Abstract

Energy Monitoring System for Smart Factory Applications in Textile Industries

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Many processes in the garment industry, such as the sewing process, still rely on manual labor. Production tracking is crucial not only for determining the current production rate but also for optimizing the process line through line balancing; however, current methods of manually counting finished products are time consuming and prone to error. Other solutions are costly and thus prevent many Small and Medium-sized Enterprises (SMEs) from implementing these technologies. In this thesis, a production tracking system that uses the sewing machines' energy consumption patterns for the Convolutional Neural Network (CNN) classifier to track the total number of sewing tasks completed is proposed. This system was tested on two target sewing tasks and was able to detect and count all five tasks. The maximum classification accuracy of the CNN model obtained was 98.6%.

Keyword : convolutional neural networks; energy monitoring; sewing process; production tracking; smart sensor; smart factory;

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Chapter 1. Introduction

1.1. Study Background

The garment industry is one of the most labor-intensive sectors in the manufacturing industry. With difficulties in automation, the sewing process still relies on hundreds and thousands of workers to produce a finished product. A typical sewing process line can be seen in Figure 1. However, varying worker skills and conditions make it difficult to optimize the production line. In order to reduce manufacturing costs, avoiding bottlenecks in the process line to ensure a smooth material flow is essential. It is crucial to obtain real-time production data for line balancing and production scheduling to avoid these bottlenecks [1-3].

Figure 1 Sewing process line (Hojeon, Ltd.)

The intense competition in the garment industry is further increasing as SMEs are unable to afford costly solutions for production tracking and therefore, rely on manual recording methods, which not only generate unreliable data and low production transparency, but also prevent access to this data in real-time [4]. A low-cost solution must be found to encourage the implementation of new technologies for SMEs seeking to improve their current production methods.

The most common method for production tracking involves the use of Radio Frequency Identification (RFID). These RFID tags are attached to the garment workpieces with readers installed to each sewing machine. This technology is typically implemented along with other Internet of Things (IoT) solutions and enterprise application software in order to ensure large-scale connectivity and data management [4-11]. However, the use of RFID tags involves high initial costs due to the required equipment, such as the RFID readers and other expenses for making the current system compatible with this technology [12].

Other methods involve the use of sensors attached to the sewing machine to detect and count the number of finished products. Xiao et al. developed a counting system using optoelectronic switch sensors for detection and microcontrollers for handling the counting logic [13]. However, little information about the hardware and the installation procedure is provided by the author.

Within the trend of smart factory, more industries are implementing IoT-based technologies into their production and manufacturing processes. One of the popular applications is energy monitoring, where the energy consumption pattern of various machines and equipment is continuously monitored for different applications, from energy savings to machine diagnostics and prognostics [14-17]. This is usually achieved through smart meters, where such devices are attached to the target equipment to measure the current consumption and sometimes voltage. These IoT-based monitoring devices have allowed many industries to easily adopt energy management practices due to the simple installation process and low costs; the use of wireless connectivity can significantly reduce the costs for wiring, which tend to be more expensive than the sensor itself [18-19]. It is, therefore, worth considering energy monitoring as a low-cost method for production tracking.

Once the data is obtained from the IoT-based devices, the benefits obtained from them highly depend on the analysis method. Various analysis techniques are available, with a popular choice being artificial intelligence algorithms, including genetic algorithms, fuzzy logic, neural networks (NN), and so on. However, in the garment industry, NN have been implemented the most [20-23]. They can both be used for function approximation or classification, especially for those that involve nonlinear and complex relationships between the input and the output. For supervised learning, in which the input and output pairs are known and can be used

for training the algorithms, two main algorithms are used for NN: feedforward and backpropagation algorithm. The former is used for calculating the output based on the input and the weight values in the hidden layers. The latter is used for training the NN model by adjusting the weight values in such a manner that the loss function, which is a function that calculates the error between the calculated output and the true value, can be minimized. Different optimization algorithms can be used to minimize this loss function in order to obtain the NN model that generates the least amount of prediction error. With proper implementation, the input can be mapped to the output with great performance without the need to clearly understand the relationship between the two, hence the ubiquitous use for data analysis. Guo, et al. and Ngai, et al. reviewed the applications of different artificial intelligence algorithms in the textile industry[21, 23]. However, no applications covered the automation of sewing task counting or the use of the energy consumption patterns of sewing machines for other purposes.

1.2. Purpose of Research

In this research, a sewing production tracking system that monitors the energy consumption of sewing machines to automatically count the sewing tasks completed is proposed. An IoT-based energy monitoring device for the sewing machines is developed to achieve real-time data acquisition. This energy consumption data is then used as an input for the CNN classifier in order to detect the sewing tasks completed.

Chapter 2. Development of Sewing Production Tracking System

The sewing production tracking system uses the energy consumption data obtained from the sewing machines as input for the CNN classifier to determine how many sewing tasks have been completed. As shown in Figure 2, this system is mainly divided into three parts: energy monitoring device, cloud server, and data processing algorithm.

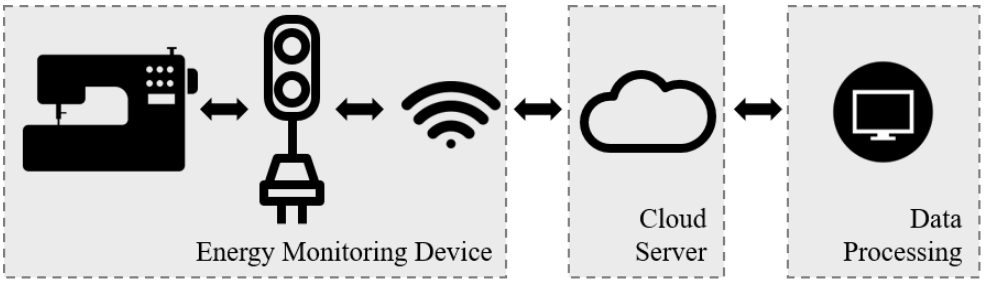

Figure 2 Overall schematic of sewing production tracking system

2.1. Energy Monitoring Device

In order to measure the energy consumption of sewing machines, an energy monitoring device was developed. This device must have a high enough sampling frequency to capture the rapid changes in the energy consumption during the sewing tasks and a communication method for storing data to a cloud server. Commercial products, such as smart plugs or smart meters, were considered but not used due to the low sampling rate, limited access to raw data, and in some cases, difficult installation process. Therefore, devices that overcame these issues were developed and fabricated. The target specifications are shown in Table 1.

Table 1 Target specifications for the energy monitoring device

Communication method	WiFi
Messaging protocol	MQTT (Message Queuing Telemetry Transport)
Sampling rate	> 4 Hz
Power Source	220VAC (50-60 Hz)
Current measurement range	0 – 8 A
Plug type	C type (South Korea)

2.2. Cloud Server

A cloud server was used to host a series of programs, as shown in Figure 3; the incoming data from the MQTT broker is stored to a MySQL database using a python script. Any local or cloud-based server could be used, but in this research, Amazon Elastic Cloud Compute (EC2) linux instance was used for convenience.

Figure 3 Programs hosted in the cloud server

The python script is subscribed to all of the number topics corresponding to each device, which then parses the incoming message into a query format that can be executed in the MySQL server; this was achieved using the paho-mqtt and the pymysql libraries. All of the incoming data is saved to a single table in the database, but is differentiated by an additional "deviceID" that corresponds to the unique device number; the columns of the database table are shown in Table 2. Similar to the embedded program of the microprocessor, the incoming data is first saved to a buffer array. The threading library in python is then used for executing a multi-insert query to save all of the data in the buffer array every second.

The data stored in the MySQL database can then be conveniently accessed through a simple query command, allowing a user to obtain the relevant energy data between certain timestamps corresponding to a specific device number.

Table 2 Columns of the table in the MySQL database

ID	deviceID	time_server	time	rmsI1	rmsI2	rmsI3	rmsI4	avgI1	avgI2	avgI3	avgI4

2.3. Sewing Production Tracking Algorithm

For the task detection and counting process using the energy consumption data as input, a CNN classifier was used. Due to the complexity of the relationship between the input and the output, four convolutional and max pooling layers, followed by two dense layers of 20 nodes each, were used. Adam optimizer and rectified linear unit were used as the optimization and activation function, respectively. This classification process was done on a separate PC using python 3 (version 3.6.5) and the open source machine learning framework, TensorFlow (version 1.8.0). PyMySQL library was used for retrieving the data from the server. The production tracking pipeline, along with the CNN structure, is shown in Figure 4.

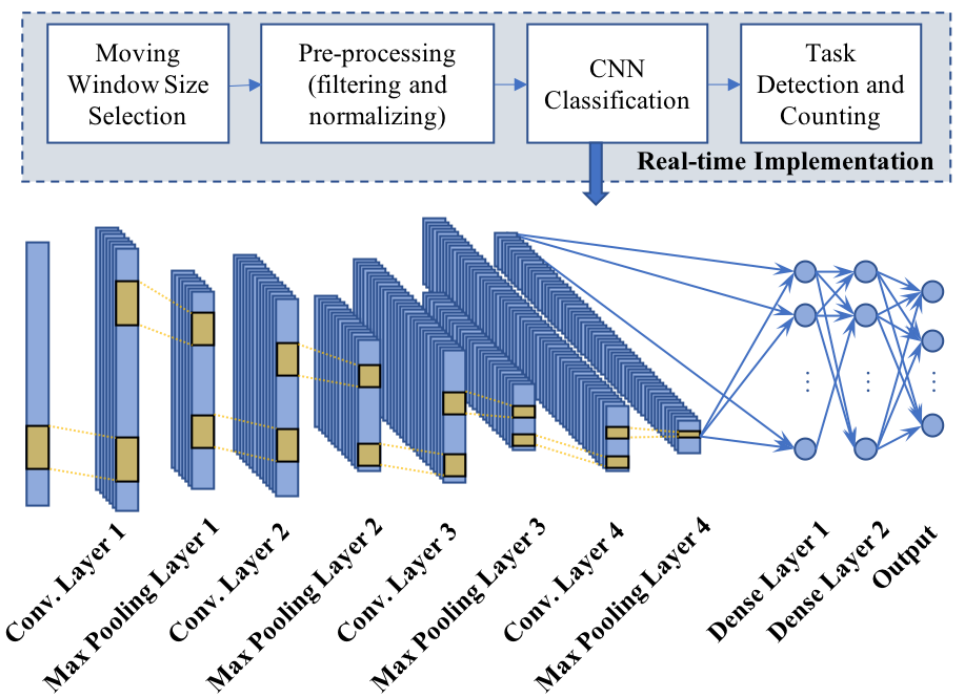

Figure 4 Task detection and counting algorithm pipeline

Chapter 3. Implementation and Evaluation

3.1. Fabrication of Energy Monitoring Device

3.1.1 Hardware Design and Fabrication

The energy monitoring device was modeled after a regular power strip, allowing easy installation and integration to any sewing machine. The installation process is similar to that of using a regular power strip, where the monitoring device's power cord is connected to an electrical outlet and the sewing machine's power cord is connected to the device. Several models were fabricated: single-port, 4-port, and a 6-port monitoring device.

The power source of the sewing machine is assumed to be at a stable 220VAC and thus only requires measuring the RMS current in order to calculate the total power consumption. For the current measurement, one of the live wires is passed through the hall effect-based current sensor, ACS712. The voltage signal generated from this sensor is then read at the ADC port from the Arduino MKR1000. An AC-DC converter, which converts the incoming 220VAC to 5VDC, powered the Arduino board and the current sensors. The device was fabricated by modifying a commercial single-port (Hyundai Electric Model HJT12) and 4-port (Promade) power strip, with the necessary components enclosed by a case fabricated by a fused deposition model (FDM) 3D printer (Stratasys F270); the material used was Acrylonitrile butadiene styrene (ABS). Although fabrication by 3D printing can be costly, the unit cost of production can be significantly reduced for mass production using plastic injection molding. A detailed schematic of a single-port device is shown in Figure 5. The multi-port device structures are simply an extension of the single-port model, with additional sensors added to the microprocessor. The CAD design and the prototype of the 4-port device along with its components are shown in Figure 6.

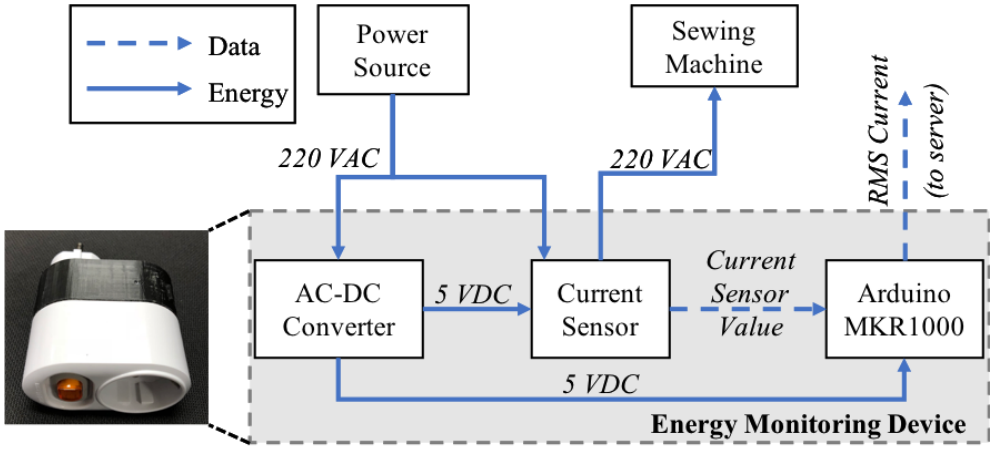

Figure 5 Detailed schematic of energy monitoring device

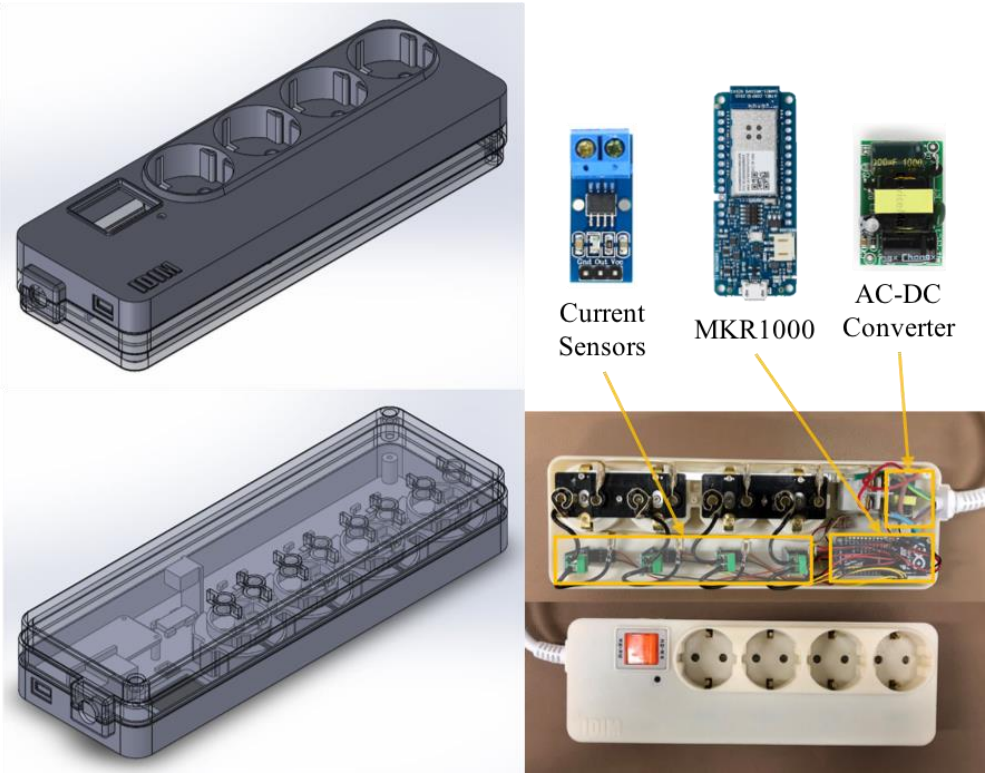

Figure 6 CAD model (left) and prototype (right) of the 4-port energy monitoring device

3.1.2 Embedded Software

Both the RMS and average current, along with the timestamp of the measurements, are calculated and sent to an MQTT broker using the on board WiFi module. Since each device is numbered, the data is sent to that specific number as the MQTT topic (e.g. /factory/3 for device number 3). Since certain sewing tasks are completed within a few milliseconds, a sampling rate of 5.7 Hz was selected. These RMS and average current values are first saved to a buffer array, which is later published to the MQTT broker in bulk at a frequency of 1.4 Hz. As a result, about 4 current datasets are published each time.

A watchdog timer of 8 seconds is also implemented in order to ensure the board reboots automatically during a connection failure to both WiFi and the MQTT broker. Any programmatic errors that cause the board to become unresponsive can be overcome by the automatic rebooting. However, it must be noted that since the reboot time is about 30 seconds to a few minutes, depending on the network stability and speed, data acquisition will not occur during the rebooting process and thus will generate a gap in the data. However, since this rebooting only occurs on rare occasions for short periods of time, this watchdog does not greatly affect the integrity of the data obtained.

3.2. Preliminary Test of Production Tracking Algorithm

3.2.1 Generating Data from a Sample Sewing Task

In order to train and test the performance of the CNN classifier, a sample sewing task was first established; three consecutive straight lines of 200, 350, and 200 mm at 90-degree angles were sewn (Figure 7 (b)). This task was performed 16 times on a lockstitch sewing machine by the same person to maintain the data as consistent as possible. The generated data can be seen in Figure 7(c), with the three peaks representing the three straight lines sewn. Five miscellaneous sewing tasks, straight lines of 100 mm, were also sewn at a slower speed at the end to generate negative data for evaluation purposes.

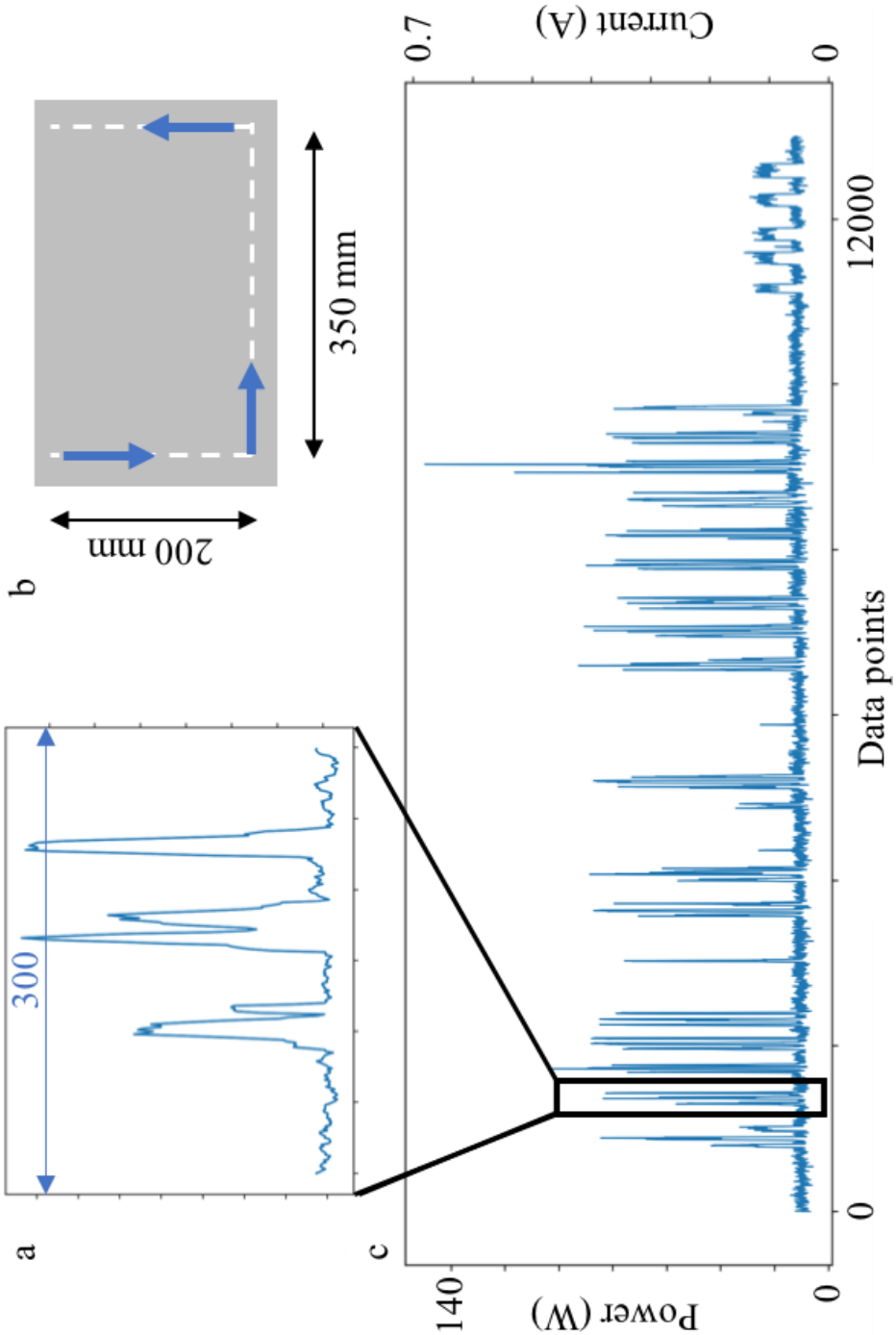

Figure 7 (a) Example of energy consumption data generated by the sample sewing task, with window size of 300 data points; (b) Schematic of the sample sewing task; (c) Raw data of the 16 sewing tasks, along with the 5 miscellaneous tasks.

It was assumed that for a skilled worker, the variation in the duration of the sewing task will be minimal. Also, since the energy data was measured at steady intervals, the number of data points within this sewing task duration remained fairly constant; therefore, a fixed number of data points was set as the window size. The average number of data points present in a single sewing task was 220, so the window size was set to be slightly larger at 300 data points, as shown in Figure 7(a). A moving average filter with a window size of 15 was then applied to the data to remove unwanted noise. The training data was then generated by sliding this window across by a step size of 10 data points, classifying the example as 'task completed' when the entire pattern with the three peaks were inside the window, and 'no task', when otherwise. Figure 8 shows a few classified examples. The CNN model was then trained using 50% of this training data. 25% of the data was used for cross validation to adjust the hyperparameters shown in Table 3.

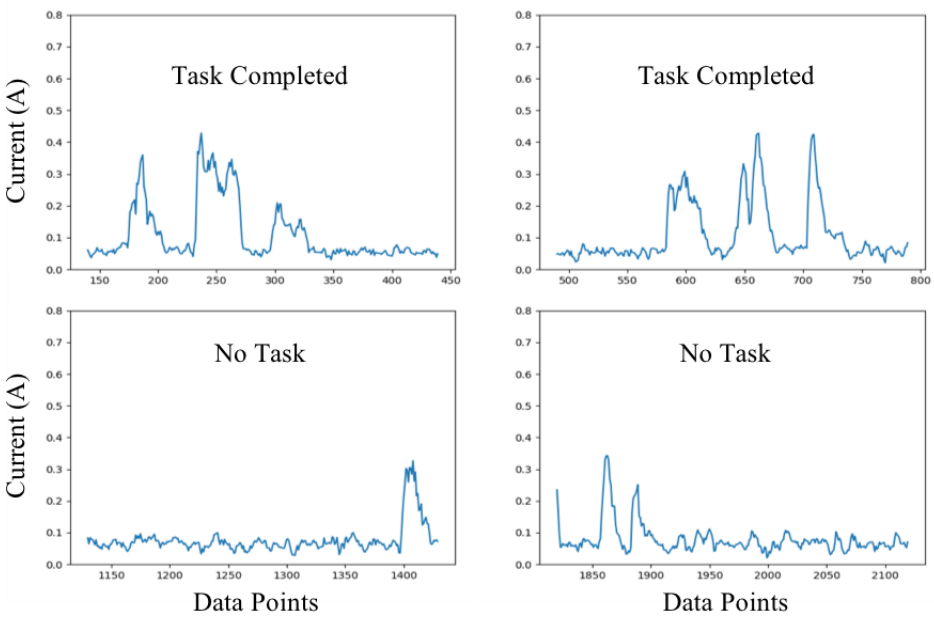

Figure 8 Examples of classified data

Table 3 Hyperparameters of CNN classifier

Hyperparameters	Value
Learning rate	0.001
Dropout Rate	0.5
Batch size	50

3.2.2 Task Detection and Counting Algorithm

As the fixed window is sliding across a given energy consumption pattern, multiple true positives can be detected, which can lead to extra sewing task counts if the classification results are used directly. Therefore, in order to ensure a single sewing task is counted for a single pattern, once a true positive is detected, the classifier will remain dormant for the next few inputs until the fixed window has slid across 90% of its window size. As shown in Figure 9, multiple true positives are shown by the multiple green boxes on the left side. After implementing this task detection and counting algorithm, only a single green box is drawn for each of the two peaks, as shown on the right side.

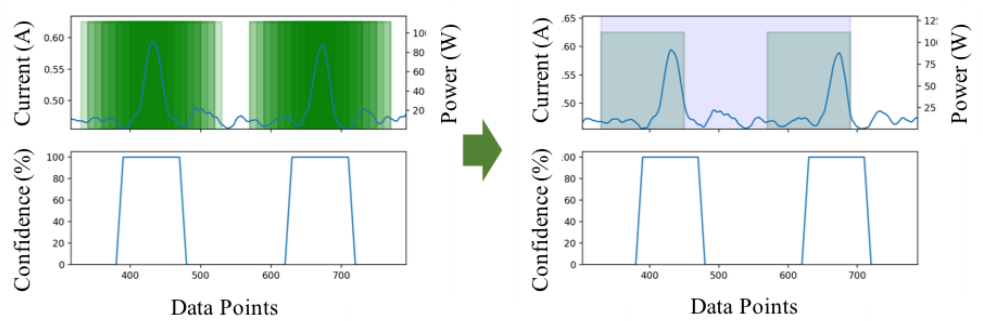

Figure 9 Result using only classifier (left), and using task detection and counting algorithm (right).

Two types of accuracies will be defined: classification accuracy and sewing task detection accuracy. The former will refer to the accuracy of the CNN model in detecting true positives and true negatives when compared to the test set, and the latter will refer to the accuracy of the overall production tracking algorithm in detecting the correct number of sewing tasks that were completed. By testing the sewing production tracking algorithm on the rest of the data, a classification accuracy

of 94.6% was achieved. A visual classification result is displayed in Figure 10, with the bottom graph showing the confidence percentages for task detection. As it can be seen in the figure, the algorithm can accurately detect when a sewing task has been completed. All 16 tasks were correctly detected, which the five miscellaneous tasks were also correctly classified as no task being present, resulting in a task detection accuracy of 100%.

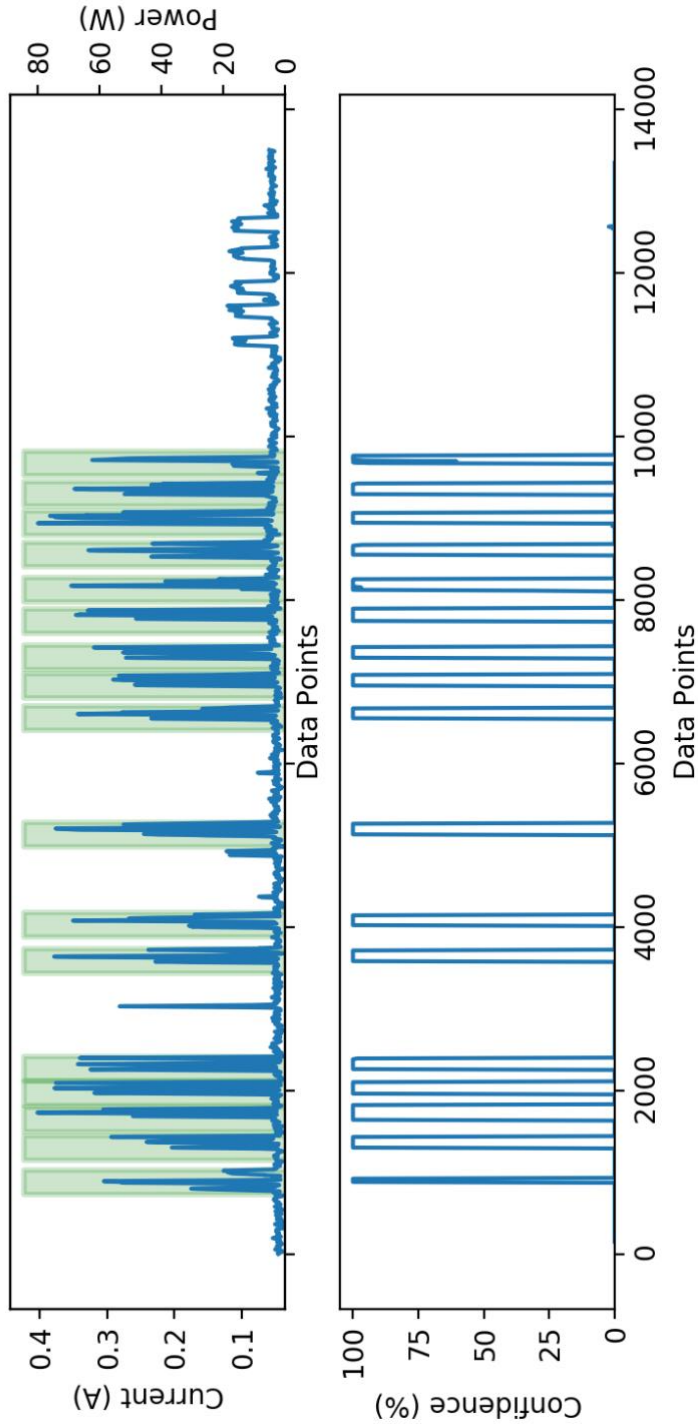

Figure 10 Task detection result on the sample sewing task

3.3. Experimental Setup

The sewing production tracking algorithm was tested on two sewing processes that were performed by a student from the Department of Clothing and Textiles. These two tasks, which were obtained from Hojeon Ltd., are part of a hoodie, and its schematic is shown in Figure 11. A full sewing task consists of smaller tasks, which are indicated by the dotted arrows. The numbers indicate the order in which the tasks must be performed.

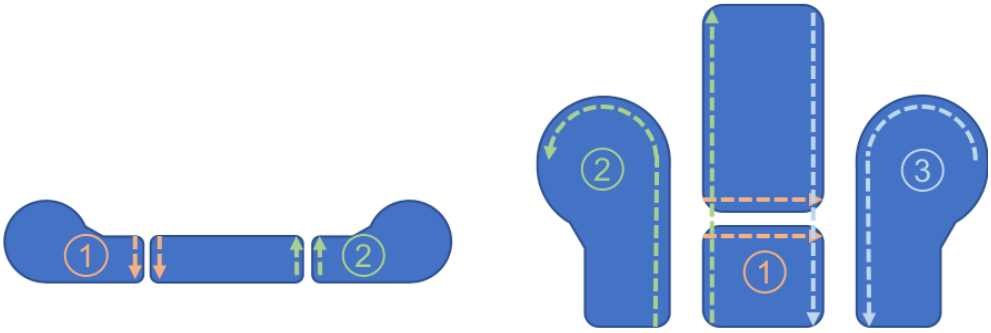

Figure 11 Schematic of sewing task 1 (left) and 2 (right) obtained from Hojeon Ltd.

Task 1 was performed a total of 9 times, and task 2 a total of 10 times. The raw data along with the indications for each of the sewing tasks are displayed in Figure 12.

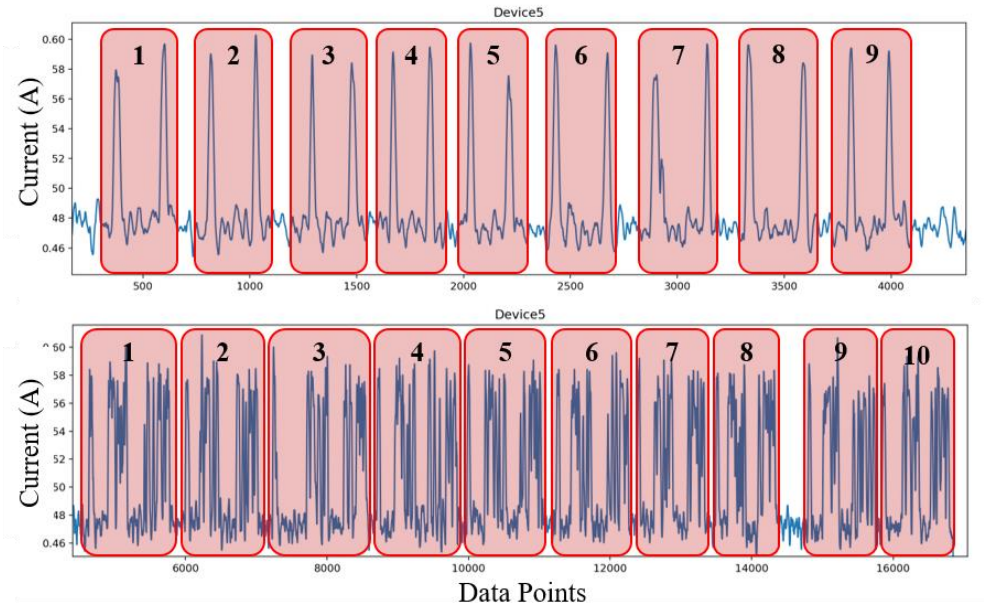

Figure 12 Raw data of target sewing task 1 (top) and 2 (bottom)

As previously mentioned, the training data is first generated from the raw data, manually classifying the input data. However, due to the more complex energy consumption patterns for both sewing tasks, the labeling procedure was approached differently. For the sewing task 1, the two subtasks are very similar in pattern and thus difficult to label as a set. Therefore, the subtasks were labeled separately using a smaller window size of 120 data points. For sewing task 2, the entire sewing procedure is very long (over 3 minutes), and thus also difficult to label the entire task. Therefore, since the subtasks consist of one short task, followed by two similar tasks, as shown on the right side of Figure 11, the two subtasks were labeled separately using a window size of 450; subtask 1 was labeled as 1, and the subtasks 2 and 3 were labeled as 2. An example of the classified data is shown in Figure 13.

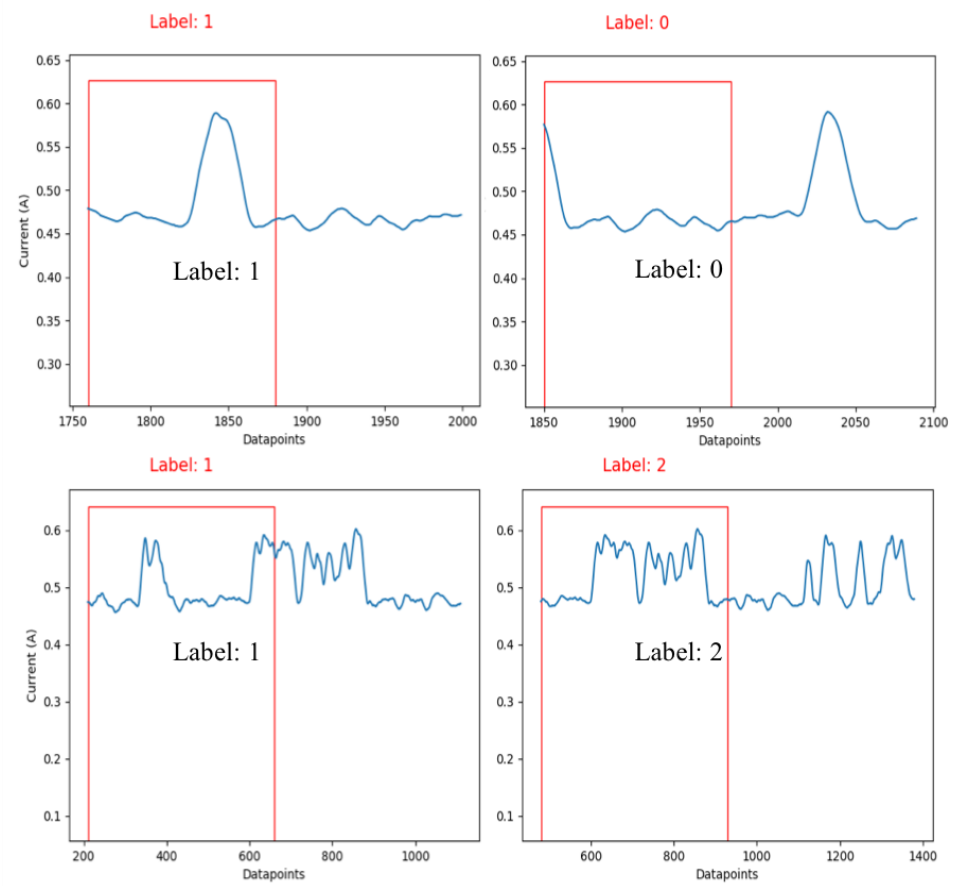

Figure 13 Example of classified data for sewing task 1 (top) and 2 (bottom)

The two CNN models for each of the target sewing tasks were trained using 50% of the generated training examples. The same hyperparameters that were previously mentioned were used.

3.4. Results and Discussion

The algorithms were tested on the other half of the training examples. A visual classification result is also displayed in Figures 14 and 15 for both target sewing tasks. A classification accuracy of 98.6% and 36.2% were achieved for sewing task 1 and 2, respectively. The sewing task detection accuracy obtained was 100% for both as all 5 sewing tasks present for both cases were accurately detected. However, a false positive is seen at the end of the graph for sewing task 2, as shown in Figure 15. This is perhaps due to the feature normalization of the noise present in the energy consumption data during an idle status, causing the algorithm to inaccurately detect the normalized noise as a subtask.

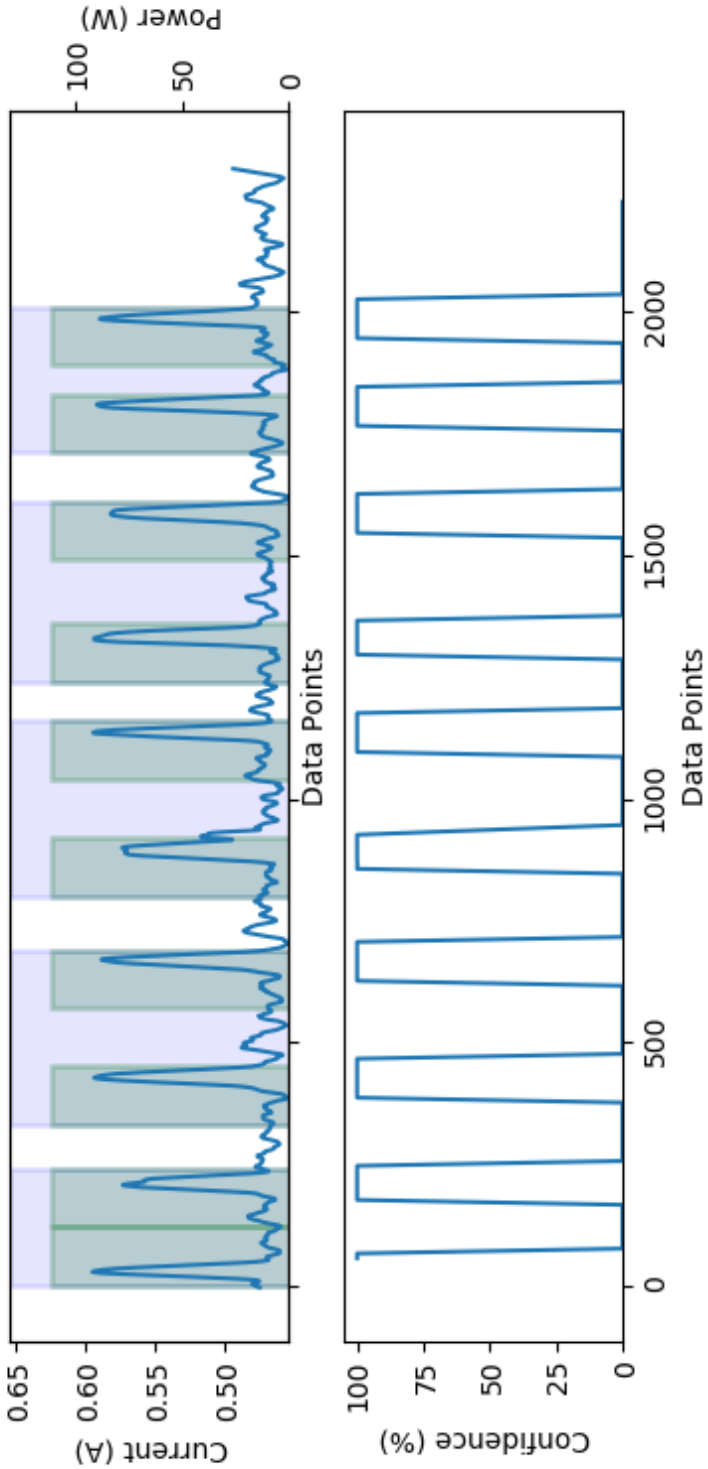

Figure 14 Task detection result for target sewing task 1

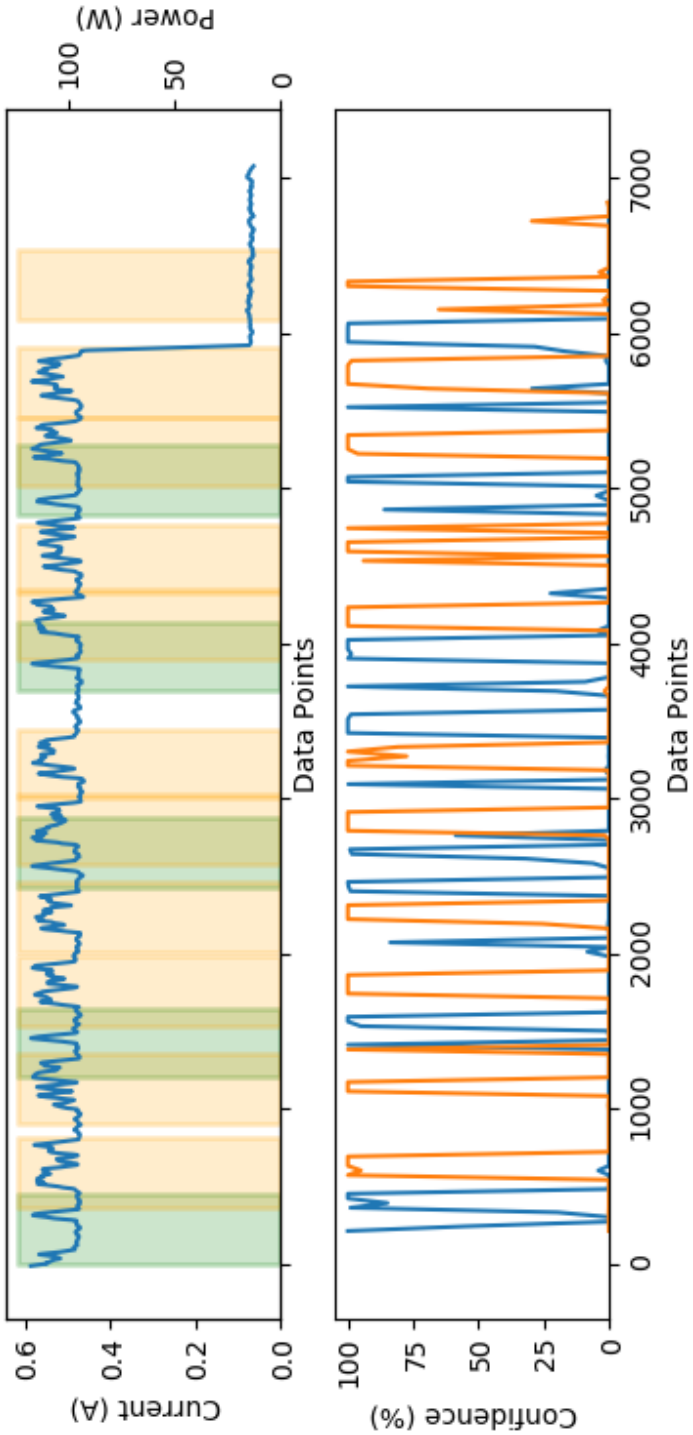

Figure 15 Task detection result for target sewing task 2

Chapter 4. Conclusion

In order to improve the efficiency and productivity of the sewing process line in the garment industry, it is crucial to obtain accurate production data in real-time. Being able to count the total number of production output can contribute to improved line balancing and production scheduling, as well as provide other information related to worker performance.

In this thesis, a production tracking system using the energy consumption data of sewing machines obtained from an energy monitoring device and a CNN classifier for detecting the sewing tasks completed is proposed. Although the classification accuracies for both target sewing tasks were 98.6% and 36.2%, the task detection accuracy of 100% was achieved.

Further research for lowering the rate of false positives for the CNN classifier is required. A hybrid CNN model that incorporates rule-based algorithms will be examined.

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Abstract in Korean

재봉과 같은 노동 집약적인 공정에 의존적인 의류 제조업에서 제품의 생산 이력 관리는 생산률을 파악하고 작업의 구성을 최적화하기 위해 매우 중요한 업무이다. 그러나 작업자가 직접 작업량을 파악하는 현재의 방법은 많은 시간이 소요되고 오류를 포함하기 쉽다. 이에 대한 대안으로 고려되는 여러 모니터링 방법은 의류 제조업의 대부분을 차지하는 중소기업들이 적용하기에는 비용적인 부담이 있다. 본 연구에서는 재봉 작업의 자동화를 위해 CNN (Convolutional Neural Network) 알고리즘을 사용하여 재봉틀의 에너지 소비 패턴을 분석함으로써 완성된 실제 생산 수량을 예측하는 방법을 제안하였다. 개발된 시스템으로 두 가지 목표 작업을 테스트하였으며, 다섯 개의 작업 이력을 모두 판단할 수 있었다. 그리고 학습된 CNN 모델 기반의 분류 알고리즘의 최대 정확도는 98.6 %였다.

주요어: 컨볼루션 신경망, 에너지 모니터링, 의류 제조업, 생산 예측, 스마트 센서, 스마트 팩토리

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