공학석사 학위논문

Data Augmentation of Sewing Machine Data for Task Recognition using Convolutional Neural Network

합성곱 신경망을 이용한 작업 인식에서 재봉틀 데이터의 데이터 증강에 관한 연구

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서울대학교 대학원

기계항공공학부

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Abstract

Data Augmentation of Sewing Machine Data for Task Recognition using Convolutional Neural Network

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Garment industry is labor−intensive and lowly automated. It leads to unreliable data and poor data transparency. Production tracking is important issue in garment industry. Power monitoring system using current sensor and convolutional neural network (CNN) algorithm was developed for production tracking. CNN has shown good performance in image or pattern recognition. However, CNN cannot show such a performance with limited training sets. Therefore, data augmentation has been introduced to overcome the lack of data. In this research, data augmentation methods for CNN which recognizes the task of sewing machine data are proposed. The data is 1−D time series data from a real garment factory in Indonesia. Among the collected data, 7 types of data are used. Proposed methods are based on the statistical analysis of the data. In the experiment, the accuracies of classification using real training data sets ranged from 90.0% to 96.0%, and that of augmented data sets ranged from 66.9% to 83.5%. Additionally, application was performed using proposed methods for real−time working data and the production counting ratio was 88.4%. This result showed that the accuracies of augmented data sets in some cases are enough high to apply in industry, but in other cases the accuracies are low. If further supplementation and improvements are made to increase accuracy, augmented data could be used in the early stages when the data lacks. This will help reduce data collection time and increase productivity in industry fields where CNN are used.

Keyword : Convolutional neural network, Garment industry, Sewing machine data, Task recognition

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Chapter 1. Introduction

1.1. Background

Garment industry is labor−intensive and lowly automated industry. The design, operation and analysis of production lines are performed by human resources. It leads to unreliable data and poor data transparency. Production tracking is important for determining the current production and optimizing the process line. For exactly and automatically tracking production, power monitoring system was developed. The system is using current sensor and convolutional neural network (CNN) algorithm [1−3].

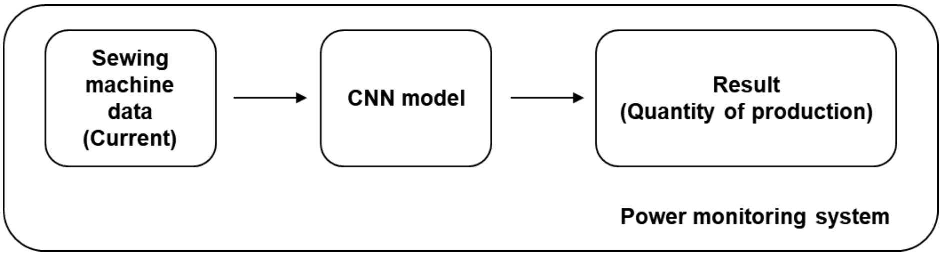


Figure 1 Power monitoring system schematic

Machine learning has been used in various fields such as image and speech recognition, autonomous car, predictive analytics and so on [4−9]. CNN, one of the machine learning algorithms, has shown good performance in pattern recognition or image recognition. For example, CNN−based framework proposed by Li Chen *et al.* [10] showed even better performance than human in certain task. However, in case of the lack of training datasets, the performance of machine learning decreases [11]. In Figure 2, accuracies of all algorithms increased when the amount of training datasets increased, showing that the amount of training datasets is critical.

In the garment factory, because the production line changes periodically, there is no enough time to collect sufficient data for learning. Therefore, in the garment factory, task counting system using machine learning algorithm, e.g. CNN, has faced challenging situation. At the initial stage of line change and production, the algorithm has low accuracy with a few data.

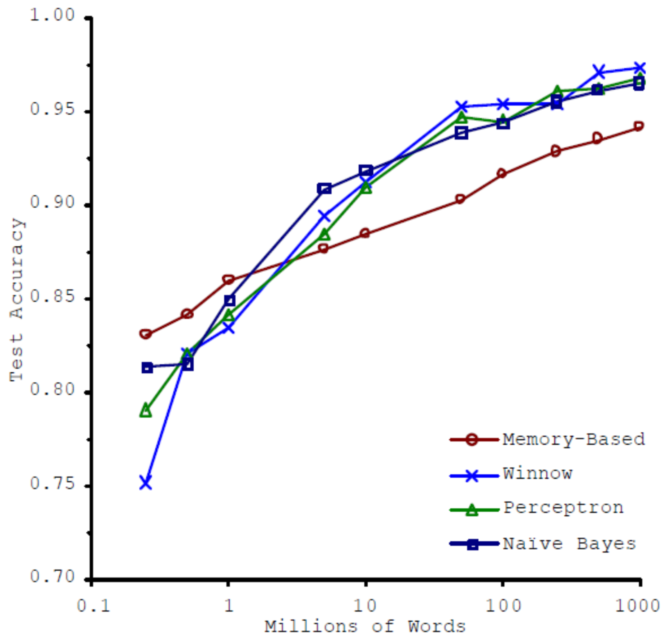


Figure 2 Learning curves for confusion set disambiguation [11]

Data augmentation can improve the performance of machine learning when the available training datasets are not sufficient [12-17]. Several data augmentation methods such as rotating, translating, cropping and so on can be used for neural net. When data augmentation is used, it is important to maintain the original characters of the data, which preserves the label of data. For example, data such as the electrical current value has x-directional dependency. Therefore, the current data cannot be transformed symmetrically, right and left.

1.2. Goal of Research

In this research, when classifying the pattern of current data acquired from garment factory in Indonesia, it was tried to overcome the lack of datasets using data augmentation. Collected data were labeled and divided into two classes – training sets and test sets. Then, statistical analysis was conducted to comprehend characteristics of the data. On the basis of this analysis, data augmentation methods for sewing machine data were proposed and verified by comparing two CNN models trained with actual and augmented data. Furthermore, proposed data augmentation methods were applied to a sewing machine in real production line of factory in Indonesia and task counting system for this machine was operated.

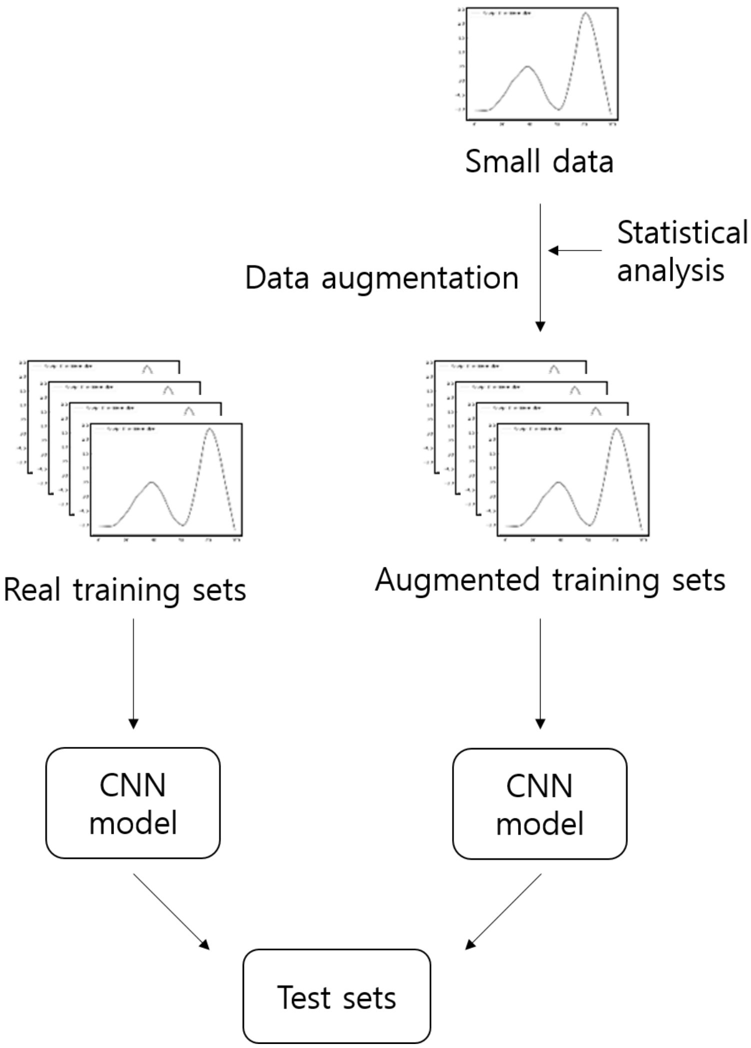


Figure 3 Goal of research

Chapter 2. Sewing Machine Data

2.1. Data Acquisition

Data used in this research were real industrial data, collected from garment factory in Indonesia. In factory there are thousands of sewing machines making different parts of clothes and dozens of sewing machines make up a production line for one kind of clothes. Flow of the data from factory in Indonesia to laboratory in Korea was shown in Figure 4. Smart plugs, devices that can measure the electrical current value and transmit it via WiFi, were installed at sewing machines. The sampling rate of smart plugs was 3Hz. Amazon web services (AWS) and MySQL were used for database.

Among the collected data from all different kinds of sewing task, seven kinds of task were selected. These were selected because the loss of data was low and the graph of data was clear. Figure 5 shows images of selected sewing tasks and the current graphs of the same tasks. The x−axis of the graph is data point meaning time, which 3 points are 1 second because the sampling frequency is 3 Hz.

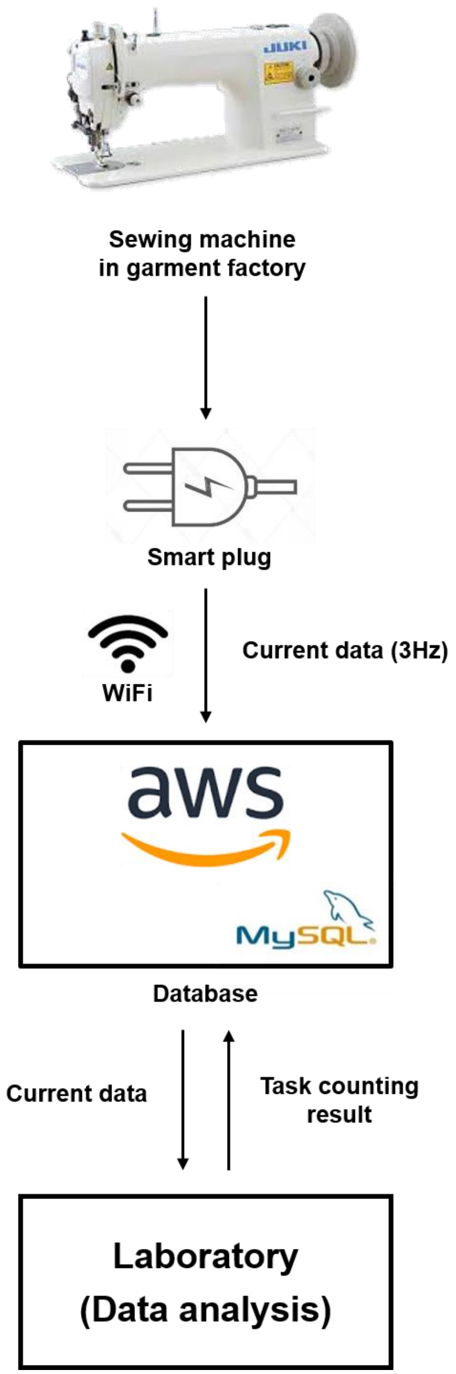


Figure 4 Diagram of data acquisition

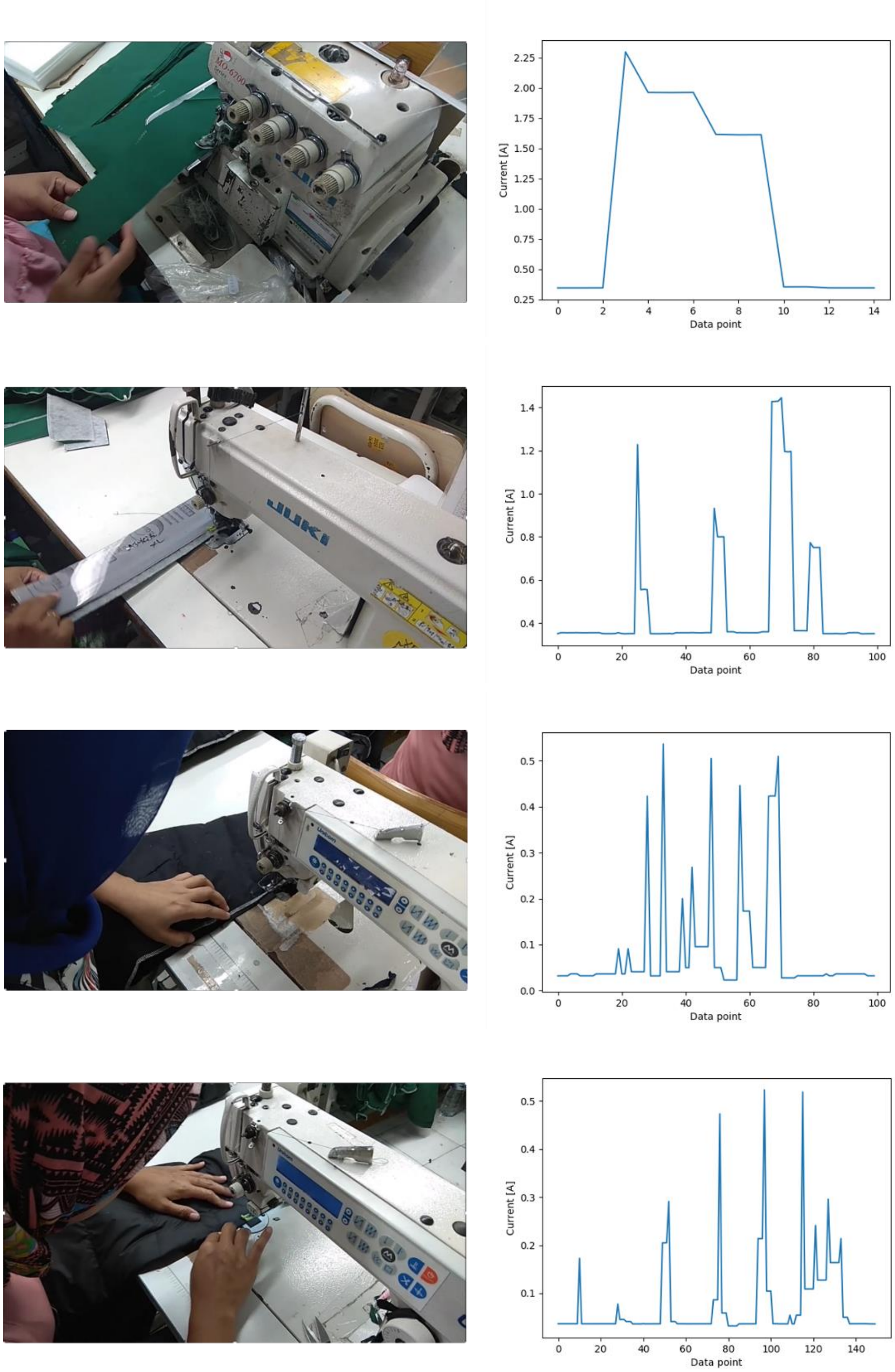


Figure 5 Images of sewing tasks (left) and the current graphs of the same tasks (right). Task numbers are task1 ~ task7 from top to bottom. (continue)

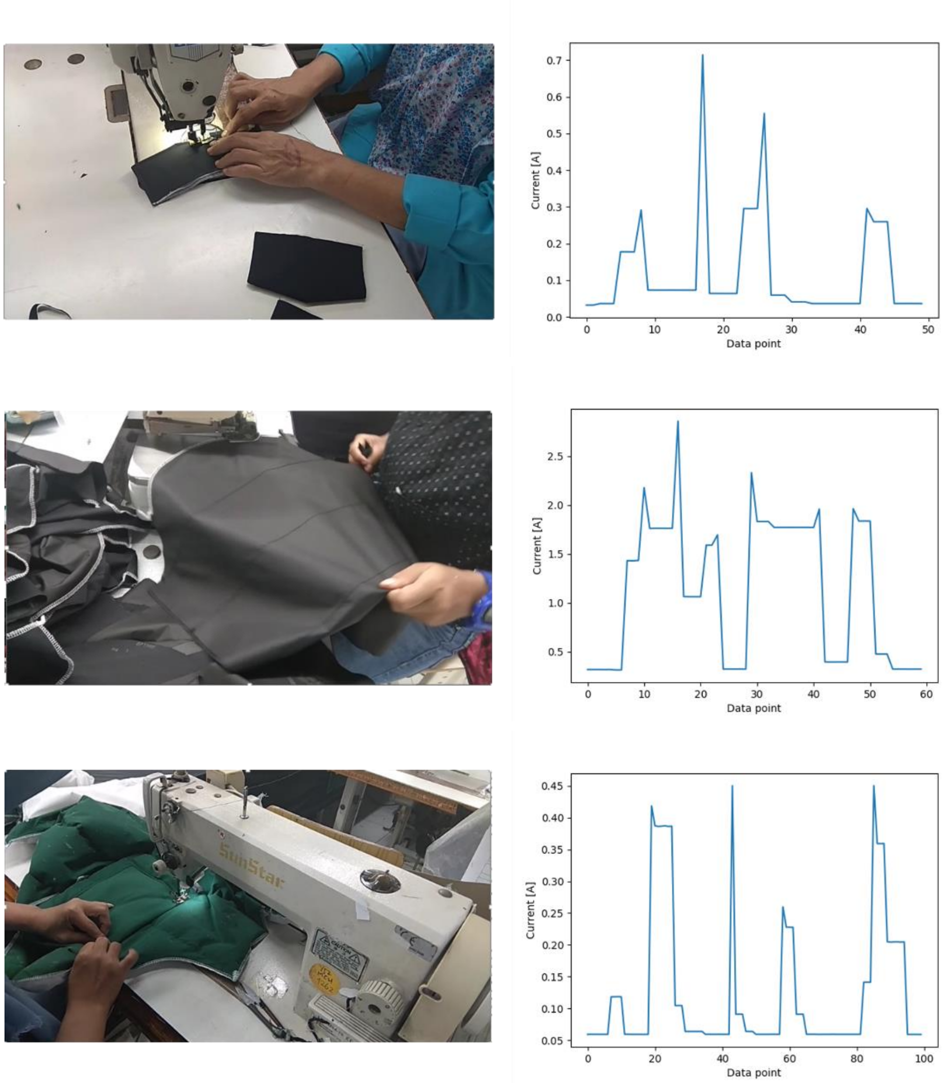


Figure 5 Images of sewing tasks (left) and the current graphs of the same tasks (right). Task numbers are task1 ~ task7 from top to bottom.

2.2. Data Processing

Selected data from seven kinds of sewing tasks were labeled as 1 or 0. When the sewing machine operator pushes the pedal and the sewing machine runs, the current value rises up instantaneously. The operator keeps on sewing a certain part of clothes, then the graph shows some peaks repeatedly, which forms a pattern. If the pattern of task is in the window, the data was labeled as 1 and if the pattern is not in the window, the data was labeled as 0. Figure 6 shows data labeling process. Labeled data were randomly divided into two datasets, training datasets and test datasets. The ratio of training datasets and test datasets was 7:3. The number of data between tasks was different. Table 1 shows the number of total datasets, training datasets and test datasets labeled as 1. The number of datasets labeled as 0 was the same with the label 1 datasets.

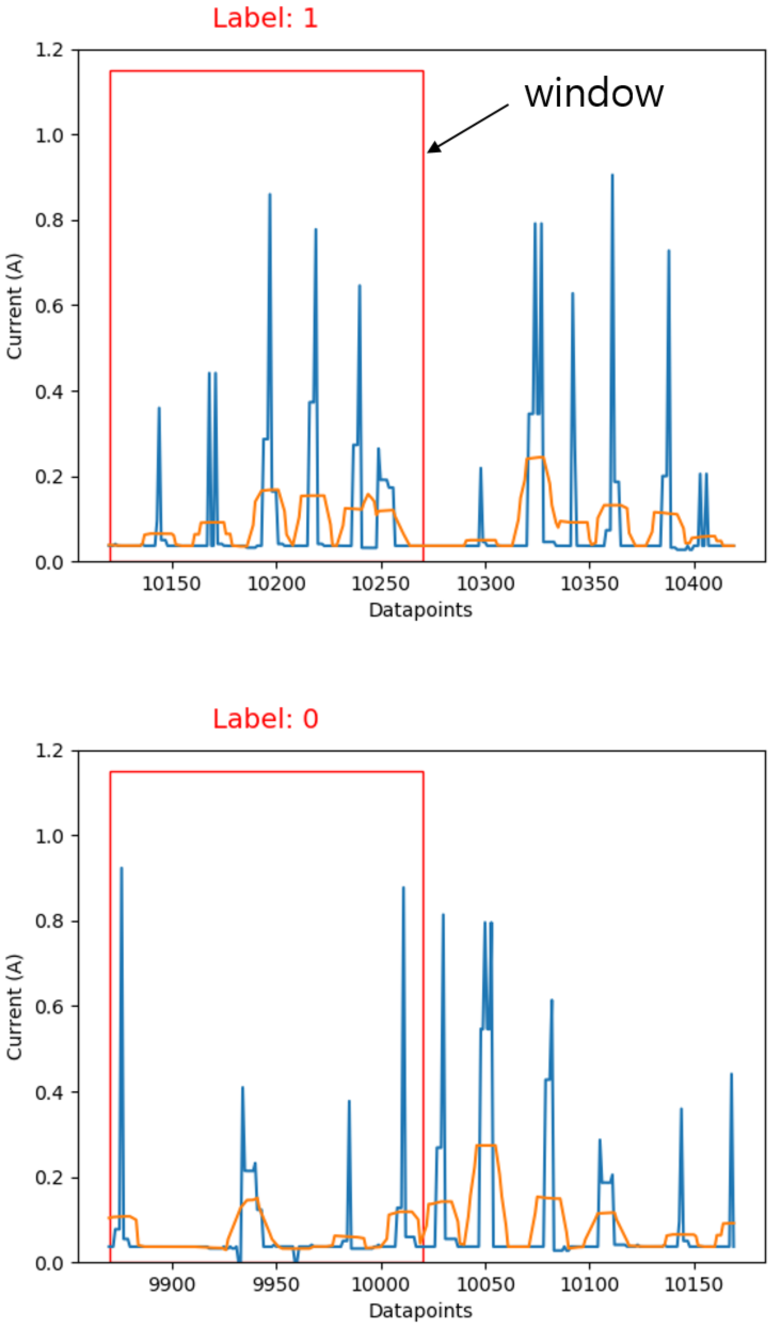


Figure 6 Process of data labeling

Table 1 The number of data labeled as 1

Task No.	Total datasets (Label1)	Training datasets (Label1)	Test datasets (Label1)
Task1	919	644	275
Task2	1223	857	366
Task3	2064	1445	619
Task4	1703	1193	510
Task5	905	634	271
Task6	803	563	240
Task7	466	327	139

2.3. Statistical Analysis

Area distribution of datasets labeled as 1 were investigated. The area histograms of task1 ~ task7 are shown in the Figure 7 and statistical values – skewness, kurtosis and standard deviation – are shown in Table 2. The absolute values of skewness from all each task were lower than 3 and the absolute values of kurtosis from all each task were lower than 8. Therefore, area distribution of all tasks could be regarded to follow a normal distribution [18].

In a graph of the current value, the area means consumed energy. Because the area distribution followed normal distribution, consumed energy during a sewing task could be considered constant at a certain value. It formed a basis for data augmentation method of sewing machine data.

However, there is variation in actual area values, it also should be considered for data augmentation. Using z–value of normal distribution, area ratio defined as (1) was calculated, which was used for a range of data augmentation.

$$\text{ratio} = \frac{A \pm z \times \sigma}{A} \tag{1}$$

where A is the area of the current data, z is 0.98 or 0.49 and σ is standard deviation in Table 2.

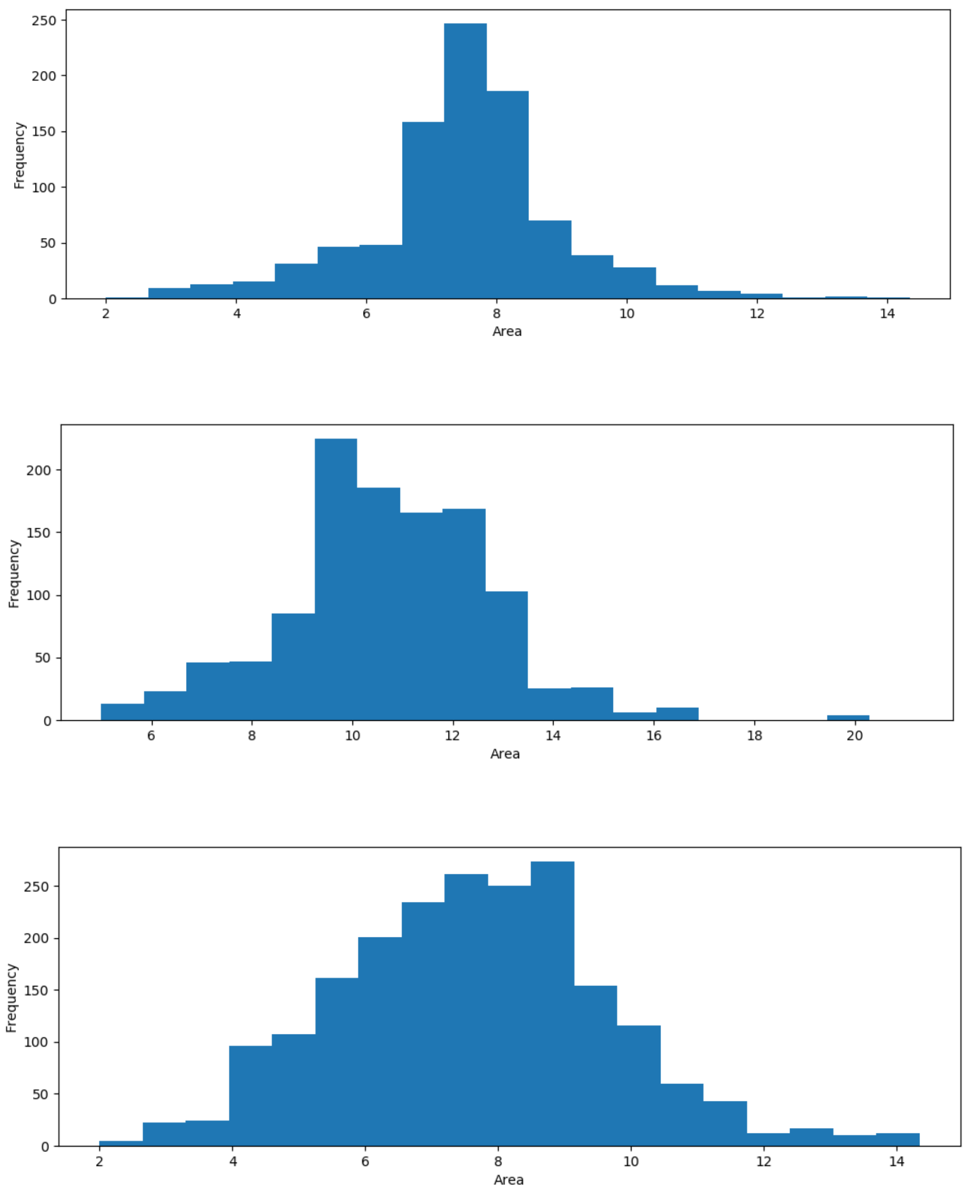


Figure 7 Area histograms of the current data of task1 ~ task7 (continue)

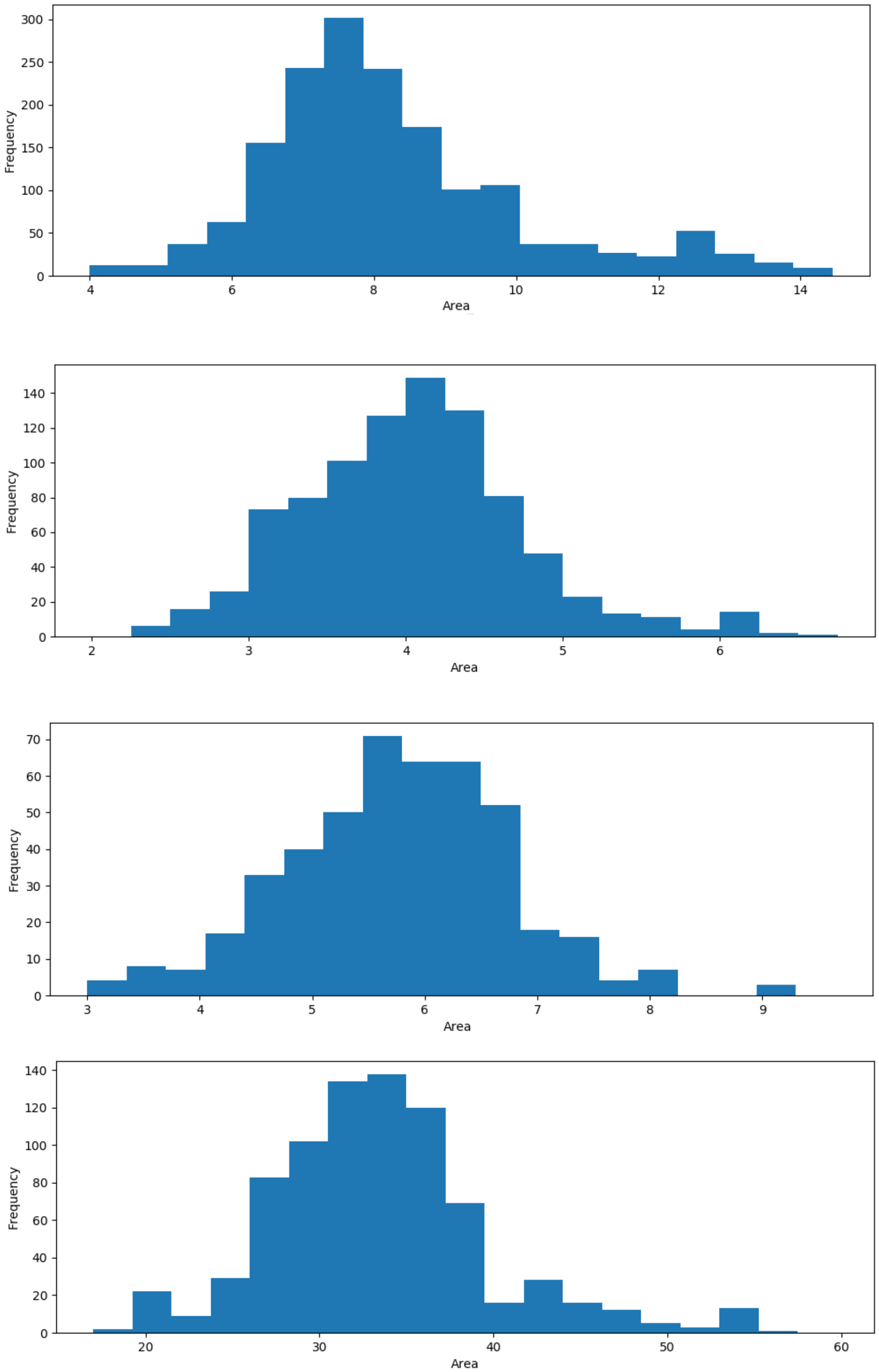


Figure 7 Area histograms of the current data of task1 ~ task7

Table 2 Statistical values of area distribution of task1 ~ task7

Task No.	Skewness	Kurtosis	Standard deviation
Task1	0.006	2.1228	1.53
Task2	0.4051	2.1863	2.11
Task3	0.259	0.2338	2.05
Task4	1.0345	1.1258	1.86
Task5	0.4787	0.7145	0.7
Task6	0.8189	1.7223	6.29
Task7	−0.0222	0.6183	0.98

Table 3 Ratio of area of task1 ~ task7

z−value / Task No.	−0.98	−0.49	0	0.49	0.98
Task1	0.81	0.91	1	1.10	1.19
Task2	0.8	0.90	1	1.10	1.2
Task3	0.72	0.86	1	1.14	1.28
Task4	0.77	0.89	1	1.12	1.23
Task5	0.84	0.92	1	1.08	1.16
Task6	0.81	0.91	1	1.10	1.19
Task7	0.81	0.91	1	1.10	1.19
Average	0.79	0.90	1	1.10	1.21

Chapter 3. Data Augmentation

3.1. Data Augmentation Methods

Data augmentation methods for sewing machine data labeled as 1 were proposed. Three methods were proposed and these were based on the result of 2.3. Statistical Analysis. Figure 8 shows three data augmentation methods and Table 4 shows the number of samples used for data augmentation, the number how many data augmentation method increased the data and the number of real datasets.

First method was to make area variations. In 2.3. Statistical Analysis, area distributions followed normal distributions. It means that areas of the current graph during real sewing task are distributed in some ranges. There are two available methods in making area variations. One is to change the width of the graph while maintaining height and the other is vice versa. In this research, the second method was used because changing height is simpler and has less data loss. The x-axis of the graph is time, so maintaining the width means that the time required for sewing task is assumed as consistent. Range of area variation was from Table 3. The last row, average, was used for data augmentation. It was 0.79, 0.90, 1, 1.10

and 1.21.

Second method was to make width and height variations. In 2.3. Statistical Analysis, area distributions followed normal distribution. Therefore, the assumption that area is constant at a certain value during the same sewing task was made. Therefore, width and height were changed simultaneously in order to maintain the area. Range of variation was calculated from the analysis of height distribution. The calculated figure was rounded up from the second decimal place for the limit of the number of data points. It was 0.8, 1 and 1.2.

Third method was to translate parallel. If the pattern of a task is in the window regardless of whether it is left side, right side or in the middle, the label is 1, which means it is a task. Translations was done for the number of augmented data to be similar to the number of real data. It was because the effect of the amount of data should be minimized.

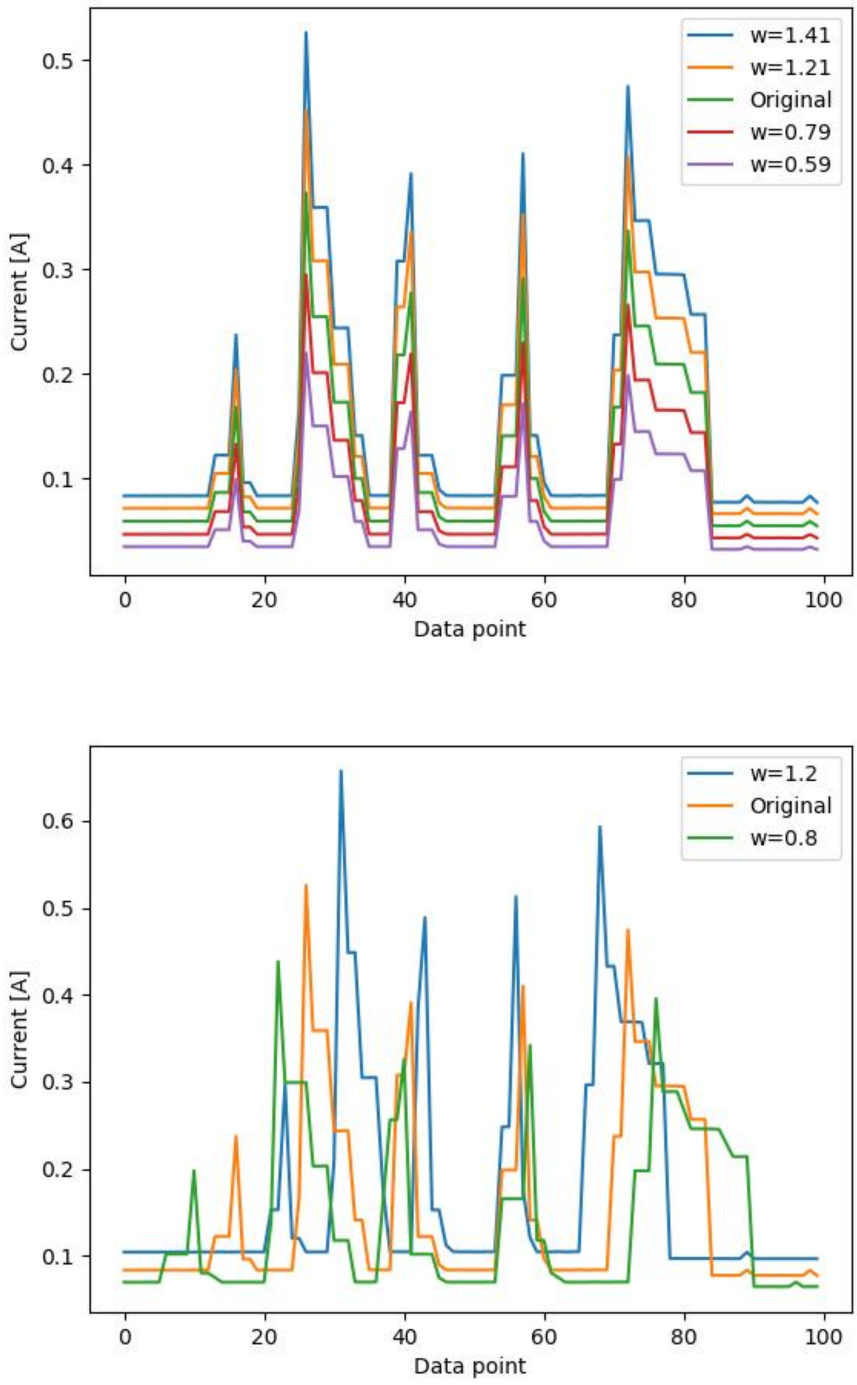


Figure 8 Data augmentation methods (continue)

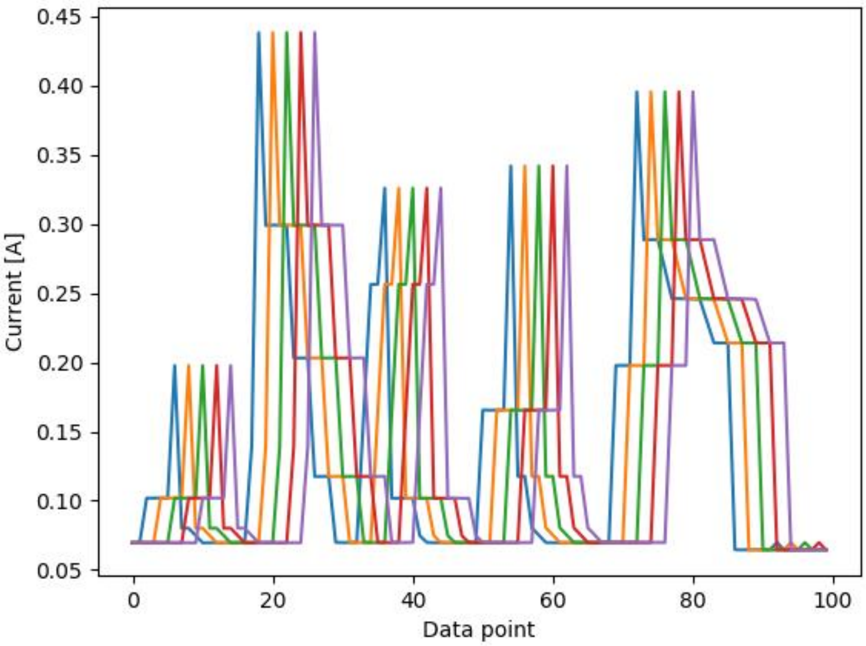


Figure 8 Data augmentation methods

Table 4 The number of samples for data augmentation, the number how many each method increased the data and the number of data labeled as 1 of data augmentation case and real case.

Task No.	Samples	Method1	Method2	Method3	Data augmentation (Label 1)	Real (Label1)
Task1	9	5	3	5	675	644
Task2	5			11	825	857
Task3	9			11	1485	1445
Task4	7			11	1155	1193
Task5	6			7	630	634
Task6	5			7	525	563
Task7	5			5	375	327

3.2. CNN Architecture

CNN architecture used in this research is shown in Figure 9. It was consisted of seven convolution and pooling layers. From the first layer to the last layer, each layer had 32−64−128−128−256−256−512 filters. Activation function was rectified linear unit (ReLU) and padding was same padding for all layer.

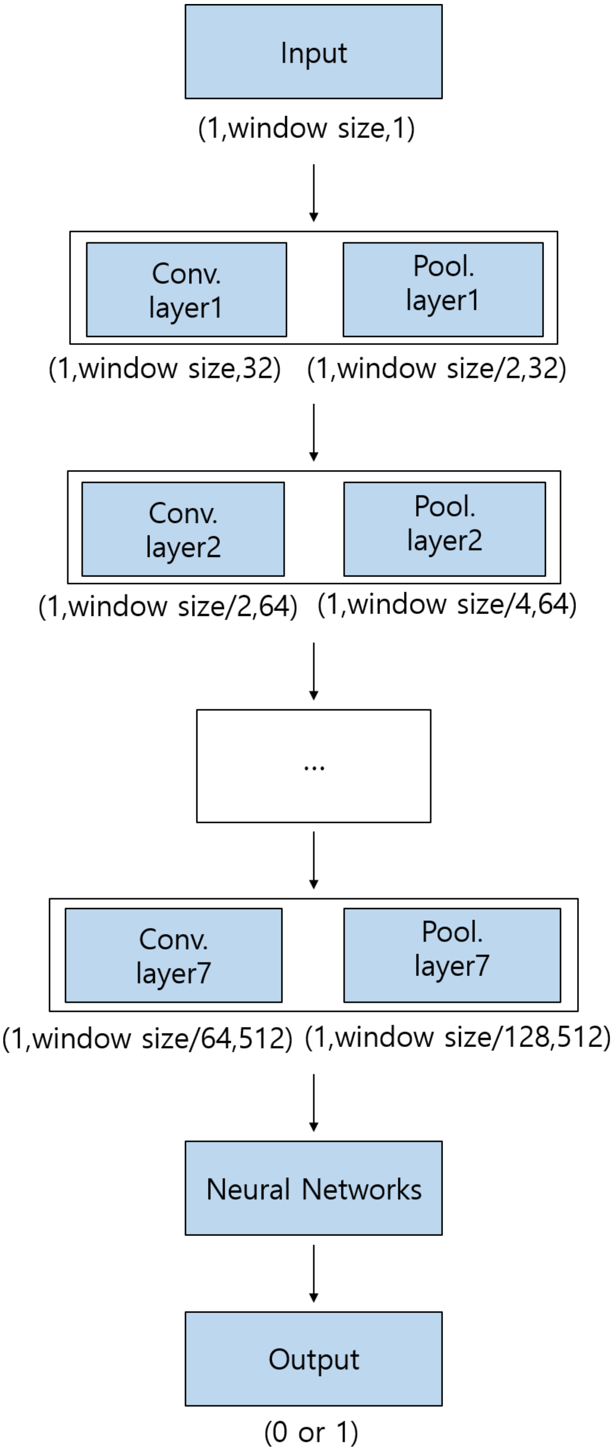
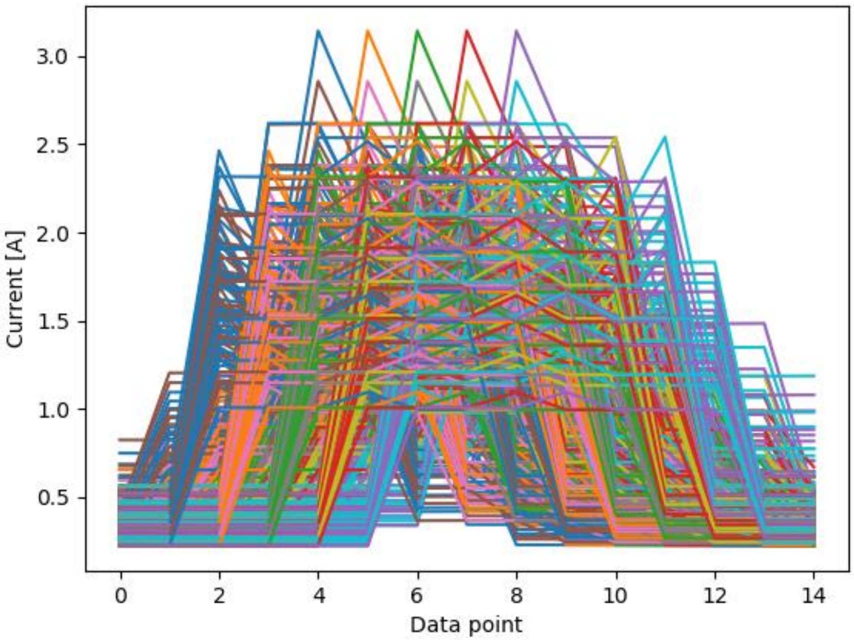


Figure 9 CNN architecture

3.3. Results

Proposed data augmentation methods were applied to seven kinds of tasks. Data augmentation was applied to only data labeled as 1 and the same data labeled as 0 with real case were used for data augmentation case. From each task, samples for data augmentation were selected randomly as the number determined in Table 4. Test datasets were the same in real case and data augmentation case.

Figure 10 shows the graphs of the entire data labeled as 1 made by data augmentation, from task 1 to task 7. Two CNN models trained with real datasets and augmented datasets respectively were compared. Test accuracies in real case ranged from 90.0% ~ 96% and test accuracies in data augmentation case ranged from 66.9% ~ 83.5%. These results are shown in Table 5.



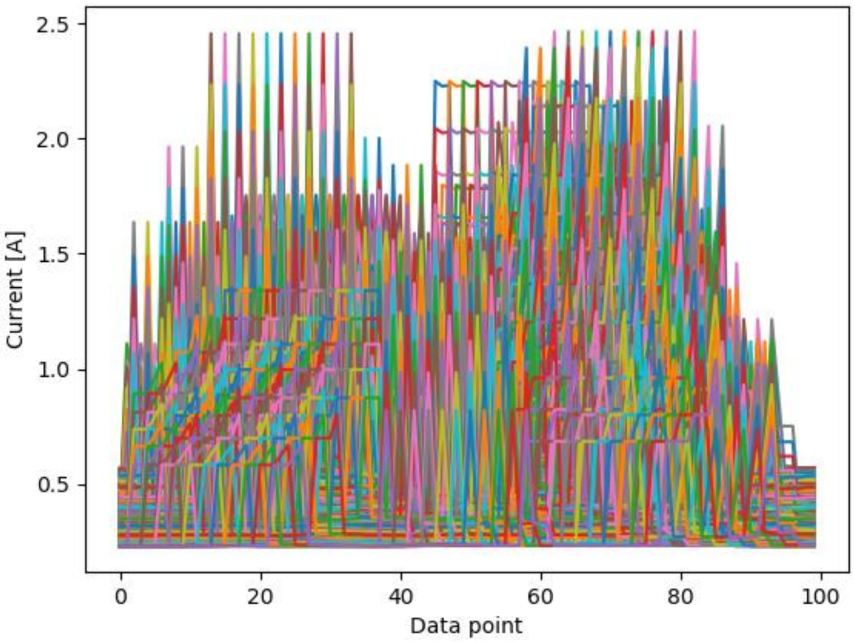
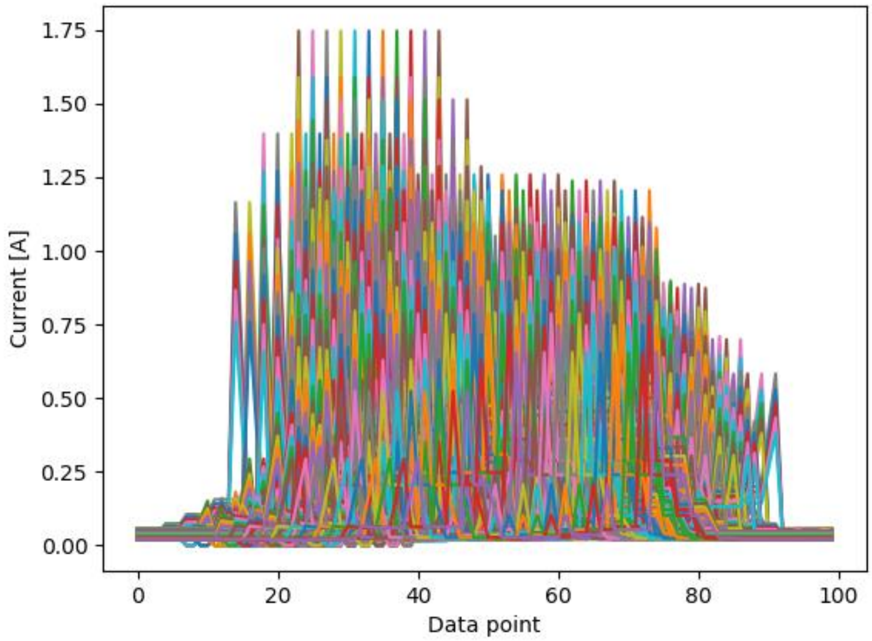


Figure 10 Graphs of augmented entire data labeled as 1 of task1 ~ task7 (continue)



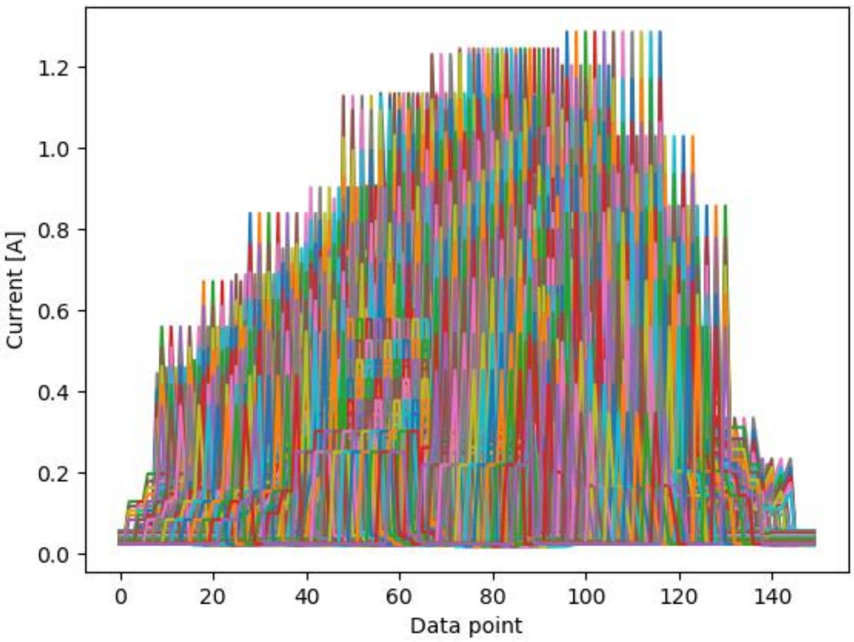
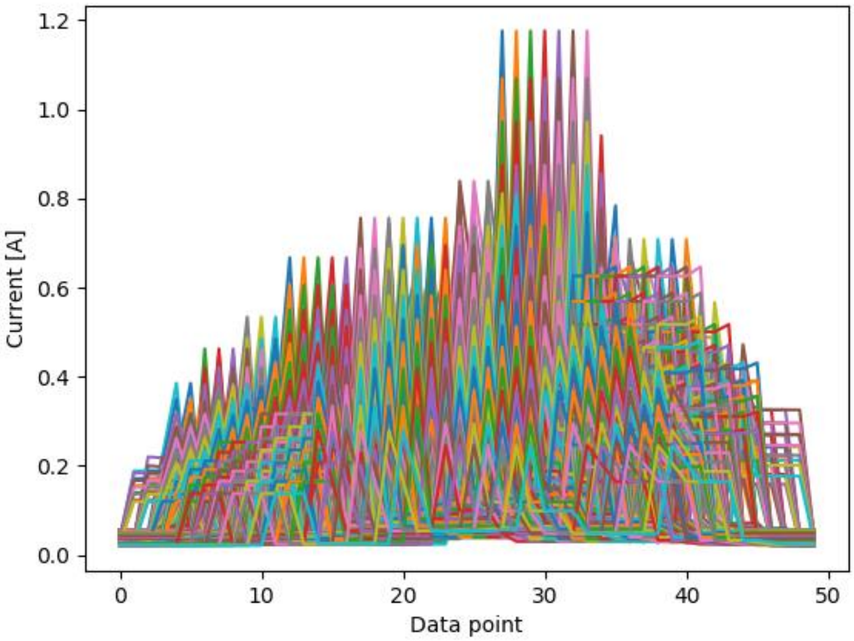


Figure 10 Graphs of augmented entire data labeled as 1 of task1 ~ task7 (continue)



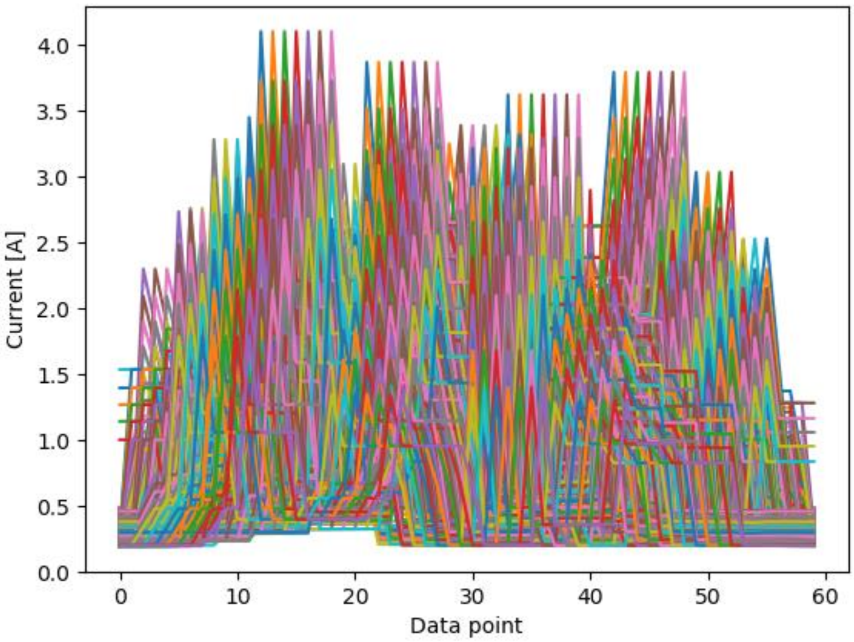


Figure 10 Graphs of augmented entire data labeled as 1 of task1 ~ task7 (continue)

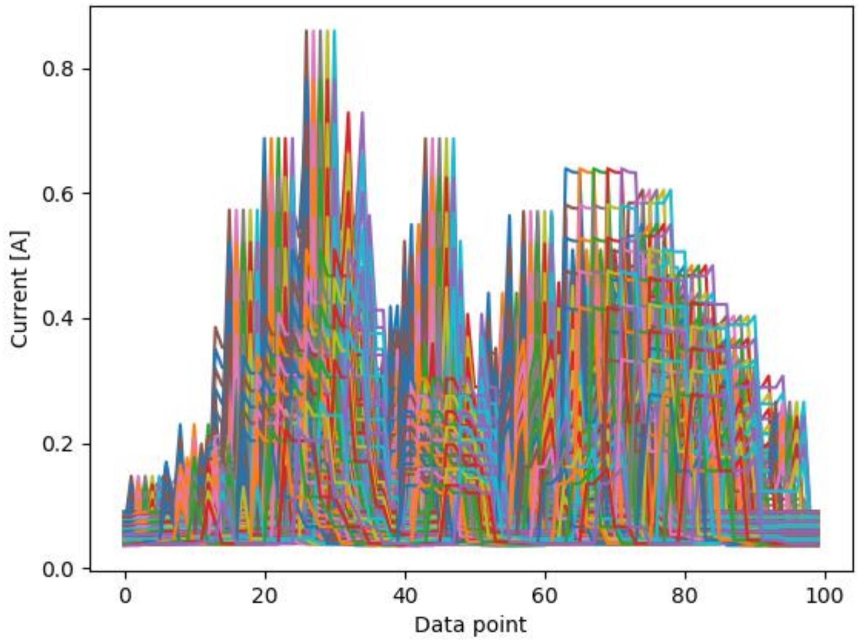


Figure 10 Graphs of augmented entire data labeled as 1 of task1 ~ task7

Table 5 Accuracies of CNN trained with real data and augmented data

Task No.	Accuracy (%)	
	Real	Data augmentation
Task1	96.0	78.5
Task2	90.7	72.4
Task3	92.7	73.7
Task4	93.7	67.8
Task5	90.0	74.7
Task6	91.0	66.9
Task7	92.1	83.5

Chapter 4. Application

4.1. Task Counting

Task counting using the CNN model trained in 3.3. Results was conducted. Data used for task counting was the same sewing task data with experimental datasets, but the date was different. It was collected from 08:00 to 20:30 on April 23, 2019 in local time. The result of task counting is shown in Table 6. The exact number of the production on this day was 250. The ratio was calculated as the number of counting divided by the number of the production. The ratio of real case ranged from 73.2% ~ 108.0% and the ratio of data augmentation case ranged from 43.6% ~ 91.6%. Task1 could not be counted because of the data loss.

Table 6 Task counting of real case and data augmentation case

Task No.	Real		Data augmentation	
	Number	Ratio (%)	Number	Ratio (%)
Task1	.	.	.	.
Task2	238	95.2	186	74.4
Task3	240	96.0	207	82.8
Task4	270	108.0	229	91.6
Task5	261	104.4	216	86.4
Task6	183	73.2	109	43.6
Task7	226	90.4	219	87.6

4.2. Task Counting System

Task counting system for a sewing machine was developed and operated. The system consisted of downloader and analyzer. Algorithm of this system is shown in Figure 11. Downloader downloads the previous 30 minutes of real-time data from the factory in Indonesia every 30 minutes. If the download finishes, the analyzer automatically begins the analysis and the result is recorded in a digital file. The analyzer used the CNN model and data augmentation was applied. Without data augmentation method, it takes whole day to collect sufficient data for training. However, with the proposed data augmentation method, the initial data of 30 minutes of a day were used for training. Seven patterns were extracted and data augmentation was applied to these patterns. CNN models were trained with these augmented datasets. Using this CNN model, the system was operated in a whole day and the result is shown in Table 7. Total number of counted productions was 221 and real production was 250, so the ratio was 88.4%.

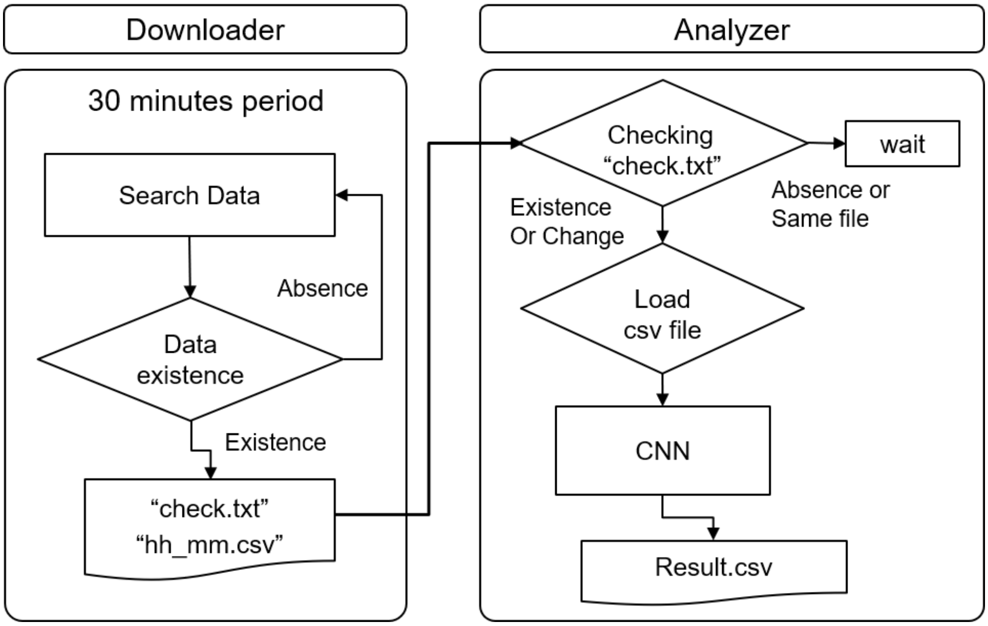


Figure 11 Algorithm of task counting system

Table 7 The result of operating task counting system

Time	Task
07:30 ~ 08:00	7
08:00 ~ 08:30	20
08:30 ~ 09:00	14
09:00 ~ 09:30	13
09:30 ~ 10:00	13
10:00 ~ 10:30	17
10:30 ~ 11:00	19
11:00 ~ 11:30	18
11:30 ~ 12:00	12
12:00 ~ 12:30	18
12:30 ~ 13:00	0
13:00 ~ 13:30	3
13:30 ~ 14:00	8
14:00 ~ 14:30	0
14:30 ~ 15:00	8
15:00 ~ 15:30	8
15:30 ~ 16:00	29
16:00 ~ 16:30	14
Total	221

Chapter 5. Conclusion

Sewing machine data of real industrial factory in Indonesia were collected using smart plug. These data were analyzed statistically and based on this analysis data augmentation methods were proposed. Proposed methods were applied to seven kinds of data among the collected data, CNN models were trained with two datasets, real datasets and augmented datasets respectively. Accuracies of these model were 90.0% ~ 96% in real case and 66.9% ~ 83.5% in data augmentation case. Using these models, task counting for another day were conducted. Also, task counting system with data augmentation method was developed and operated for one day.

The accuracy of the CNN model trained with augmented datasets was lower than that of real datasets. However, accuracy of some tasks was higher than 80%, which means that if data augmentation method is modified, there is a possibility to increase the accuracy. Furthermore, although test accuracies were lower, the ratios of task counting in Chapter 4. Application were higher a little than accuracies. It means that task counting in real field can show better performance.

Bibliography

[1] Z. Guo, "Intelligent production control decision-making for apparel manufacturing process," The Hong Kong Polytechnic University, 2008.

[2] Z. Guo, W. Wong, and C. Guo, "A cloud-based intelligent decision-making system for order tracking and allocation in apparel manufacturing," *International Journal of Production Research,* vol. 52, no. 4, pp. 1100-1115, 2014.

[3] Z. Guo, E. Ngai, C. Yang, and X. J. I. j. o. p. e. Liang, "An RFID-based intelligent decision support system architecture for production monitoring and scheduling in a distributed manufacturing environment," vol. 159, pp. 16-28, 2015.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," in *Advances in neural information processing systems*, 2012, pp. 1097-1105.

[5] A. Graves, A.-r. Mohamed, and G. Hinton, "Speech recognition with deep recurrent neural networks," in *2013 IEEE international conference on acoustics, speech and signal processing*, 2013, pp. 6645-6649: IEEE.

[6] A.-r. Mohamed, G. E. Dahl, G. J. I. t. o. a. Hinton, speech,, and

l. processing, "Acoustic modeling using deep belief networks," vol. 20, no. 1, pp. 14-22, 2011.

[7] S.-M. Lee, S. M. Yoon, and H. Cho, "Human activity recognition from accelerometer data using Convolutional Neural Network," in *Big Data and Smart Computing (BigComp), 2017 IEEE International Conference on*, 2017, pp. 131-134: IEEE.

[8] M. Frid-Adar, I. Diamant, E. Klang, M. Amitai, J. Goldberger, and H. J. N. Greenspan, "GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification," vol. 321, pp. 321-331, 2018.

[9] A. Mikołajczyk and M. Grochowski, "Data augmentation for improving deep learning in image classification problem," in *2018 international interdisciplinary PhD workshop (IIPhDW)*, 2018, pp. 117-122: IEEE.

[10] L. Chen, S. Wang, W. Fan, J. Sun, and S. Naoi, "Beyond human recognition: A CNN-based framework for handwritten character recognition," in *2015 3rd IAPR Asian Conference on Pattern Recognition (ACPR)*, 2015, pp. 695-699: IEEE.

[11] M. Banko and E. Brill, "Scaling to very very large corpora for natural language disambiguation," in *Proceedings of the 39th annual meeting on association for computational linguistics*, 2001, pp. 26-33: Association for Computational Linguistics.

[12] H. I. Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P.-A. J. a. p. a. Muller, "Data augmentation using synthetic data for time series classification with deep residual networks," 2018.

[13] L. Perez and J. J. a. p. a. Wang, "The effectiveness of data augmentation in image classification using deep learning," 2017.

[14] J. Salamon and J. P. J. I. S. P. L. Bello, "Deep convolutional neural networks and data augmentation for environmental sound classification," vol. 24, no. 3, pp. 279-283, 2017.

[15] N. Takahashi, M. Gygli, B. Pfister, and L. J. a. p. a. Van Gool, "Deep convolutional neural networks and data augmentation for acoustic event detection," 2016.

[16] T. T. Um *et al.*, "Data augmentation of wearable sensor data for parkinson's disease monitoring using convolutional neural networks," in *Proceedings of the 19th ACM International Conference on Multimodal Interaction*, 2017, pp. 216-220: ACM.

[17] Z. Wang and O. J. a. p. a. Veksler, "Location Augmentation for CNN," 2018.

[18] R. B. Kline, *Principles and practice of structural equation modeling*. Guilford publications, 2015.

Abstract in Korean

의류 산업은 노동 집약적이며 자동화가 덜 진행된 산업 분야이다. 이 때문에 생산 데이터들의 신뢰성과 투명성이 낮다. 의류 산업에서 생산량 측정은 매우 중요한 일이다. 생산량을 정확하고 자동으로 측정하기 위해 파워 모니터링 시스템이 개발되었다. 이 시스템은 전류 센서와 합성곱 신경망 알고리즘을 사용한다. 합성곱 신경망은 사진이나 패턴 인식 분야에서 좋은 성능을 보여주고 있다. 하지만 데이터의 수가 부족한 상황에서는 그렇지 못하며, 이를 극복하기 위해 데이터 증강 방법이 사용되곤 한다. 본 연구에서는 재봉틀 작업량을 측정하는 합성곱 신경망을 위한 데이터 증강 방법을 제시한다. 재봉틀 데이터는 1차원 시계열 데이터이며 실제 인도네시아의 공장에서 얻은 것이다. 수집된 데이터 중 7 종류의 작업에 대해 연구를 진행하였다. 제시된 데이터 증강 방법은 이 데이터들의 통계적 분석에 근거하였다. 실험 결과 실제 데이터 셋을 사용한 모델의 정확도는 90.0%~96.0% 였고, 증강된 데이터 셋을 사용한 모델의 정확도는 66.9%~83.5% 였다. 추가로 제시된 데이터 증강 방법을 실제 실시간 작업에 대해 적용해 보았고, 작업 측정 비율은 88.4% 였다. 이 결과는 일부 작업에서는 데이터 증강 방법이 효과가 있어 실제 현장에 사용될 수 있으나, 몇 작업에서는 정확도가 너무 낮아 그렇지 못함을 보여준다. 추가적인 보완과 개선을 통해 데이터 증강 방법을 수정하여 정확도를 올린다면, 데이터가 부족한 산업 현장에서 증강된 데이터를 활용할 수 있을 것이다. 이를 통해 합성곱 신경망이 사용되는 산업에서 데이터 수집 시간을 줄이고 생산성을 향상시키는데 도움이 될 수 있을 것이다.