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A Deep Learning Based Quality Monitoring System for Injection Moulding Process

Doan Ngoc Chi Nam[1,#], Chan Wing Fook[1] and Michelle Nguyen Thanh Truc[1]

1 Manufacturing Execution and Control Group, Singapore Institute of Manufacturing Technology, 2 Fusionopolis Way #08-04, Innovis 138634, Singapore
Corresponding Author / Email: doanncn@simtech.a-star.edu.sg, TEL: +65-6319-4471

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Abstract: Online quality monitoring and defect detection is critical for realising high quality manufacturing. This paper presents a quality monitoring system via deep learning based for early detection of defects at an injection moulding process. Main contribution of this paper is a light CNN (Convolutional Neural Network) - LSTM (Long Short-Term Memory) model implemented on an edge-device to detect possible defects in real-time. The proposed model was designed to use features from both manufacturing parameters and products images; and was trained with a real manufacturing dataset. Its performance was also benchmarked with other candidates to evaluate the effectiveness in prediction accuracy and computational costs. Thanks to its advanced performance, the proposed model has been implemented at Model Factory @ SIMTech for real-time quality monitoring of an injection moulding machine.

1. Introduction

In the context of Industry 4.0 – Internet of Things (IoT), manufacturing data have been made ready in real-time for further applications, e.g., planning, executing, control, and monitoring processes. Among these applications, quality monitoring and defect detection has been an attractive topic to many researchers. In a quality monitoring application, system information, e.g., sensors measurements data, controller parameters, and visual images can be used to predict the quality and detect possible defects during production. This can help to significantly reduce cost and waste while ensuring overall quality of the production line. In this paper, we propose a quality monitoring system via deep learning model for an injection moulding process.

In this work, a light neural network model running on Raspberry Pi 3 is introduced to utilize information from both controller's parameters and images of products for products' quality prediction in realtime. Key features of the paper are as follows:

- A Convolution Neural Networks – Long Short-Term Memory (CNN – LSTM) model is presented for products' quality classification at an injection moulding machine. The CNN branch is designed to detect visual defects from products' images. The CNN model in this paper is simplified from one of state-of-the-art networks for mobile applications – MobileNetv2 [1]. This simplification makes the model lighter while ensuring accuracy for this specific application. Meanwhile, the LSTM branch is constructed to handle parameters from machine's controller and is employed to detect potential defects which cannot be detected by the CNN model.
- A training scheme is built for the proposed network on a mixed dataset consisting of time series parameters and product's images from different working conditions. This dataset is collected from an injection moulding machine in real manufacturing setting (Model Factory @ SIMTech) [2].
- Finally, the model is implemented on a Raspberry Pi 3 (edge – device) to online monitor manufacturing quality of the injection moulding process. Performance of the proposed methodology is also compared with the other models, i.e., CNN – MLP model, MobileNetv2 – LSTM, etc. to evaluate the effectiveness and the applicability.

2. Experimental setup

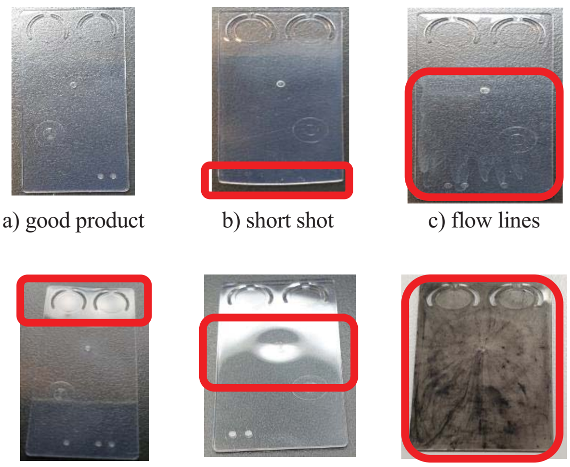
The injection moulding machine (Arburg Injection moulding machine) considered in this paper is an Allrounder 420A 1000 – 400 with SELOGICA controller [3]. This machine is used to mass produce a transparent thin film – a component in the final product – eScent. In injection moulding process, defects may occur when there is a variation occurs in process's parameters or in the quality of input material [4].

In this paper, we consider 5 common types of defects in injection moulding processes: short shot, flow lines, sink mark, wrapping, contaminated material. An illustration of a good transparent thin film and considered defects are shown in Fig.1. To identify the quality of this product, an image of one shot (4 products per shot) and total of 48 time series parameters from machine's controller are captured for every production cycle. The quality monitoring task then becomes a multi-classes classification problem for mixed dataset and will be discussed in the following section.

3. Quality Monitoring Model

3.1 Double heads CNN – LSTM model

As mentioned earlier, the quality monitoring engine in this paper is a CNN – LSTM model. The overall schematic of the engine is shown as in Fig. 2. In order to extract features from product's images, the CNN branch in this paper is designed based on the inverted residuals block with linear bottlenecks introduced in MobileNetv2 (Sandler et al. 2018). This computational unit allows the convolution tasks to be done in an efficient way. Comparing with the original MobileNetv2, the CNN branch used in this paper is much simpler and thus the generated model is much lighter in term of computational requirements. Details design parameters of the CNN branch (MobileNet_Sim) is shown in Table 1. Here, t is the expansion factor, c is the number of channels (filters), n is number of repeating times of the layer and s is the stride size of the convolution.



a) good product b) short shot c) flow lines

d) sink mark e) wrapping f) contamination

Fig.1 Transparent film from injection moulding machine

Input	Operator	t	c	n	s
128^2 x 3	*Conv2d (relu6)*	-	32	1	2
64^2 x 32	*Inverted_residual_block*	1	16	1	1
64^2 x 16	*Inverted_residual_block*	3	32	1	2
32^2 x 32	*Inverted_residual_block*	3	64	1	2
32^2 x 64	*Conv2d 1x1*	-	128	1	1
32^2 x 128	*GlobAvePool*	-	-	1	-
1x1x128	*Dropout*	-	-	-	-
1x1x128	*Conv2d 1x1 (relu)*	-	6	-	-

Table 1 Design parameters of the *MobileNet_Sim*

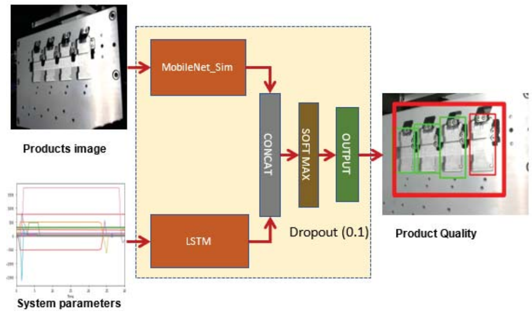


Fig. 2 Schematic of the proposed LSTM-CNN model

	precision	recall	f1-score	support
Class 0	*1*	*1*	*1*	*306*
Class 1	*1*	*1*	*1*	*300*
Class 2	*1*	*1*	*1*	*301*
Class 3	*1*	*1*	*1*	*286*
Class 4	*1*	*1*	*1*	*321*
Class 5	*1*	*1*	*1*	*304*
Accuracy	-	-	*1*	*1818*
Macro avg	*1*	*1*	*1*	*1818*
Weighted avg	*1*	*1*	*1*	*1818*

Table 2 Validating performance of the proposed model

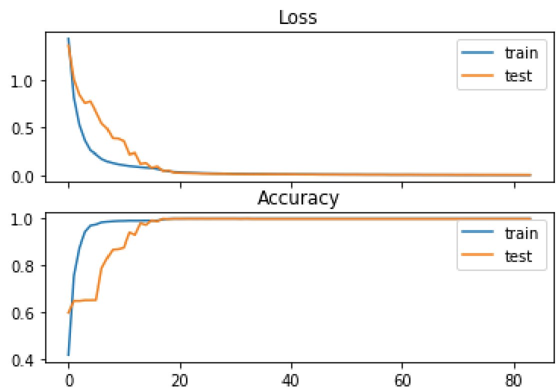


Fig.3 Training and validating of the proposed model

To cope with all time-series data from process parameters, LSTM branch is designed with 32 cells. LSTM network – a special type of Recurrent Neural Network – is capable for learning with short term and long term dependencies thanks to its control gates implemented within the cell [5].

3.2 Training for double heads CNN – LSTM model

In order to train the proposed quality monitoring model, a mixed dataset was captured and labelled for 6 six working conditions (refer to Fig. 1). Firstly, production parameters of all conditions were obtained directly from SELOGICA controller via OPC-UA in real-time. The production parameters signals were then normalized and split into single cycle data samples. Moreover, padding was applied to standardize the size of controller's data. Corresponding to each sample of system parameters a product image was also taken and labelled. Cropping and resizing were also applied to images to generate regions of interest (ROIs) of interest. Finally, the dataset is randomly split into two datasets for training and validating the proposed model.

Training facility for this model is a personal workstation (AMD Ryzen 5 3600 CPU, RTX 2070 GPU, 32GB RAM) with Tensorflow 2.1 and Keras. The model was trained with Adam optimizer and categorical_crossentropy loss fucntion.

From Fig.3, it is obvious that the proposed MobileNet_Sim_LSTM model was well trained for the given dataset with accuracy 100% (for both training set and validating set) and no over-fitting. Meanwhile, it can be seen from Table 2 that precision, recall and F1-score of all categories are with perfect scores. Moreover, the validating dataset is also well distributed with samples quantities range from 286 to 321 for all classes. Consequently, the potential of the proposed model for the quality monitoring task can be confirmed.

4. Experimental Evaluation

In this section, performance of the proposed quality monitoring model is investigated for running on a Raspberry Pi 3 Model C (OS: Raspbian GNU/Linux 9 stretch, Tensorflow 2.1). In order to further evaluate the effectiveness of the proposed model, benchmarking is also carried out. Other candidate models include LSTM, MobileNet_Sim, MobileNetv2_LSTM, CNN_LSTM, MobileNet_Sim_MLP, MobileNetv2_MLP, and CNN_MLP. The designs of these models are as follows:

- The MobileNet_Sim model and LSTM model are two branches of the proposed model. Here, they are investigated as two separate models with 'softmax' activation function at output layers.
- The MobileNetv2 model is the original model with 6 channels for the output layer.
- The multilayer perception (MLP) branch is a 4 layers network in size of (64, 32, 16, and 6).
- The CNN branch is designed using conventional convolution structure with 3 layers with filters size (32, 64, and 6).

All 8 models were trained with same dataset and the performance indexes are listed in Table 3. Here, it can be seen that the proposed model, MobileNetv2_LSTM and MobileNetv2_MLP are 3 best candidates in term of prediction accuracy with perfect scores for precision, recall and F1-score. Predictions of others model are all with less accuracy. Especially when system parameters (pars) and visual information (img) of the products are considered separately, F1-scores of LSTM and MobileNet_Sim models drops significantly to 0.84 and 0.66, respectively. This strongly supports the proposed idea of using both controller's parameters and product images as inputs to classify product's quality.

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Next, 6 models with prediction accuracy above 0.9 are tested on the Raspberry Pi 3 to evaluate processing speeds under limited computational resources. From Table 5, it is obvious that our proposed model is with smallest number of parameters as well as number of required Floating Point Operations (FLOPs) [6].

Models	Input(s)	Parameters	FLOPs	Runtime R Pi3(s)	Weighted average		
					Precision	Recall	F1-Score
Proposed model	*img, pars*	*36,986*	*91,066*	*1.046*	*1*	*1*	*1*
MobileNet_Sim	*img*	-	-	-	*0.66*	*0.67*	*0.66*
LSTM	*pars*	-	-	-	*0.84*	*0.84*	*0.84*
MobileNetv2_LSTM	*img, pars*	*2,260,378*	*4,505,048*	*2.193*	*1*	*1*	*1*
MobileNet_Sim_MLP	*img, pars*	*382,570*	*764,079*	*0.908*	*0.98*	*0.97*	*0.97*
MobileNetv2_MLP	*img, pars*	*2,615,082*	*5,195,917*	*2.058*	*1*	*1*	*1*
CNN_LSTM	*img, pars*	*38,842*	*95,541*	*1.737*	*0.98*	*0.98*	*0.98*
CNN_MLP	*img, pars*	*385,194*	*769,970*	*1.147*	*0.93*	*0.92*	*0.92*

Table 3 Performance benchmarking of 8 quality prediction models on Raspberry Pi3 model C

Average runtimes for 6 models on the Raspberry Pi 3 are also listed. To reduce uncertainties that may affects the measurement, runtimes were tested for a stack of 8 input samples. Apparently, among top 3 models for prediction accuracy (F1-score=1), the proposed model costs least computational resources and is roughly 2 time faster than the other 2 models. Moreover, it can be concluded that the proposed model is one runner – up in term of runtime while providing best performance accuracy.

3. Conclusions

The proposed MobileNet_Sim_LSTM based in-situ quality monitoring system has been successfully developed and implemented on a low-cost edge-device (Raspberry Pi 3) for an injection moulding machine. Validation results prove the abilities of the proposed methodology in accurately classifying products quality with short runtime comparing with other candidates. With the help from the proposed methodology, quality monitoring task can be automated with a low-cost edge-device while ensuring high quality manufacturing for injection moulding process. Future works can be focused on two aspects:

- The model can be further optimized to handle more types of defects and faster runtime for better overall quality performance
- Online learning scheme for the proposed model can be developed to train and adapt the model during its operation. Update can be made when there is a golden reference available for quality performance, e.g. test report from an inspector on sampled products.

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