Regular Progress Report 3 - Image Classification Using Radon Cumulative Distribution Transform

Abeed Pasha Sirajus Salekin Mohiuddin Sarker
2131353042 2132275642 1821404042

***Abstract*—In this week's research update, we expand the evaluation of the RCDT-NS model developed by RohdeLab to demonstrate its versatility and effectiveness across a broader range of datasets. Specifically, we tested the model on the EMNIST dataset, which contains handwritten English letters in both uppercase and lowercase. Our results indicate that the RCDT-NS maintains robust performance across the diverse character set, providing promising insights into its adaptability to different types of image data. These findings underscore the model's potential for more generalizable applications in handwriting recognition and beyond.**

I. Introduction

The RCDT-NS (Radon Cumulative Distribution Transform - Nearest Subspace) model, which we applied to the EMNIST dataset, is specifically designed for image recognition tasks. The model utilizes the Radon Transform and Cumulative Distribution Transform to extract both local and global features from images by transforming them into higher-dimensional spaces. The Nearest Subspace method is then employed to map the transformed data to its nearest subspace for classification. This combination allows RCDT-NS to capture complex patterns in the data, making it highly effective for tasks such as handwriting recognition, where both fine details and broad structure must be captured.

The primary purpose of our research is to evaluate the versatility and effectiveness of RCDT-NS across various datasets. By testing the model on a range of datasets, we aim to assess its generalization capability and adaptability to different types of data. In this particular study, we focused on the EMNIST dataset to evaluate its performance in recognizing handwritten English letters in both uppercase and lowercase forms. We hypothesized that RCDT-NS would perform well across these variations and demonstrate strong generalization despite the variability in handwriting styles present in the dataset.

Upon running the EMNIST dataset through the model, the results were promising. RCDT-NS achieved high accuracy on both the training and test sets, effectively recognizing characters across the range of uppercase and lowercase letters. The model's performance remained robust despite the diverse handwriting styles, showcasing its ability to handle variability in input data. These findings reinforce our belief in the model's versatility and its potential to be applied to a wide range of datasets and image recognition tasks, not only in handwriting recognition but also in areas like medical imaging and other domains that require high-level pattern recognition.

II. Methodology

Datasets

1) **Datasets**: We chose to run the model through the English Alphabets in lower and upper cases in the EMNIST datasets.
   The EMNIST (Extended MNIST) English Letter dataset is a collection of handwritten letters designed to extend the original MNIST dataset, which consists of handwritten digits. The EMNIST dataset contains a larger variety of handwritten characters, making it suitable for a wider range of classification tasks involving text recognition.
   - **Number of Classes:** 26 classes, each representing a different uppercase English letter (A-Z).
   - **Image Dimensions:** The images are 28x28 pixels, just like the original MNIST dataset.
   - **Number of Samples:**
     - **Training Set:** 145,600 images (8,800 images per class)
     - **Test Set:** 24,000 images (1,600 images per class)
   - **Data Format:** The images are grayscale, with each pixel representing a value between 0 (white) and 255 (black).
2) **Dataset preparation**: We first prepared the EMNIST dataset for use with the RCDT-NS model by converting the dataset files into the .mat format, which is compatible with our processing pipeline. We then adjusted the dataset's structure by modifying the keys to represent labels and their corresponding data, ensuring the correct organization of the images. Additionally, we standardized the dimensions of the images to 28x28 pixels to match the input requirements of the model, and the final structure was set as 28x28xK, where K represents the number of samples per class. For training, we selected 2% of the dataset to feed into the model, ensuring a manageable size for initial experimentation while still maintaining a diverse range of characters from the EMNIST dataset. This subset was then normalized and processed before being passed through the RCDT-NS model for classification.

III. Results

Performance Analysis: The achieved accuracy of 81.851% on the EMNIST dataset using the RCDT-NS model is a

Fig. 1. Samples of EMNIST letter dataset

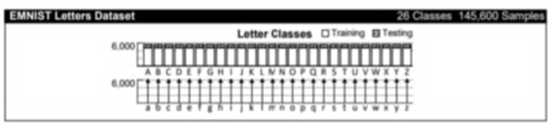
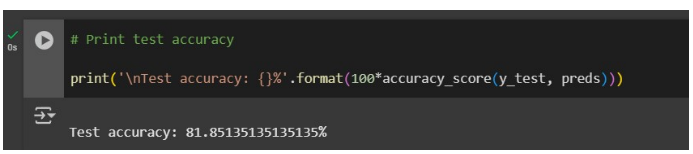


Fig. 2. EMNIST letter dataset overview

promising result, indicating that the model effectively captures important features despite the dataset's complexity and variability in handwriting styles.



```
# Print test accuracy
print('\nTest accuracy: {}%'.format(100*accuracy_score(y_test, preds)))

Test accuracy: 81.85135135135135%
```

Fig. 3. Accuracy of EMNIST letter dataset on RCDT-NS

IV. Conclusion

In conclusion, our analysis of the RCDT-NS model on the EMNIST dataset has been successful, achieving an accuracy of 81.851%, which demonstrates its strong performance in handwritten character recognition. This result indicates that the model is well-suited for handling diverse and complex data. Encouraged by these findings, we will now apply the model to additional datasets to further explore its effectiveness and compare its performance across various tasks, providing a more comprehensive understanding of its capabilities.

References

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