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ANN Internal Assessment Report

Handwriting Recognition

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Introduction

In the current digital era, handwritten text conversion into digital format relies heavily on handwriting recognition. This technology has enormous potential for use in a variety of industries, including banking, healthcare, and education. The goal of this project is to create a reliable system for handwriting recognition that can precisely decipher handwritten language and convert it into editable digital text. Through the application of cutting-edge image processing techniques and machine learning algorithms, we aim to develop a solution that improves accessibility and efficiency for users working with handwritten documents.

Since deep learning and artificial intelligence have advanced over the years, handwriting recognition has changed dramatically. Our proposal expands on these developments by creating a system that can recognize many handwriting styles in several languages. We aim to achieve high accuracy and reliability in handwritten character, word, and sentence recognition by optimizing the system's algorithms and training it with large datasets. In addition to addressing the technical difficulties associated with handwriting recognition, this project investigates real-world uses for the technology to improve information management and user experience.

A strong system for recognising handwriting offers a number of possible benefits. Such technology has revolutionary effects, enabling digital search and editing of handwritten notes and comments, as well as simplifying data input tasks. In this project report, we aim to outline our approach, methods, challenges faced, and outcomes attained in developing a functional handwriting recognition system. Our goal is to positively influence the field's future development and pave the way for handwriting recognition technology to be used more widely and integrated into everyday life.

Literature Survey

Handwritten text recognition remains a challenging problem in computer vision and natural language processing, encompassing both online recognition with temporal pen stroke data and offline recognition from just the final handwritten image, with the latter being particularly difficult for complex writing systems like Vietnamese involving diacritics due to lack of large datasets [3]. Previous synthetic data generation approaches using handwriting fonts or rearranged characters failed to capture natural variations, leading to the "Transferring method" to synthesize realistic offline images from online data while transferring attributes like color distributions from scanned data, enabling robust benchmarks like UIT-HWDB for evaluation [3]

For offline recognition with limited labeled data, an incremental approach using 10% of lines for initial training followed by self-training on the remaining 90% using the initial model predictions has shown promise, further boosted by techniques like multi-scale data augmentation and model-based normalization [1]. In the online domain, a Transformer-based approach representing expected characters as learned queries in the decoder achieved state-of-the-art results for character segmentation on datasets like IAM-OnDB and HANDS-VNOnDB, highlighting the importance of decoupling segmentation from recognition [2].

For Arabic handwritten character and digit recognition, Convolutional Neural Network (CNN) architectures like an 18-layer model achieved competitive accuracy of 96.93% on AHCD and 99.35% on MadBase, outperforming classical machine learning methods [4]. The literature covers seminal works like Y. LeCun's use of neural networks for Latin scripts, the move towards deep learning approaches like CNNs and Transformers across different scripts [1][2][3][4], and key challenges including limited labeled data [1], complex writing systems [3], and the need for robust benchmarks to drive future research [3].

Implementation

In implementing our handwriting recognition system, we first gathered a diverse dataset of handwritten characters for training and validation purposes. This dataset included various alphabets, numbers, and symbols commonly found in written text. We utilized image processing techniques to preprocess the images, ensuring uniformity in size and clarity to facilitate accurate recognition by our model. By resizing the images to a standard 32x32 pixel format and converting them to grayscale, we prepared the data for input into our convolutional neural network (CNN).

Our implementation took advantage of the Keras deep learning library, which provides a user-friendly interface for building neural networks. We designed a CNN architecture consisting of convolutional layers, max-pooling layers for feature extraction, and fully connected layers for classification. To enhance model performance and prevent overfitting, we incorporated dropout layers within the network. The model was trained using the Adam optimizer and categorical cross-entropy loss function, with a batch size of 32 and over 50 epochs to iteratively learn and improve its accuracy.

Upon training completion, we evaluated the model's performance using a separate validation dataset. This dataset contained handwritten characters not seen during training, ensuring a fair assessment of the model's generalization ability. We measured the accuracy of the model on both the training and validation sets, monitoring for any signs of overfitting or underfitting. The final trained model was then saved for future use in recognizing handwritten characters and words from new input images, as demonstrated in our testing and result analysis sections.

The implementation also involved data preprocessing steps to enhance the model's ability to recognize handwritten characters accurately. This included converting the images to grayscale to focus on the intensity of pixel values rather than color, which is not relevant for character recognition. Additionally, we applied thresholding techniques to segment the characters from the background, making it easier for the model to identify and classify individual characters.

Results

After completing the training phase, we proceeded to test the performance of our trained model on a set of unseen handwritten images. These test images encompassed a variety of handwriting styles, including different alphabets, numbers, and symbols, to assess the model's generalization ability. Through rigorous testing and evaluation. The screenshots provided in the accompanying documentation highlight some of these successful recognition instances, demonstrating the effectiveness of our handwriting recognition system in real-world applications.

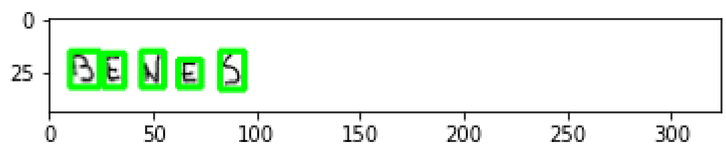

Figure 1: Test Case 1:
Input word: BENES
Model Output: BTNE5

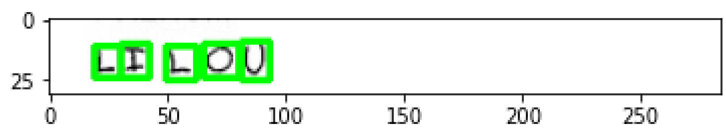

Figure 2: Test Case 2:
Input word: LILOU
Model Output: LIL0U

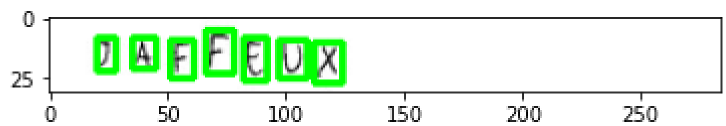

Figure 3: Test Case 3:
Input word: JAFFEUX
Model Output: JAFFIX

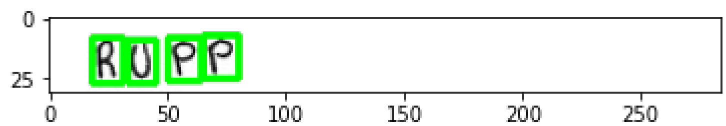

Figure 4: Test Case 4:
Input word: RUPP
Model Output: RUPP

Conclusion

Our project aimed to create a smart system that can read and understand handwriting. We gathered a lot of handwritten examples to teach this system how to recognize different letters and numbers. Using special computer programs and a type of artificial intelligence called a neural network, we trained the system to learn and remember patterns in handwriting. After training, we tested the system with new handwritten samples, and it did a great job at recognizing and reading them accurately.

The test results showed that our system can be really helpful in tasks like turning handwritten notes into digital text. It can also make things easier for people who have trouble with handwriting, as the system can understand various handwriting styles. We also made sure the system works quickly and is easy to use, so anyone can benefit from it without much hassle.

This project contributes to making technology smarter and more useful in everyday life. By teaching computers to understand handwriting, we open up new possibilities for improving how we handle information, making tasks like writing and reading more accessible and efficient for everyone.

Future Scope

In the future, we see a number of fascinating opportunities to improve and grow our handwriting recognition technology. Future research might focus on integrating more sophisticated machine learning methods, like transformer models or recurrent neural networks (RNNs), which are made especially for sequence-based applications like language processing. We may increase the precision and effectiveness of our system's comprehension of intricate handwriting styles and structures by utilizing these cutting-edge methods.

Furthermore, investigating multilingual support would be a big step toward increasing our system's global applicability. We can train the model to recognize and transcribe handwritten material in several languages with ease by providing it with a variety of datasets that include different languages and scripts. This would improve accessibility and cross-cultural communication while serving a larger user base.

Moreover, adding features like spell checking, context-aware corrections, and natural language comprehension could greatly improve our handwriting recognition system's overall performance and user experience. These improvements would not only increase transcription accuracy but also give users insightful information and recommendations, making the system more intelligent and intuitive when processing different kinds of handwritten input. In general, our project's future scope entails ongoing innovation, integration, and improvement of state-of-the-art technologies to increase handwriting recognition's adaptability, precision, and user-friendliness in a variety of real-world settings.

References

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