Quality Classification of Defective Parts from Injection Moulding

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Abstract - This report examines machine learning algorithms for detecting short forming and weaving in plastic parts produced by injection moulding. Transfer learning was implemented by using pretrained models and finetuning them on our dataset of 494 samples of 150 by 150 pixels images. The models tested were Xception, InceptionV3 and Resnet-50. Xception showed the highest overall accuracy (86.66%), followed by InceptionV3 (82.47%) and Resnet-50 (80.41%). Short forming was the easiest fault to identify, with the highest F1 score for each model.

Keywords – Injection Moulding, Machine Learning, Smart Manufacturing, Machine Vision, Image Processing

1 INTRODUCTION

Injection Moulding is a popular method of manufacturing plastic and metal products by injecting molten materials into moulds at high pressure. This process is subjected to several random and systematic variations that sometimes lead to faults in the products that may be difficult to identify rapidly at large scales. This report focuses on data collected from the SIMTech Model Factory’s Injection Moulding Machine that produces plastic parts for perfume cartridges. Two types of faults were examined – short-forming and weaving – and classified automatically by several machine learning algorithms.

Short-forming leads to smaller-than-required parts and occurs when the molten material does not cover the entire mould, typically occurring when either the holding pressure or injection speed of the molten material is too low. Weaving generally occurs due to inconsistent cooling of the molten material and may lead to lower durability. The models were therefore used for classification of parts into 3 categories: “Good”, “Short-forming” and “Weaving”.

Figure 1: Injection Moulding Machine

This report examines several baseline Machine Learning algorithms for image classification and compares their effectiveness in classifying parts from injection moulding. Models examined include Xception, Resnet-50 and InceptionV3.

2 DATA COLLECTION

The data consisted of 25 experiments based on various settings of the injection moulding machine. The labels were then assigned by human supervisors at the SIMTech Model Factory based on 3 classes: Good, Weaving and Short forming.

Each image in the dataset was precisely 150 by 150 pixels and was registered with 3 channels –
red, blue and green. The number of images from each class are summarised below:

| Class          | Number of Images |
|----------------|------------------|
| Good           | 148              |
| Weaving        | 147              |
| Short forming  | 199              |
| Total Dataset  | 494              |

Figure 2: Dataset Summary

3 MODELS USED FOR TRANSFER LEARNING

Several benchmark models were used for classification, using a test-train split with 80 percent training data and 20 percent testing data. These models were implemented in python using the TensorFlow library and the pretrained models made available by the authors of the original publications.

Transfer learning was implemented by customising the input layer of each pretrained model to accept the new input photo size, and a custom classifier head was added to predict 3 classes instead of 1000 in the Imagenet dataset [5]. The preloaded weights of the remaining layers were retained and finetuned.

The models used for finetuning were chosen for being sufficiently complex to model the Imagenet dataset and are listed below:

1. Xception

   Deep Convolutional Neural network inspired by Inception V3 and is known to slightly outperform it [1] on the Imagenet dataset.

2. Inception V3

   ![Inception V3 filter architecture](image)

   A deep convolutional neural network model using several units of “filters” and pooling layers [2].

3. Resnet-50

   ![Resnet Cell](image)

   Solved the problem of vanishing gradients in very deep networks by using skip connections [3].
4 RESULTS USING TEST-TRAIN SPLIT

| Model     | Best Validation Accuracy | Pretrained Model Size [4] |
|-----------|--------------------------|--------------------------|
| Xception  | 0.86598                  | 88 MB                    |
| Inception V3 | 0.82474                  | 92 MB                    |
| Resnet-50 | 0.80412                  | 98 MB                    |

Figure 7: Accuracy Results

| Xception | Predictions | Recall |
|-----------|-------------|--------|
|           | Good  Weaving Short forming |     |
| Actual    | 0.6897      |
| Good      | 20  6  3    |
| Weaving   | 1  27  1    |
| Short forming | 2  0  37    |
| Precision | 0.8696 0.8182 0.9024 |

Figure 8: Confusion Matrix for Xception

| Inception V3 | Predictions | Recall |
|--------------|-------------|--------|
|              | Good  Weaving Short forming |     |
| Actual       | 0.6207      |
| Good         | 18  7  4    |
| Weaving      | 3  24  2    |
| Short forming | 1  0  38    |
| Precision    | 0.8182 0.7742 0.8636 |

Figure 9: Confusion Matrix for Inception V3

| Resnet-50 | Predictions | Recall |
|-----------|-------------|--------|
|           | Good  Weaving Short forming |     |
| Actual    | 0.7931      |
| Good      | 23  3  3    |
| Weaving   | 5  21  3    |
| Short forming | 2  3  34    |
| Precision | 0.7667 0.7778 0.8500 |

Figure 10: Confusion Matrix for Resnet-50

5 CONCLUSION

The results reveal that image models can be useful to detect faults in injection moulding, including weaving, which is difficult to identify with the naked eye.

All the models tested performed the best at detecting short forming, with the highest precision, recall and F1 score. This is expected, as it is easy to manually distinguish such parts with the naked eye.

Xception and Inception V3 performed better at detecting Weaving than good parts (with a higher F1 score for both models) while the opposite was seen in Resnet-50. Weaving was detected with a lower F1 score than for short forming. This could be attributed to the fact that weaving is difficult to identify visually as the fault is mainly internal, and only limited signs are observed on closer examination.

Given the limited usefulness of feeding images to detect subliminal faults, it may be necessary to design a dedicated neural network architecture to incorporate both images and sensor data which could carry information on internal faults.

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REFERENCES

[1]. Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1251-1258).

[2]. Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2818-2826).

[3]. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[4]. Team, K. (n.d.). Keras documentation: Keras Applications. Retrieved June 26, 2020, from https://keras.io/api/applications/

[5]. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., ... & Berg, A. C. (2015). Imagenet large scale visual recognition challenge. International journal of computer vision, 115(3), 211-252.