Title: Handwritten English Capital Alphabet Recognition Using CNN

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Introduction

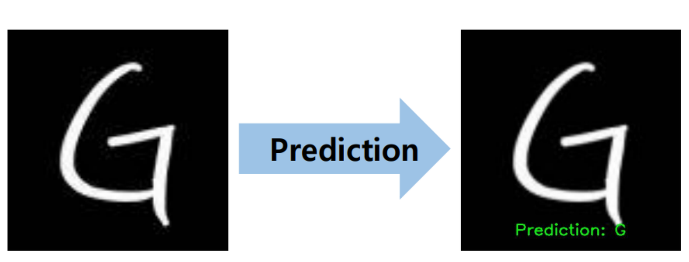
Handwriting recognition is a technology that plays an important role in various applications. For example, handwriting recognition technology helps increase automation and efficiency in a variety of areas, including zip code recognition, license plate recognition, and financial document processing. For this reason, the development and research of handwriting recognition models continue to evolve.

Existing handwriting recognition models were mainly based on traditional machine learning algorithms. Recently, however, due to advances in deep learning technologies and improvements in computing power, handwriting recognition using CNN models has been studied a lot. CNNs perform well in image processing and have the structure to effectively learn visual patterns such as handwriting.

In this work, we developed a **CNN model** for handwriting recognition using a handwritten alphabet dataset. Normalization and dimensionality were performed through the preprocessing of data, and data augmentation techniques were applied to increase the diversity of data. This allows the model to accurately recognize and predict various handwriting inputs.

The CNN model consists of alternating layers of convolutional and pooling. We apply batch normalization and dropout to improve the stability and generalization capabilities of the model. In addition, we used hyperparameter tuning and Adam optimizer to obtain optimal learning results.

Experiments have shown that the handwriting recognition model developed has shown excellent performance on alphabetical datasets. This model can be the basis for handwriting recognition systems available in real-world applications, and is expected to contribute to automation and increased efficiency.



Methods

CNN Modeling

We conducted studies to enhance the analysis and prediction of English handwriting data. These studies focused on improving the stability and learning speed of neural networks.

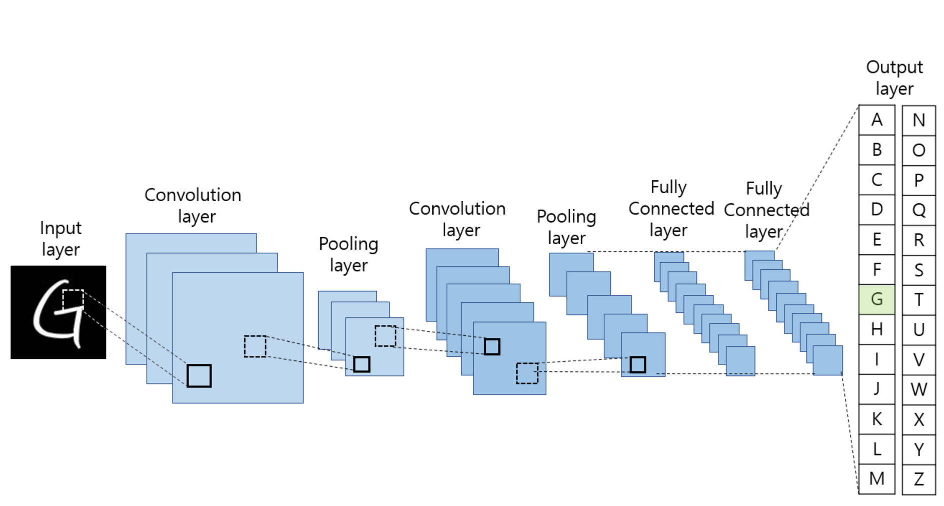
Batch normalization was applied to normalize input values within each mini-batch. This technique adjusted the mean to 0 and the standard deviation to 1, improving the model's stability and accelerating training speed.

Image Augmentation, a technique in image transformation, increased data diversity by applying rotations, translations, shearings, and scalings. This enhanced the model's generalization performance by exposing it to data from various angles and positions.

The model architecture was **enhanced by incorporating convolutional and pooling layers**. A deeper architecture was designed to capture more complex features and intricate patterns in the data.

To prevent overfitting, **Dropout layers** randomly deactivated neurons, promoting the learning of generalized patterns. The output from the convolutional and pooling layers was flattened into a 1D vector, enabling multi-class classification based on the extracted features.

Various hyperparameters such as learning rate, batch size, and dropout rate were fine-tuned during model modifications. The model was compiled using the categorical crossentropy loss function and the Adam optimizer, optimizing its performance. Through these studies and improvements, the performance of the model for analyzing and predicting English handwriting data was significantly enhanced.

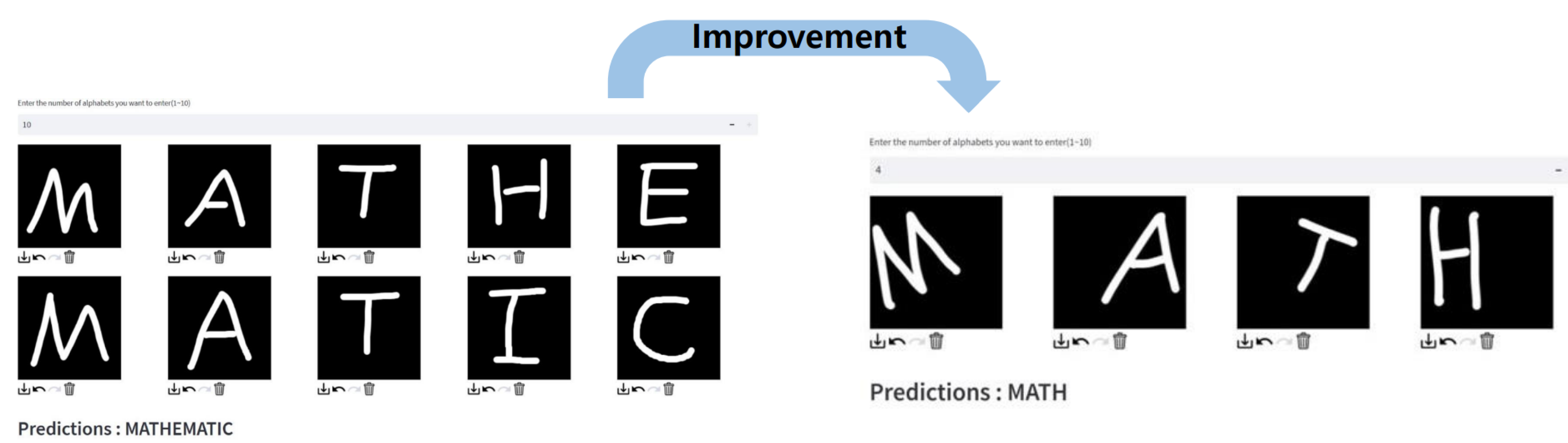


Results

Based on the table below, it can be observed that both the Accuracy and Loss have improved compared to the previous model.

Techniques	Accuracy	Loss
Original	0.9337	0.2390
Add convolutional and pooling layers Add batch normalization Use Hyperparameter tuning Image Augmentation	0.9822	0.0661

The accompanying images represent a web application implemented for real-time experimentation with the model. The left image corresponds to the web implementation using the original model, demonstrating its capability to recognize only neatly written characters. In contrast, the right image showcases the improved model's web implementation, which successfully recognizes text even when it is written at an angle or in the corners.



Thus, we have developed a superior performing model that exhibits the ability to accurately recognize and process text in various scenarios.

Conclusions

In conclusion, our research focused on the development of a robust **Convolutional Neural Network (CNN)** model for handwriting recognition, leveraging advancements in deep learning and image processing techniques. By **incorporating convolutional and pooling layers**, implementing **batch normalization, dropout**, **hyperparameter tuning**, and **image augmentation**, we achieved remarkable improvements in the model's performance and its ability to accurately recognize and process handwritten text.

Through extensive experiments and evaluations, our model demonstrated exceptional accuracy and significantly reduced loss compared to the original version. The inclusion of convolutional and pooling layers, along with techniques like batch normalization and image augmentation, enhanced the model's capability to recognize diverse handwriting inputs, even when written at various angles or in corners. This surpasses the limitations of previous models, which were limited to neatly written characters.

The implementation of a web application further showcased the real-time capabilities of our improved model. It successfully recognized text in different scenarios, highlighting its potential for real-world applications such as zip code recognition, license plate recognition, and financial document processing. The automation and efficiency enabled by our model contribute to streamlining processes and increasing productivity in these domains.

While our study focused on English handwriting data, the advancements we made in model architecture and techniques can be applied to other languages and scripts, expanding the scope of handwriting recognition technology.

Looking ahead, further research and advancements in deep learning and image processing will continue to push the boundaries of handwriting recognition. Future endeavors could explore more complex models, larger datasets, and innovative techniques to further enhance accuracy and expand the range of applications.

In summary, our study showcases the power and potential of CNN models and deep learning techniques in handwriting recognition. We are confident that our findings lay a strong foundation for future advancements in this field, paving the way for more accurate, efficient, and versatile handwriting recognition systems that drive automation and productivity in various domains.

References

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2) Data Source : https://www.kaggle.com/datasets/sachinpatel21/az-handwritten-alphabets-in-csv-format