Fabrics Defects Detection System Based on Convolution Neural Network

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Abstract

Defective fabric inspection is very important from the raw materials preparation, manufacturing and after manufacturing before market delivery, these procedures are very important in product quality control. The failure of proper inspection leads to a loss of 45% to 65% from market profit. The Convolution Neural Network system employed on fabric defects detection to replace the human labor force. The architecture used as VGG16. In this paper many factors affecting underfitting and overfitting were studied these were: target size, fine-tuning, dropout, data augmentation, optimizers, and batch size. The variation of any of those factors leads to overfitting or underfitting or the stable stage where there is neither overfitting nor underfitting.

Keywords

Defective fabric inspection, Quality control, VGG16, Overfitting and underfitting.

1. Introduction

Inefficiencies in the industrial process are costly in terms of time, money, and consumer satisfaction. Compared to the 60-75% defect detection accuracy of human visual judgment, a typical state-of-art automatic fabric inspection system can achieve a detection rate of up to 90% [2]. As a result, intelligent visual inspection systems to ensure high quality of products in production lines are in increasing demand [3]. In recent years, image defect detection has mainly relied on machine vision, which can detect the spots, pits, scratches, chromatic aberration, and defect on the surface of the workpiece. It has been widely used to detect various products, such as textiles, steel surfaces, metal, glass, paper, and electronic components, etc. With the increasingly stringent requirements for the quality of the products, the defect detection becomes an indispensable part of the industry [4]. The defect detection technique is nothing however the one which may need less labor value, less detection time, and a lot of accuracy [5]. If there are defects in fabric then the price is reduced by 45–65% [1]. We propose a convolutional neural network for fabric defect detection.

2. Methodology

2.1 The Architecture of the Proposed Convolutional Neural Network

The deep convolutional neural networks (CNN), can learn a hierarchy of features from the raw image input by automatically update the filters during training on massive amounts of training data [13]. As the basic framework of the network, in the first phase, the classical VGG16 is used see Table 2.1. It consists of the repeated application of a stack of 3 X 3 convolution layers and 2 X 2 pooling layers, each convolution layer followed by a rectified linear unit (ReLU) for non-linearity rectification. Then, the fully connected layers in VGG16 are convolved so that the generated feature maps can retain complete spatial information. VGG16 with three fused layers can not only accurately detect different scales defects but also generate more precise prediction results in different defect types [11]. Dropout, applied to a layer, consists of randomly dropping out (setting to zero) several output features of the layer during training. Data augmentation takes the approach of generating more training data from existing training samples, by augmenting the samples via several random transformations that yield believable-looking images. Fine-tuning is the way at which some layers during training are frozen, this is to reduce the number of parameters to avoid overfitting, VGG16 yields more than 16millions of parameters, this huge number should be reduced by freezing some layers.

Table 2.1 Architecture of the proposed convolutional neural network for fabric detection (VGG16)

	Description	Layer(type)	Output Shape	Number of Param
Convolution2D		input_6 (Input Layer)	(None, 253, 253, 3)	0
Convolution2D	Conv block1: frozen	block1_conv1 (Conv2D)	(None, 253, 253, 64)	1792
Convolution2D		block1_conv2 (Conv2D)	(None, 253, 253, 64)	36928
Maxpooling2D		block1_pool (MaxPooling2D)	(None, 126, 126, 64)	0
Convolution2D	Conv block2: frozen	block2_conv1 (Conv2D)	(None, 126, 126, 128)	73856
Convolution2D		block2_conv2 (Conv2D)	(None, 126, 126, 128)	147584
Maxpooling2D		block2_pool (MaxPooling2D)	(None, 63, 63, 128)	0
Convolution2D	Conv block3: frozen	block3_conv1 (Conv2D)	(None, 63, 63, 256)	295168
Convolution2D		block3_conv2 (Conv2D)	(None, 63, 63, 256)	590080
Convolution2D		block3_conv3 (Conv2D)	(None, 63, 63, 256)	590080
Maxpooling2D		block3_pool (MaxPooling2D)	(None, 31, 31, 256)	0
Convolution2D	Conv block4: frozen	block4_conv1 (Conv2D)	(None, 31, 31, 512)	1180160
Convolution2D		block4_conv2 (Conv2D)	(None, 31, 31, 512)	2359808
Convolution2D		block4_conv3 (Conv2D)	(None, 31, 31, 512)	2359808
Maxpooling2D		block4_pool (MaxPooling2D)	(None, 31, 31, 256)	0
Convolution2D		block5_conv1 (Conv2D)	(None, 15, 15, 512)	2359808
Convolution2D	We fine tune conv block5.	block5_conv1 (Conv2D)	(None, 15, 15, 512)	2359808
Convolution2D		block5_conv1 (Conv2D)	(None, 15, 15, 512)	2359808
Maxpooling2D		block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
	We fine tune our own fully connected classifier.	vgg16 (Model)	(None, 7, 7, 512)	14714688
Flatten		flatten_6 (Flatten)	(None, 25088)	0
Dense		dense_11 (Dense), Activation1, Relu	(None, 512)	12845568
		dropout_6 (Dropout)	(None, 512)	0
Dense		dense_12 (Dense), Activation2, Sigmoid	(None, 1)	513
	Total params			14,714,688
	Trainable params			14,714,688

3. Results and Discussion

3.1 Dataset

In the experiments, we are mainly concerned with the fabrics. The dataset collected from fabrics manufacturing line. The data set includes 92 training images, 46 validation images, and 117 images for testing the trained model, batch size was 46, the optimizer was optimizers. RMSprop(lr=2e-5) [14], dropout was 0.5 and data augmentation of rotation range was 50, Width shift range was 0.3, Height shift range was 0.3, Shear range was 0.31, Zoom range was 0.3, Horizontal flip was True, Fill mode was nearest and Target size was 253 x 253 as shown in Table 1. NVIDIA GeForce GTX computer used for those experiments to be done. Network hyperparameters used and the network architecture is shown in Figure 2.0.

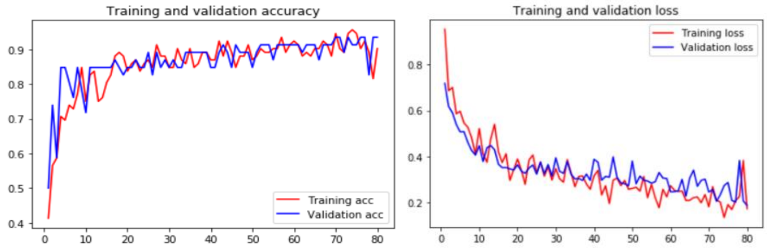

Fig. 3.1 The performance of the proposed fine-tuned VGG16 model. Test accuracy was 95.92%.

Table 3.1 The performance of the different VGG16 models

Variation Factor	Target size	Optimizer	Batch size	Dropout	Test Accuracy %
Nil	253 x 253	optimizers. RMSprop(lr=2e-5)	46	0.5	95.92
Optimizer	253 x 253	optimizers. RMSprop(lr=2e-4)	46	0.5	94.56
Target size	150 x 150	optimizers. RMSprop(lr=2e-5)	46	05	89.12
Batch size	253 x 253	optimizers. RMSprop(lr=2e-5)	5	0.5	91.84
Dropout	253 x 253	optimizers. RMSprop(lr=1e-5)	46	0	92.41
Data Augmentation	253 x 253	optimizers. RMSprop(lr=2e-5)	46	0.5	93.85

3.2 Confusion Matrix

The symbols TP and FN denote the real defect images are correctly detected as defective ones and misclassified as normal ones, respectively. Correspondingly, the symbols TN and FP denote the real normal images are correctly detected as normal ones and misclassified as defective ones, respectively. In confusion matrix we got; TP = 23, FN = 0, FP = 6 and TN = 88. In this paper we only calculate the accuracy for evaluation of the VGG16 model performance.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{23+88}{23+88+6} = 94.87\%$$

Table 3.2 Confusion matrix of the fabric detection algorithms

	Precision	Recall	F1-score	Support
Bad	0.79	1.00	0.88	23
Good	1.00	0.94	0.97	94
Accuracy			0.95	117
Macro avg	0.90	0.97	0.93	117
Weighted avg	0.95	0.94	0.95	117

4. Conclusion

As experiments shown above, during setting an architecture and training; Target size, fine-tune, batch size, dropout, optimizer, and data augmentation should be paid attention. The variation of those factors changes the output significantly.

In this paper, a convolution neural network is proposed to be used for fabric defects detections. The best and powerful model architecture is VGG16, this helps to generate more millions of parameters from images which help to avoid the model underfitting. Also, the convolution neural network algorithm is the automated extraction of features, model training and detection is done without human assistance. But the best and complex model is one trained with a big dataset, thousands or millions of images, but VGG16 even if the dataset is very small, is capable to generate several parameters and make the model very strong. The authors warmly recommend using a convolution neural network VGG16 model for fabric defect detection.

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