Handwritten Text Recognition using Fully Convolutional Network

Dewi Ayu Nirmalasari, Nanik Suciati*, Dini Adni Navastara
Department of Informatics, Faculty of Intelligent Electrical and Informatics Technology, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia

E-mail: *Corresponding author’s e-mail address: nanik@if.its.ac.id

Abstract. Handwritten text recognition from images is challenging because there are many variations in handwriting as each person has a different writing style. This research implements multilevel recognition to solve this problem. In the first level, a Lexicon Convolutional Neural Network (CNN) model is used to recognize words (containing a set of word) that often appear in the text. If a word is not recognized by the Lexicon CNN model, which is designed for a limited number of words, then it goes to the next level. A character sequence recognition consisting of predicting the number of characters using CNN, cropping each character using a sliding window, and character recognition using Fully Convolutional Network (FCN), is applied at the second level. Experiments show that the system performance is promising. The experiment conducted using NIST Special Database 19 as a training dataset and a handwritten text on screen as a testing dataset. The best accuracy of word recognition, character number prediction, and character recognition is 99.98%, 98.56%, and 83.52%, respectively.

1. Introduction
Along with the development of technology, handwriting activities have not been abandoned. This is because handwriting activities are still easier, more efficient, and cheaper. Moreover, many important documents still need to be filled out manually and need to be digitized. Automatic recognition of handwritten text images is difficult because there are many variations in writing styles. Letters are often different even though the same person writes them.

Convolutional Neural Network (CNN) is often used in the image recognition process. CNN itself has many modifications, one of which is the Fully Convolutional Network (FCN). FCN still uses the convolution layer when predicting, however FCN does not depend on image size.

There are several deep learning approaches to recognize handwritten images. One of these approaches is to create a word image recognition system by training a system with word images [1]. This system itself will later be able to produce highly accurate recognition, but it is limited to word selection in the training data. In this approach, a large enough dataset is needed because of its dependence on word images.

Another approach is a character by character recognition of handwritten images [2]. This method itself is still a challenge because of the frequent errors in reading the characters from an image. Common mistakes are missing words or duplicated characters. Another challenge with word recognition is the difference in the width of the characters in one image. In this case, the use of FCN will be advantageous because it can accept input without any length limitation [3].
Based on those things, this research implements multilevel recognition system to solve the problem of handwritten text recognition. The first level recognizes word image using the Lexicon CNN model trained on a predefined word dictionary. When the system is unable to provide convincing recognition results, the word image will be recognized character by character using FCN.

2. Literature Review
Multiple works have been done to recognize handwriting text. Doetsch et al. [4] used RNN-HMM for recognizing offline handwriting. HMM is applied on training data to get frame-wise labeling, while the result of HMM will be feed into RNN. Wue et al. [5] used the character level convolutional method in feed-forward and RNN for recognizing handwritten Chinese character. In this experiment, it showed an improvement when combining neural network with back-off N-gram language models. Xie et al. [6] used CNN and multilayer LSTM for recognizing handwritten Chinese character. Other works of recognizing text from a natural image have shown using CNN to do feature extraction RNN give impressive results, such as Yin et al [7], and Su and Lu [8]. Wigington et. al [9] used bidirectional LSTM with normalization and augmentation. Pharm et. al [10] proposed multidimensional RNN with dropout to prevent over-fitting on the training dataset.

FCN method [11] takes an arbitrary size image and output region level classification. It benefits this research because the handwritten word has a different length. Bai et al. [12] using FCN and it shows it can outperform RNN on sequence modelling problem.

3. Our Approach
The system will perform handwritten text recognition using three neural networks. The three neural networks are Lexicon CNN, Character Count CNN, and Character Prediction FCN. Initially, after the image is pre-processed, the image will enter the word recognition process from image on a predefined dictionary. This process is called the Lexicon CNN. When the Lexicon CNN prediction results have confidence that exceeds the specified limits, the Lexicon CNN prediction results are recognized as a whole system output.

![Figure 1. Flowchart of System](image)

However, when the Lexicon CNN has low confidence, the image will be forwarded to the Character Count CNN. The Character Count CNN will provide numeric output that represents amount of
characters in the word image. Later, before the image enters the Character Prediction FCN, the image will be resized to a size of 32x16 N, where N is the output of the Character Count CNN. In Character Prediction FCN, the image will be read using a sliding window and a series of prediction results that have high confidence will be said. This complete flow can be seen in Figure 1.

3.1. Lexicon CNN
Lexicon CNN is a word image recognition process based on predefined word dictionary that used in training process. These words are taken from the 50 words that appear most frequently in Brown corpus and 50 words that appear most frequently in Gutenberg corpus. Brown and Gutenberg are corpus provided by NLTK (Natural Language Toolkit), one of the famous libraries for natural language [13]. Brown corpus has 50 categories, 500 articles and 1.15 million words in English. Gutenberg Corpus contains approximately two million words from 18 e-books.

Fifty words from each of corpus are combined to create a new dictionary containing 59 different English words. In the training process, Lexicon CNN uses synthetic training data by combining the characters on the NIST Special Database 19 (SD19) into words. NIST (SD19) is a dataset of numeric and alphabetic characters, both upper and lowercase letters. The dataset itself is drawn from 3,669 handwritten forms and has a total of 814,225 characters [14].

Lexicon CNN architecture itself can be seen in Figure 2. Max pooling has a stride of 2x2. All layers use ReLU. Lexicon CNN training process uses batch size 64 with 30 epochs. In this training process, training data is divided into 9:1 with validation data. In this process, 1,000 images for 59 classes were created so that there were 59,000 training data on each word list.

3.2. Character Count CNN
Character Count CNN works to recognize the number of characters in word image. In Character Count CNN, there are 16 classes, which represent the number of characters from 1 to 16. Character Count CNN also use synthetic word image as training data as in Lexicon CNN. In Character Count CNN, it uses words from a randomize characters so it may have no meaning. The characters used in making this word string are taken from 62 classes that will be recognized by the system, which can be seen in Figure 3.

Character Count CNN architecture itself can be seen in Figure 4. Max pooling has a stride of 2x2. Unlike Lexicon CNN, convolutional layer in Character Count CNN uses maxout. Character Count CNN training process uses batch size 32 with 50 epochs. In this training process, training data is divided into 9:1 with validation data. In this process, 1,000 images were also created for 16 classes so that there were 16,000 training data.

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**Figure 2.** Architecture of Lexicon CNN

**Figure 3.** Character Classes to be recognized
3.3. Character Prediction FCN

Character Prediction FCN works to recognize word images by reading character by character in the image using a sliding window. Recognizable characters can be seen in Figure 3. The training data image used is the character image on NIST SD19.

Later in the testing process, the input word image will have a size of $32 \times 16N$ where $N$ is the output of the Character Count CNN. Character Prediction FCN architecture can be seen in Figure 5. Max pooling has a stride of $2 \times 2$. All layers use ReLU. Character Prediction FCN training process uses batch size 64 with 50 epochs. In this training process, training data is divided into 9:1 with validation data. In each class, 1,467 images were used so that there were 90,954 training data images.

3.4. Evaluation

The evaluation process is carried out on each neural network and as a whole system. The evaluation process for each neural network is carried out using validation data from each neural network. For the evaluation of a single system, the evaluation uses test data written by 10 different people who each write 60-62 English words. This word image is written on the touch screen using black ink with different thicknesses and levels of transparency and has a white background. These images then go through a selection process in which the image with overlapping characters will be deleted from the test data.

In these four evaluations, the evaluation process is carried out by measuring accuracy, precision, recall, and F1-score. In Lexicon CNN and the whole system, the evaluation process is also carried out by calculating the character error rate (CER) to measure how far the word image read error. The CER equation can be seen in Equation (1) [3].

$$\text{CER} = \frac{R + D + I}{R + D + I + C}$$

where $R$ is the number of characters that have changed, $D$ is the number of characters that are deleted, $I$ is the number of characters that are increased and $C$ is the number of correct characters.
Before the evaluation process is carried out, the test data image will go through a pre-processing first so that the system can better recognize the word image. The pre-processing can be seen in Figure 6. This pre-processing is carried out to improve the ink used in writing, which is sometimes more transparent, by using Otsu thresholding. After that the word image will also be cut right into the word bounding box and then resized to 32x128, adjusted to the input size that has been installed on the neural network.

4. Results

4.1. Parameter Testing on Lexicon CNN

At Lexicon CNN, three trial scenarios will be carried out, namely testing on the regularizer type, testing on the optimizer type, and testing on the learning rate. The trials will be carried out on the Lexicon CNN on both Brown and Gutenberg word lists. The regularizers tested were L1 and L2. The optimizers tested were Adam, SGD, and RMSProp. The learning rates tested were 0.01, 0.001, and 0.0001. All these evaluation result will be shown in Table 1. In Lexicon CNN system, we use parameter that has best accuracy, which is using L2 regularizer, Adam optimizer, and a learning rate of 10e-4 in recognizing images based on a word dictionary. The best accuracy resulting from the use of parameters is 99.98% and the average CER is 0.01%.

| Table 1. Evaluation Result on Lexicon CNN |
|------------------------------------------|
| **Accuracy (%)** | **Precision (%)** | **Recall (%)** | **F1-score (%)** | **CER Avg (%)** |
| **Regularizer** | | | | |
| L1 | 99.76 | 99.77 | 99.76 | 99.76 | 0.14 |
| L2 | **99.93** | **99.93** | **99.93** | **99.93** | **0.05** |
| **Optimizer** | | | | |
| Adam | **99.93** | **99.93** | **99.93** | **99.93** | **0.05** |
| SGD | 99.81 | 99.82 | 99.81 | 99.81 | 0.01 |
| RMSProp | 99.78 | 99.79 | 99.78 | 99.78 | 0.02 |
| **Learning Rate** | | | | |
| 10e-3 | 99.93 | 99.93 | 99.93 | 99.93 | 0.05 |
| **10e-4** | **99.98** | **99.98** | **99.98** | **99.97** | **0.01** |
| 10e-5 | 99.97 | 99.97 | 99.97 | 99.97 | 0.03 |

4.2. Parameter Testing on Character Count CNN

In Character Count CNN, five trial scenarios will be carried out, namely testing the architecture, testing the regularizer type, testing the optimizer type, testing the learning rate, and testing the dropout. Architectural testing was carried out by comparing the performance of the character count on Lexicon CNN architecture and Character Count CNN architecture. The regularizers tested were L1 and L2. The optimizers tested were Adam, SGD, and RMSProp. The learning rates tested were 0.01, 0.001, and 0.0001. The dropouts tested were 0.1, 0.3, 0.5, 0.7, and 0.9. All these evaluation result will be shown in Table 2. In Character Count CNN, we use parameter that has best accuracy, which is using architecture same with Lexicon CNN, L2 Regularizer, Adam optimizer, learning rate 10e-4, and dropout 0.1.

The system is more able to provide good accuracy when using the same CNN architecture as the Lexicon CNN. This shows that the maxout activation function processes too many neurons, causing overfitting and causing the convolution process to take more time. The use of ReLU is considered sufficient because ReLU will give a value to all neurons that have a negative activation function, so that
these neurons are considered inactive. In Character Count CNN, the best accuracy is obtained when using the L2 regularizer with Adam optimizer, learning rate 0.001 and dropout 0.1.

4.3. Parameter Testing on Character Prediction FCN
In the Character Prediction FCN, three trial scenarios will be carried out, namely testing the optimizer type, testing the learning rate, and testing the dropout. The optimizers tested were Adam, SGD, and RMSProp. The learning rates tested were 0.01, 0.001, and 0.0001. The dropouts tested were 0.3, 0.5, 0.7, and 0.9. All these evaluation result will be shown in Table 3.

In Character Prediction FCN, we will use parameter that has best accuracy, which is using Adam optimizer, a learning rate of 10e-4 with an L2 regularizer and a dropout of 0.9. The best accuracy is 83.52%. In contrast to the CNN Character Count, the smaller the dropout, the better the accuracy will be for the model. The character prediction accuracy is not high enough because FCN has not been able to distinguish uppercase, lowercase and numbers properly.

Table 2. Evaluation Result on Character Count CNN

| CNN Architecture | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) |
|------------------|--------------|---------------|------------|--------------|
| Count Character CNN | 6.25 | 0.39 | 6.25 | 0.74 |
| Lexicon CNN     | **96.25** | **96.33** | **96.25** | **96.25** |
| Regularizer     |             |               |            |              |
| L1              | 96.06       | 96.20         | 96.06      | 96.06        |
| L2              | **96.25** | **96.33** | **96.25** | **96.25** |
| Optimizer       |             |               |            |              |
| Adam            | **96.25** | **96.33** | **96.25** | **96.25** |
| SGD             | 70.31       | 69.74         | 70.31      | 69.61         |
| RMSProp         | 96.06       | 96.12         | 96.06      | 96.06         |
| Learning Rate   |             |               |            |              |
| 10e-3           | 96.25       | 96.33         | 96.25      | 96.25         |
| **10e-4**       | **97.75** | **97.76** | **97.75** | **97.74** |
| 10e-5           | 59.00       | 59.72         | 59.00      | 58.22         |
| Dropout         |             |               |            |              |
| 0.1             | **98.56** | **98.57** | **98.56** | **98.56** |
| 0.3             | 98.19       | 98.21         | 98.19      | 98.18         |
| 0.5             | 97.75       | 97.76         | 97.75      | 97.74         |
| 0.7             | 95.69       | 95.97         | 95.69      | 95.97         |
| 0.9             | 94.19       | 94.26         | 94.19      | 94.18         |

4.4. Parameter Testing on the Whole System
In testing one whole system, three test scenarios will be carried out, namely testing the use of Lexicon CNN, testing on Lexicon CNN confidence levels, and testing on the sliding windows’ size. All these evaluation results will be shown in Table 4.

In Character Prediction FCN, the best accuracy is generated using the Adam optimizer, a learning rate of 0.001 with an L2 regularizer and a dropout of 0.9. The best accuracy is 83.52%. In contrast to the Character Count CNN, the smaller the dropout, the better the accuracy will be for the model. The
character prediction accuracy is not high enough because FCN has not been able to distinguish uppercase, lowercase and numbers properly.

| Table 3. Evaluation Result on Character Prediction FCN |
|------------------|------------------|------------------|------------------|------------------|
|                  | Accuracy (%)     | Precision (%)    | Recall (%)       | F1-score (%)     |
| Optimizer        |                  |                  |                  |                  |
| Adam             | 82.55            | 83.81            | 82.55            | 82.29            |
| SGD              | 81.87            | 82.36            | 81.87            | 81.79            |
| RMSProp          | 81.45            | 81.92            | 81.45            | 81.37            |
| Learning Rate    |                  |                  |                  |                  |
| 10e-3            | 82.55            | 83.81            | 82.55            | 82.29            |
| 10e-4            | **82.86**        | **83.48**        | **82.86**        | **82.78**        |
| 10e-5            | 82.29            | 82.96            | 82.29            | 81.96            |
| Dropout          |                  |                  |                  |                  |
| 0.3              | 81.85            | 84.98            | 82.85            | 82.54            |
| 0.5              | 82.86            | 83.48            | 82.86            | 82.78            |
| 0.7              | 82.95            | 83.51            | 82.95            | 82.90            |
| **0.9**          | **83.52**        | **84.42**        | **83.52**        | **83.29**        |

| Table 4. Evaluation Result on Overall System |
|------------------|------------------|------------------|------------------|------------------|
|                  | Accuracy (%)     | Precision (%)    | Recall (%)       | F1-score (%)     | CER Avg (%)     |
| Lexicon CNN Usage|                  |                  |                  |                  |                |
| Without Lexicon CNN | 4.43           | 12.36            | 4.43             | 5.49             | 63.08          |
| Using Lexicon CNN  | **57.31**       | **83.17**        | **57.31**        | **64.98**        | **29.86**      |
| Sliding Windows’ Size |               |                  |                  |                  |                |
| 32x16             | 57.31            | 83.17            | 57.31            | 64.98            | 29.86          |
| 32x32             | 56.91            | 82.59            | 56.98            | 64.67            | 35.19          |
| Confidence Level Limit |             |                  |                  |                  |                |
| 65%               | 68.80            | 83.45            | 68.80            | 73.97            | 22.25          |
| 70%               | 57.31            | 83.17            | 57.31            | 64.98            | 29.86          |
| 75%               | 46.80            | 79.65            | 46.80            | 55.60            | 36.81          |

5. Conclusion
Based on the trials that have been carried out, we can obtain many information. First, based on the test parameters on Lexicon CNN, the model that was built produced the best accuracy of 99.98% with an average CER of 0.01%. The best model was obtained with L2 regularizer, learning rate 0.001, and using Adam optimizer. Second, based on the test parameters in the Character Count CNN, the model that was built has the best accuracy of 98.56%. This model was obtained using L2 regularizer, same architecture with Lexicon CNN, learning rate 0.001, Adam optimizer, and dropout 0.1. Third, in Character Prediction, the model that was built produced the best accuracy of 83.52% for the introduction of 62 classes. The FCN Character Prediction Model has not been able to predict characters well, because it is still unable to distinguish between uppercase and lowercase letters and numbers. The best model was built using Adam optimizer, learning rate 0.001 and dropout 0.9. Fourth, based on testing on a single
system, the system is only able to produce an accuracy of 68.80% with an average CER of 22.25%. This was built using best model on Lexicon CNN, Character Count CNN, and Character Prediction FCN. This shows that the sliding windows algorithm has not been able to minimize the addition, replacement, and deletion of characters in reading handwritten images. In addition, here it can be seen that the recognition based on a word dictionary is indeed very helpful in handwritten text recognition. From all of these trials, we can see that Lexicon CNN helps a lot on handwritten recognition while we need to improve character prediction and the reading algorithm for every character on image. Moreover, there are some future works that need to be explored in the handwritten text recognition problem, such as how to handle text images with various colour ink, reading offline handwritten text, and automatic segmentation of word or letter in a sentence or paragraph image.

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