Two Phases Anomaly Detection Based on Clustering and Visualization for Plastic Injection Molding Data

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Abstract

The importance of smart factory is increasing. Among them, the importance of sensor data-based anomaly detection research is increasing. Accordingly, this paper presents a framework by using sensor data of plastic injection machine and deep learning models to perform anomaly detection and cluster secured outliers. This study aimed to be a practical solution and proposal for factories that want to introduce smart factory system. According to this goal, three main contributions are assumed. The three main contributions are as follows. First, assuming a situation suitable for the manufacturing site, and appropriate approach was used. Second, it is possible to secure outliers by applying Auto Label using with pseudo labeling technique. Third, the decision maker can identify the potential cause of the defect. These three advantages can be found in the Two Phases Anomaly Detection system architecture. The artificial intelligence model used as a classifier in the pseudo labeling technique was LSTM and Accuracy showed high reliability of more than 90%. And through the SOM algorithm, clustering visualization of defective data is shown.

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Keywords: plastic molding injection machine; semi supervised learning; pseudo labeling; clustering and visualization

1. Introduction

As the Fourth Industrial Revolution becomes a task of the eras, the importance of smart factories is increasing at the same time. As a major task of smart factories, combinations of network, artificial intelligence, and sensor technology are becoming important [1]. In this study, an anomaly detection study is conducted on injection products from plastic injection molding machine. Among the plastic molding techniques, there is a technique called injection molding. This is a method of making a molded article by heating a thermoplastic resin and injecting it into the cavity of a mold when it becomes a liquid state and cooling it into a mold. Injection molding is largely divided into three stages: charging, pressing, and holding pressure. In this process, molding conditions are set based on temperature, pressure,
and speed. However, various defects occur in injection molding. Dealing with defects is not an easy solution because it requires multiple domain knowledge. With the identification of the cause of these defects, most factories are currently diagnosing and solving based on human experience. Methods based on these experiences are insufficient and may be dependent on people [2-5].

Therefore, this study detects outliers for injection molding with a deep learning-based model. It provides the construction of an artificial intelligence model that determines normal and abnormal conditions using various data from the injection process. Furthermore, a framework named Two Phases Anomaly Detection is proposed. This framework explains from sensor data collection to defect detection.

This study was prepared for researchers who want to progress anomaly detection of injection products and practitioners who want to apply smart factories to factories. In addition, the following major contributions can be found in this paper.

1. Assuming a situation suitable for the manufacturing site and using an appropriate approach. There are two situations suitable for the manufacturing site. First, Class Imbalanced situation. Most normal data and very few abnormal data are mainly used at the manufacturing site. This study also shows the process of solving problems using datasets with that situation in mind. The second situation is the semi-supervised approach. There were a few label data and multiple unlabeled data as data held. It is virtually impossible for a person to label all millions of data themselves from an actual factory. In the future, smart factory’s anomaly detection study will be even more helpful in the field to approach unsupervised or semi-supervised. Accordingly, this study also focused on semi-supervised learning research.

2. Using the pseudo labeling technique, being able to secure outliers by applying Auto Label. Most of the abnormal detection studies have performed abnormalities detection, presented performance, and just completed the study. This study takes it to the next level, utilizes unlabeled data by applying the pseudo labeling technique, and performs the function of a data filter for abnormal data analysis.

3. It can inform potential defects for decision makers. Through this process, this paper would like to propose a more efficient approach to factories that want to detect machine malfunctions through sensor data including the actual plastic injection molding machine. Through bad data clustering and visualization, decision makers can detect potential defects in advance.

2. Related Work

2.1. Defect Detection for the Plastic Injection Molding

The following studies related to plastic injection molding have been preceded. Lucy Hyn et al. [2] conducted a study to identify the transition temperature used to calculate shrinkage in injection molding simulations. Kramschuster et al. [3] Experimental design was applied to conduct quantitative studies on the contraction and distortion of micropores and conventional injection molds. Kwon et al. [4] conducted a study on anisotropic shrinkage during amorphous polymer injection molding in consideration of pressure, volume, and temperature state equation, molecular orientation, and elastic recovery. Kurt et al. [5] investigated the effects of packing pressure, melting temperature, and cooling time on the contraction of the injection mold. Santis et al. [6] investigated the effects of inhibition, time, and geometric constraints on the contraction of semi-crystalline polymers with strain gauges.

2.2. LSTM

Long Short Term Memory (LSTM) is an artificial intelligence neural network model developed from RNN. LSTM is mainly used in time series data research. It is used in fields such as speech recognition and natural language processing, and this is because of its characteristics that deal with sequences of LSTM. Sensor data also have repeated sequences, and accordingly, time series-based sensor data and studies on the utilization of LSTM vary [7]. Research on LSTM and defect detection was preceded as follows. Kim et al. [8] studied the production of a plastic injection molding detection LSTM prediction model that overcomes a biased dataset environment. Nagorny et al. [9] conducted a model study to predict the diagnosis of quality from injection products using the LSTM model.
2.3. Clustering

The following studies have been preceded by clustering studies on defective values. Loh et al. [11] detecting defects in semiconductors and applies clustering techniques from these defects, to detect those defects in advance. Wu, Guoqing, et al. [12] shows a clustering visualization study for 3D irradiation damage. Yuan, Jian, et al. [13] presents a method to visualize the fault data of the underwater thruster by clustering it.

3. Two Phases Anomaly Detection

Section 3 describes the Two Phases Animation Detection system architecture proposed in this paper. The system architecture is configured as shown in Figure 1. Phase 1 describes the purification of collected data and the modeling process. In addition, in Phase 2, the final goal is to cluster and visualize the collection of abnormal data classified through Phase 1 and deliver it to the decision maker so that the expected number of defects in the device can be determined.

Figure 2 shows process of Figure 1 in terms of the model of artificial intelligence. Red dotted box that can be found in Figure 2 means pseudo labeling method and abnormal data which this paper stresses. On the left side of the red dotted box, the diagram of pseudo labeling process can be seen. LSTM classifier Neural network models were used as classifier of pseudo labeling. And the right side red dotted box points abnormal data that went to the cloud platform. The established studies just stayed in a faulty product classification, but the framework proposed in this study can abnormal data go up to cloud platform and be clustered at phase 2.
3.1. Phase 1: Modeling

In section 3.1, detailed descriptions of Phase 1 - Modeling 1 shown in Figure 1 and Figure 2 are conducted. Phase 1 explains what data collection is performed and how the collected data is utilized to proceed with anomaly detection from a plastic injection molding machine.

Phase 1 describes data collection first. Data is collected from various types of sensors attached from an injection molding machine. Plastic injection molding machines collect data after attaching sensors to the following parts from an empirical point of view. Regarding temperature, screw/cylinder, resin, mold, drying, hydraulic data are collected. Regarding pressure, data that are related to filling pressure, holding pressure, back pressure, release pressure, mold pressure, and shape pressure are collected. Regarding time, data of filling time, holding pressure time, cooling time, and drying time are collected. Regarding speed, data of injection speed, screw rotation speed, shaping speed, and ejecting speed are collected. [2-4] And it belongs to the Phase 1 data collection stage until the labeling process to determine whether there is a defect. The collected data is transmitted through Edge Device. Edge Device processes data collection and model learning at the same time and releases this learned weight. Data entered the Edge Device involves the following tasks. Some data label work is required at the same time as data collection. However, you don’t have to do all the labels. Labeling hundreds of thousands of unlabeled data is a considerable burden on practitioners both in terms of time and finance. However, creating a predictive model through unsupervised learning without labeling may be difficult to improve artificial intelligence performance. Therefore, it was the semi-supervised learning approach that could take both advantages. Among the numerous semi-supervised learning approaches, the reason for choosing the pseudo labeling method was that the output of abnormal data could come out through the pseudo labeling process. Through the operating principle of pseudo labeling to find lower entropy values, the task of Auto Label can be performed simultaneously.

Figure 3 shows the pseudo labeling method used in this study. (a) describes generating a model with label data. This model plays the role of classifier. And (b) describes the process of classifier distinguishing unlabeled data. And pseudo labeled data is attached to the unlabeled data identified through process (b) to become pseudo labeled data. In addition, the model proceeded to model learning again by combining Pseudo-labeled data and labeled data and is shown in (c) [14-16].

The reasons for using the LSTM artificial intelligence neural network model in the pseudo labeling process were as follows. First, the reason for this data was that the data collected from the device was time series data. LSTM is an artificial intelligence neural network model responsible for long-term memory that remembers sequences in time series data. Another big reason was that there were many previous studies using time series data to detect defects. As a result, the LSTM model was used to achieve an Accuracy value of 90% or more [8].
Section 3.2 describes the process immediately after Phase 1. The core of Phase 2 is to use Abnormal Data, the output of Phase 1. Cluster abnormal data collections raised to cloud platform systems. It is not possible to determine what kind of defect the clustered abnormal data is. However, classes that appeared immediately after clustering may have caused potential defects to decision makers inside the factory and may serve as an early warning.

Among the various clustering techniques, this study decided that SOM (Self-Organizing Map) is the most suitable framework. The reasons for selecting SOM among clustering techniques are as follows. SOM is an artificial intelligence neural network algorithm that converts high-dimensional input space into simple low-dimensional output space while preserving the phase in data. SOM has an evaluation index called Quantization Error, and the smaller this value, the better the map fits the data. The visualization results of SOM are expressed as close distances when visual understanding is easy and data distribution is similar. In this regard, we judged that SOM is the most intuitive algorithm to help decision makers [17].

4. Experiments

4.1. Experiments Setting

The hardware used in experiments intel core I7 - 9750h cpu @ 2.60 ghz 2.59 ghz 32.0 gb ram, Nvidia GeForce GTX in 1650.Google Colap pro(GPU : T4 or P100) showed the same or similar level results. The performance of algorithms generally system apart from the environment. However, in empirical terms also can change the performance of the model according to the environment.

4.2. Dataset

This experiment was taken from the Korea AI Manufacturing Platform (KAMP) [18]. KAMP is an online platform that provides open datasets related to manufacturing in Korea. The data used in this experiment are said to have been taken from a product model called cn7 of the actual plastic injection molding machine Woojin-650Ton. KAMP provides guidelines for data and dataset. The guidelines showed the source of the data and how it was collected from Woojin-650Ton. In addition, for this study, it was possible to conceive the process for Phase 1 by actually observing the injection equipment and interviewing factory engineers.
4.3. Metrics

Accuracy, Precision, Recall, and F1score were selected as Metrics, and the formula and description are as follows. Accuracy is the most intuitive indicator. However, there is a limitation that unbalanced data can distort performance.

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN}
\]

It is the percentage of real classes that artificial intelligence models predict as True. The formula is as follows.

\[
\text{Recall} = \frac{TP}{TP + FN}
\]

This is the ratio to the actual class that the artificial intelligence model classifies as True. The formula is as follows.

\[
\text{Precision} = \frac{TP}{TP + FP}
\]

F1-Score is an indicator mainly used when data is unbalanced. The harmonious mean of Precision and Recall is as follows.

\[
F1 - \text{score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}
\]

4.4. Results

As for the initial data, 20% of the training data was used as verification data. Depending on the pseudo labeling method, the learning was conducted by gradually permeating some of the unlabeled data into the entire data. 10% of the unlabeled data was divided and set to be combined into total data. When batchsize is set to 32, optimizer to Adam, learning rate to 0.0001, and epochs to 50, the model’s performance was the best. And the performance indicators according to metrics are shown in Table 1.

<table>
<thead>
<tr>
<th>Metrics</th>
<th>results</th>
</tr>
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<tbody>
<tr>
<td>Accuracy</td>
<td>0.99</td>
</tr>
<tr>
<td>Recall</td>
<td>0.88</td>
</tr>
<tr>
<td>Precision</td>
<td>1.00</td>
</tr>
<tr>
<td>f1-score</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Figure 4 shows the training loss, training accuracy, validation loss, and validation accuracy according to the training progress. As can be seen in Figure 4, Accuracy exceeds 90%, showing high accuracy.

The experiment generated classifier based on 1300 normal data and 15 defect data. And by psudo-labeling the unlabeled data, a total of 42 abnormal data could be secured. Finally, it is the process of clustering 42 abnormal data. Clustering visualization was carried out through SOM algorithm. The miniSOM package was used. The initial miniSOM values for drawing the cluster are map size 5x5, sigma 0.1 learningrate 0.4. This initial value represents 12 nclusters at 0.27, which is the result of inducing the smallest cluster and the smallest qe value. Figure 5 is a diagram of data clustered from abnormal data in Phase 2. This figure is the result of the cluster clustered through the SOM algorithm. In conclusion, it could be clustered into a total of 7 classes. The darker the color of the hexagonal node, the better it is separated from other nodes. It can be seen that clusters are well separated.

5. Conclusion

In this paper, anomaly detection for plastic injection molded products is described. And we present a framework called Two Phases Anomaly Detection. Phase 1 describes the process of modeling from data collection. Phase 2 describes the process of visualizing outliers selected by the model after clustering. Through the framework, the decision
maker can check how many potential defects there will be in the injection machine from the injection device. The three contributions of this framework study are as follows. Assuming the appropriate situation for the manufacturing
site, a matching approach was used. A system for labeling outliers was established. Clustering and visualization of outliers were conducted for decision makers. In addition, more than 90% Accuracy was achieved using the LSTM model, proving that practical classification is possible. This study is based on sensors and artificial intelligence, which are currently being studied most actively in smart factories. Through this study, factory practitioners can get ideas to build an anomaly detection framework for machines. And smart factory solution companies will be able to build abnormal detection systems through this framework. As a follow-up study, we plan to secure different datasets to conduct comparative experiments or to increase performance by replacing better classifiers in pseudo labeling systems.

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