately.

3) CRNN: The Convolutional Recurrent Neural Network (CRNN) brings together the strengths of CNNs and RNNs, leveraging both spatial and temporal information for improved performance in HTR tasks.
CRNNs typically consist of convolutional layers for feature extraction followed by recurrent layers for sequence modeling. CNN layers extract spatial features from input images, capturing visual patterns and structures present in handwritten text samples. These features are then passed to recurrent layers, which model the sequential nature of handwritten text, capturing dependencies between characters and words. By integrating CNNs and RNNs into a unified architecture, CRNNs can effectively handle the complexities of handwritten text recognition, achieving high accuracy and robustness across diverse datasets and handwriting styles.

E. Evaluation Metric

The edit distance, also known as the Levenshtein distance, is a popular evaluation metric used in Handwritten Text Recognition (HTR) to quantify the similarity between predicted and ground truth text sequences. It measures the minimum number of single-character edits (insertions, deletions, or substitutions) required to transform one sequence into another. The edit distance provides a quantitative measure of the accuracy of the HTR model's predictions, taking into account both the correctness and alignment of individual characters within the text sequences. By comparing predicted and ground truth text sequences, the edit distance captures the overall performance of the HTR model in transcribing handwritten text accurately, accounting for variations in handwriting styles, spelling errors, and word order.

F. Model Training

In the training phase, the Connectionist Temporal Classification (CTC) loss function is utilized to train the models. CTC loss is specifically designed for sequence prediction tasks, making it well-suited for Handwritten Text Recognition (HTR). We were able to find this out by trying out various loss functions, namely Binary cross-entropy loss and Hinge loss. Binary cross-entropy loss is typically used for binary classification tasks where each sample belongs to one of two classes. It measures the difference between probability distributions, making it suitable for tasks where the output is

$$p(Y \mid X) = \sum_{A \in \mathcal{A}_{X,Y}} \prod_{t=1}^{T} p_t(a_t \mid X)$$

The CTC conditional **probability** | **marginalizes** over the set of valid alignments | computing the **probability** for a single alignment step-by-step.

Fig. 3. CTC loss Formula

a binary decision. In the context of handwriting recognition, binary cross-entropy loss would be less appropriate because it assumes a fixed-length output and does not handle variable-length sequences well. Hinge loss is commonly used for binary classification tasks, especially in SVM (Support Vector Machine) models. It's suitable for tasks where the output is a binary decision and aims to maximize the margin between classes. Similar to binary cross-entropy loss, hinge loss assumes a fixed-length output and does not handle variable-length sequences well, making it less appropriate for handwriting recognition tasks. We then proceeded with the CTC loss function to learn the alignment between the input image and the corresponding label. During training, the model is trained to minimize the CTC loss between the predicted sequence of characters and the ground truth labels associated with the input images. The CTC loss function accounts for variable-length input sequences and enables the model to learn the alignment between input features and output labels.

Following training with the CTC loss function, each model architecture (CNN, RNN, CRNN) is evaluated on the validation dataset to assess its accuracy in transcribing handwritten text. The accuracy of each model is computed based on metrics such as edit distance, which quantify the similarity between predicted and ground truth text sequences. The accuracy scores obtained from the validation process are compared to identify the model architecture that achieves the highest accuracy and performs optimally for the given HTR task.

G. Model Evaluation

Following training with the CTC loss function, we compare the accuracies of different model architectures (CNN, RNN, CRNN) on the validation dataset. The model with the highest accuracy is selected for further optimization and evaluation. The model selection is based on accuracy, computational efficiency, and generalization capability. We prioritize models that achieve high accuracy while maintaining practical feasibility.

IV. Result and Analysis

After running the CNN and RNN models we were able to infer that the CRNN (Convolutional Recurrent Neural Network) model is the most appropriate choice for handwriting recognition due to its ability to effectively capture both spatial features, such as the shape of characters, and sequential information, such as the order of strokes. By integrating convolutional layers for feature extraction with recurrent layers for sequence modeling, CRNNs can jointly learn spatial and sequential representations from handwritten text data. This

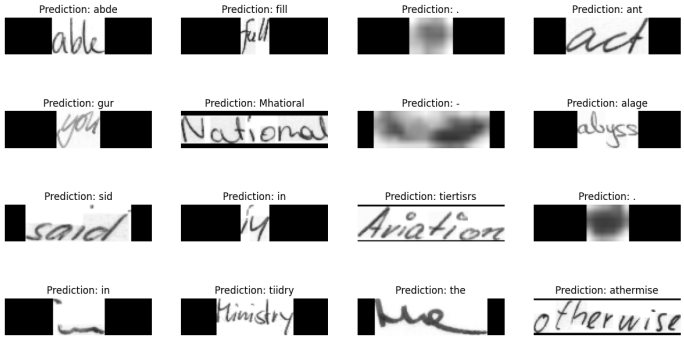

Fig. 4. Prediction for testing dataset

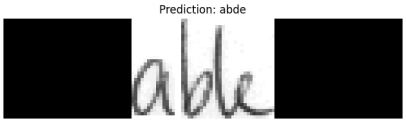

Fig. 5. Prediction for input image

enables the model to better understand the structural context of handwriting, leading to improved recognition accuracy compared to using CNN or RNN models in isolation. Thus, CRNNs offer a comprehensive approach to handwriting recognition by leveraging the complementary strengths of both convolutional and recurrent architectures. After our analysis on the three different loss functions,CTC loss is the most appropriate for handwriting recognition because it handles variable-length sequences effectively and does not require explicit alignment information during training, which is crucial for tasks where the alignment between input and output sequences is uncertain or variable. Fig. 4 shows the predictions for the testing dataset and Fig.5 shows the prediction for a single input image.

V. Conclusion

Our paper on handwritten text recognition utilizing the IAM dataset has uncovered significant insights, showcasing the technology's substantial potential in real-world applications. Our methodology started with meticulous data preprocessing, wherein we carefully segmented the IAM dataset. Allocation of 80% of the data for model training, with the remaining 10% each for testing and validation, ensured comprehensive evaluation and robust performance assessment across various stages.

In model development, we explored a spectrum of architectures, encompassing Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Convolutional Recurrent Neural Networks (CRNNs), and models utilizing hinge loss, binary cross-entropy loss, and Connectionist Temporal Classification(CTC) loss. The CRNN model seemed to give the best accuracy among the three models trained while using CTC loss as the loss function.

While testing our model with real-time inputs, it showcased robust performance, accurately transcribing handwritten text

from provided images across various complexities. This underscores the profound impact of handwritten text recognition technology, with CRNNs and the best selection of loss functions.

The future scope involves the exploration of advanced neural network architectures, optimization algorithms, and training techniques to further refine model accuracy and robustness. Additionally, the integration of graphical user interfaces (GUIs) can facilitate seamless interaction with HTR systems, enabling users to intuitively input handwritten text and access transcription results with ease. By using emerging technologies, we can pave the way for more accurate, efficient, and user-friendly HTR solutions for diverse applications and user needs.

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