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Article

Classification of Guide Rail Block by Xception Model

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Abstract: Linear guide rail blocks are used in linear slide rail accessories to scrape off oil stains in the rails, installed on the front and rear ends of the slider. They are also used in milling machines, lathes, automated machines, robotic arms, electronic instruments, and so on. At present, the industry relies on manpower to carry out the quality inspection of this rail block which is difficult to standardize. Thus, automatic and digital deep learning inspection technology is introduced for the inspection. To understand the suitability of deep learning techniques applied to the linear guide block inspection process, we adopt the convolutional neural network model architecture and use the Xception model. In model training, the training effect is improved by amplifying the image method and testing many different defects. Through the Xception model, the training accuracy is about 98.7% after 30 epochs, the validation accuracy is about 97.4%, and the test accuracy is about 91.8%.

Keywords: Deep learning, Guide rail block, Classification, Xception

1. Introduction

In recent years, the development of computer vision has made it possible to perform various image recognition tasks with high accuracy. One of the applications of computer vision is the classification of objects in images, which has a wide range of practical implications. In the automated industry, the accurate classification of guide rail blocks is particularly important for ensuring safety and improving efficiency. Chollet [1] proposed a convolutional neural network (CNN) architecture, the Xception model. It is designed to handle the problem of overfitting by using depth-wise separable convolutions, which is common in traditional CNNs. Therefore, the Xception model was adopted in this study to classify the guide rail blocks. We trained the Xception model on a large dataset of guide rail block images, using a transfer learning approach. The pre-trained weights from the ImageNet dataset [2] were used as the initial weights for the Xception model, and the model was then fine-tuned on the guide rail block dataset. The performance of the Xception model was evaluated on a test set of guide rail block images and compared to two baseline models, a support vector machine (SVM) [3] and a traditional CNN [4]. Girshick et al. [5] proposed a semantic R-CNN model to improve the accuracy and performance of the object detection. Rismiyati et al.[6] fine-tuned their garbage classified model with a dataset of garbage images by using pre-trained Xception models. Feng et al.[7] proposed the pre-trained Xception model to classify the surface of strip steel after hot rolling processing. Li et al. [8] designed a two-statge trianing model to overcome the lag problems of the non-stationary time series prediction, they got better performance and predicted more accurately. The Xception model could be able to classify guide rail blocks in real-time, which is a crucial requirement for practical applications. The study result presents an approach for classifying guide rail blocks using the Xception model. The results demonstrate that the Xception model is capable of achieving high accuracy in the classification of guide rail blocks and outperforms traditional machine learning and deep learning models. The use of the Xception model holds the potential for enhancing the efficiency and safety of the automated industry by providing a fast and reliable method for classifying guide rail blocks.

1.1. Research Purposes

The linear guide block is an important component for linear slide rail accessories (Fig. 1). It is made of high-precision steel with high strength and wear resistance. As industrial equipment and machinery, it is often used to support and guide heavy loads such as turning and milling machines and measuring instruments. The slider is a wide metal block which is in contact with the guide rail and slides. The contact point between the two is small in μm. To effectively reduce friction and wear and prolong the service life of the equipment, using the high-yield guide rail block can effectively keep the mechanical equipment clean, remove and discharge the grease and dirt on the surface of the equipment by contacting it, and maintain the lubrication system. It also ensures the best performance in high-speed equipment and high-temperature environments.

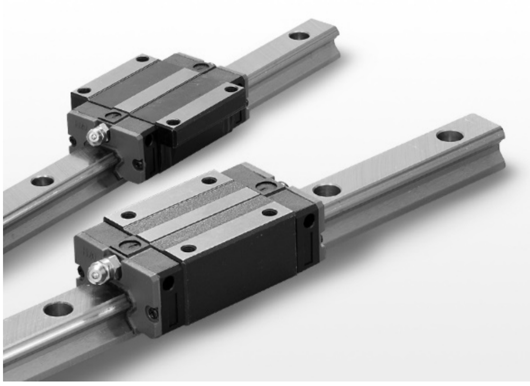


Fig. 1. Linear slide rail.

2. Deep Learning Prediction Framework

2.1. Guide Rail Block Data Collection

The guide rail block manufacturing process may cause product instability or affect product strength and form defects if there are no proper temperature, pressure, and time controls shown in Fig. 2. The possible reasons are as follows: (1) Process control issues: if there is no proper temperature, pressure, or time control during the manufacturing process, the product's surface may not be smooth; (2) Material quality problems: the use of inferior rubber raw materials or additives may cause the surface of the product to be uneven; (3) Mold wear: if the mold is worn, it may affect the smoothness of the product surface; (4) Personnel operation problem: if the operator does not have proper training or experience, it may lead to errors in the process or uneven product surface; (5) Mold design problem: If the mold design is unreasonable, it may affect the smoothness of the product surface.

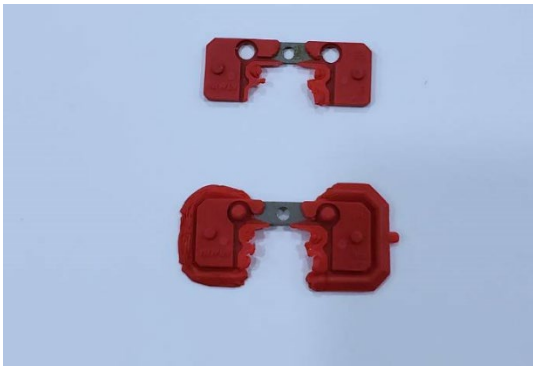
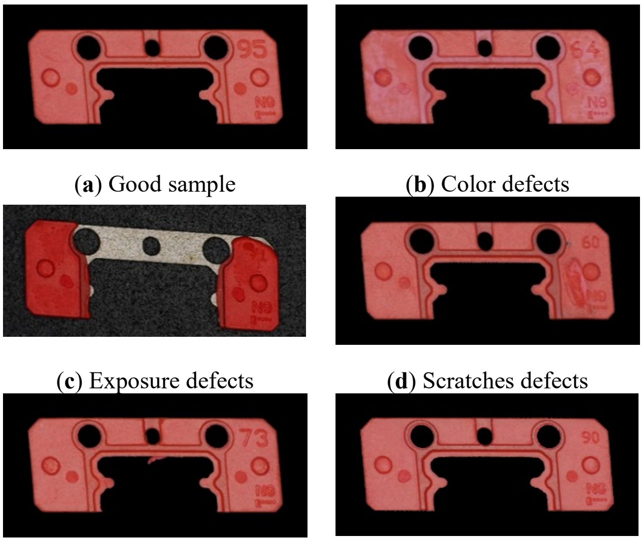


Fig. 2. Rail block defects

In this study, 5272 images were collected as data materials whose image size is 299 × 299. There are mainly 3 folders: train, test, and validate. Each folder contains 6 subfolders. One good and five bad samples are shown in Table 1. The image dataset of the guide rail block for building the Xception model consists of 2,220 pictures of good samples, 504 pictures with color defects, 384 pictures with exposure defects, 479 pictures with scratches defects, 464 pictures with burrs defects and 468 pictures with mark defects. The 80% pictures were used as training data and the other 20% pictures were used as validation data. Additionally, the test data for testing whether the builded model is feasible consist of 370 pictures of good samples, 84 pictures with color defects, 64 pictures with exposure defects, 80 pictures with scratches defects, 77 pictures with burrs defects and 78 pictures with mark defects. Among them, 5 bad samples contain—color defects, exposure defects, scratches defects, burrs defects and mark defects as shown in Fig. 3.

- Color defects: color differences are caused by unclean production environments or operators without proper training;
- Exposure defects: The steel sheet inside the slide rail block is exposed due to improper temperature or pressure during manufacture processing;
- Scratches defects: Scratches defects are caused by insufficient pressure or temperature during manufacture processing;

- Burrs defects: Burrs defects are caused by poor material quality or improper temperature or pressure during manufacture processing;
- Mark defects: The text on the rail block may be unclear or wrong during manufacturing process.



(**a**) Good sample (**b**) Color defects (**c**) Exposure defects (**d**) Scratches defects (**e**) Burrs defects (**f**) Mark defects

Fig. 3. Samples of guide rail block.

Table 1. Image dataset for training and testing.

Data Type	Train	Validate	Test	Total
Good	1850	370	370	2590
Color	420	84	84	588
Exposure	320	64	64	448
Scratches	399	80	80	559
Burrs	387	77	77	541
Mark	390	78	78	546
Total pictures				5272

2.2. Research Equipment

In order to quickly detect the defects such as burrs and scratches on the linear guide block and ensure the quality of the collected images, a defect detection system for the linear guide rail block was established. The system mainly includes appropriate CCD for image-acquiring and a lighting environment. A uniform and moderate-intensity ring light illumination is adopted to reduce image shadows and reflections and improve image contrast and clarity. NEON-203B-JNX CCD with a sensor size of 1/3.7” is used for acquiring the images of linear guide block. The specifications are 2vM resolution, rolling shutter, 1920 × 1080 (H × V) resolution, 30 fps frame rate, and color (Fig. 4).

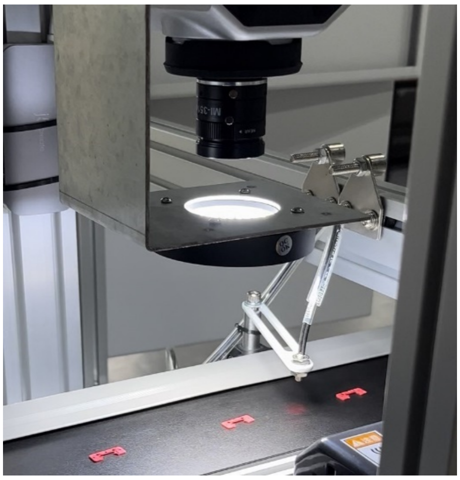


Fig. 4. Structure for acquiring sample image.

2.3. Xception Model Method Theory

In the recent actual production of the industry, full-visual manual inspection and judgment are used in quality inspection. However, it is difficult to find the details of defects and standardize them. It is rather easy to make misjudgments due to personnel fatigue, resulting in poor yields. Therefore, it is important to establish a database and inspect and judge through deep learning algorithms to effectively improve the accuracy and speed of detection. Using the Xception [1] (Extreme version of Inception) model for training which is another improvement of Google's InceptionV3, depth-wise separable convolution is used to replace the convolution operation in the original InceptionV3. However, in Xception, the spatial convolution and channel-wise convolution are separated. This is achieved by using a corresponding 3×3 depth-wise convolutional layer for each spatial dimension and a 1×1 pointwise convolutional layer for each channel shown in Fig. 5. By separating the spatial and channel dimensions, Xception reduces the number of parameters required in the network and allows for more efficient use of computation resources. Under the premise of basically not increasing the complexity of the network, the performance of the model is improved. Combined with image processing, image features can be learned from it. Also in the field of defect detection, Xception can effectively detect various types of defects such as cracks, peeling, and oxidation, and is usually trained on a large number of defect images to recognize various types of defects [6]. Once the training is completed, defects are automatically detected in new images, which significantly improves the accuracy of defect detection and makes it easier for us to complete image recognition.

The Xception architecture has 36 convolutional layers that form the basis of the neural network for feature extraction and is divided into 14 blocks. Except for the first and last modules, there is a linear residual connection technology to connect the outputs of each guide rail block [7]. To sum up, on the premise of reducing the gradient disappearance problem, the network further is used to extract more features in depth. The output of the last convolutional layer uses global average pooling for feature sampling and then inputs it into the fully connected layer for classification.

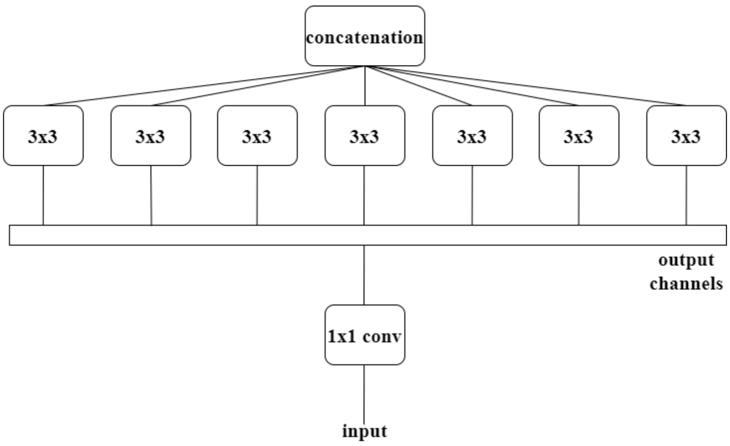


Fig. 5. Xception model with one spatial convolution per output channel of the 1×1 convolution.

3. Experimental Evaluation

3.1. Image Preprocessing Process

The purpose of deep learning image preprocessing is to make the training data more suitable for deep learning model processing and to improve the prediction accuracy of the model[8]. Common preprocessing methods include image scaling, rotation, flipping, contrast, and brightness adjustment. These preprocessing steps help the model better capture the features in the image and reduce the risk of overfitting. In this study, the images were brightness adjusted, rotated, cropped, and grayscaled. The process is shown in Fig. 6. The original size of the CCD sampled data is 1920×1080 and there is considerable noise during modeling. After image preprocessing, the data size is reduced to 299×299 grayscale image with less noise to improve the image features and detection accuracy.

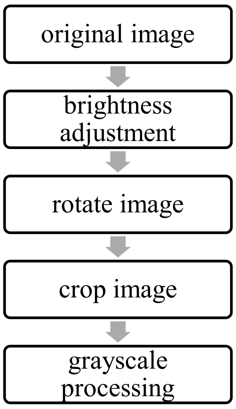


Fig. 6. Image processing flowchart.

3.2. Application Framework of Classification of the Guide Rail Block

The application architecture of the classification of the linear slide rail block accessories in this study is divided into image acquiring, image preprocessing, model training, and verification results as shown in Fig. 7. The sample images of the linear guide rail block are acquired by CCD. Then 299×299 grayscale images are obtained after image preprocessing. Futhurmore, the model is trained with the training dataset in Table 1 built after image preprocessing. The image data of one good sample and five bad samples were collected, including various types of defects such as color defects , exposure defects, scratches defects, burrs defects and mark defects. Finally, the Xception neural network model is tested using the testing dataset in Table 1, and the performance of the model is evaluated by verifying the test results.

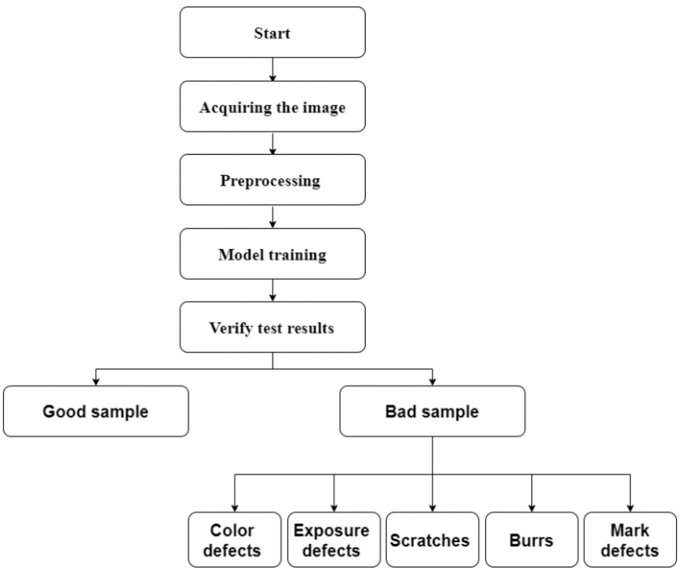


Fig. 7. Flowchart of classification for the guide rail block.

4. Experimental Results

With the Xception network model, the guide rail block picture data set was established, and the training and testing were carried out on the surface detection of the guide rail block. The training environment used is Colab developed by Google Research, which has GPU computing resources and free access. It is a cloud development environment based on the Jupyter Notebook interface for data analysis and machine learning. The programming language is Python 3.9, the deep learning framework used is Keras based on Tensorflow 2.5, the batch size is 32, the number of categories is 6, the number of rounds (Epoch) is 30, and the initial learning rate is 0.001.

In this study, the collected guide block data are preprocessed and the parameters are adjusted. A dataset of rail block images is constructed and trained using the Xception network model. The model is then subjected to a track block surface inspection test, and the results are evaluated and verified. It is observed that the training accuracy of the guide rail block is about 98.7%, while the validation accuracy is about 97.4%, as shown in Fig. 8. The training and veridation loss curves show a continuous downward trend, and the gap between them is very small, as shown in Fig. 9. Therefore, this study improved the yield and quality inspection quality.

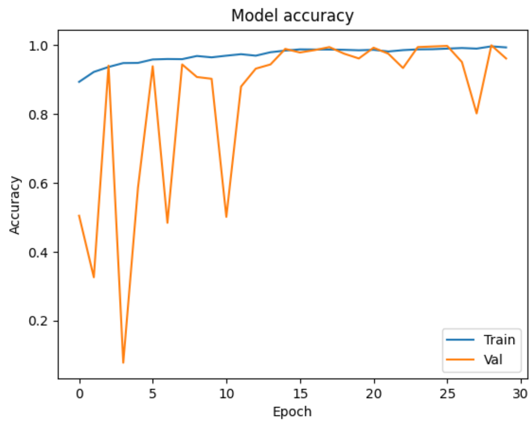


Fig. 8. Training and validation accuracy of the Xception model.

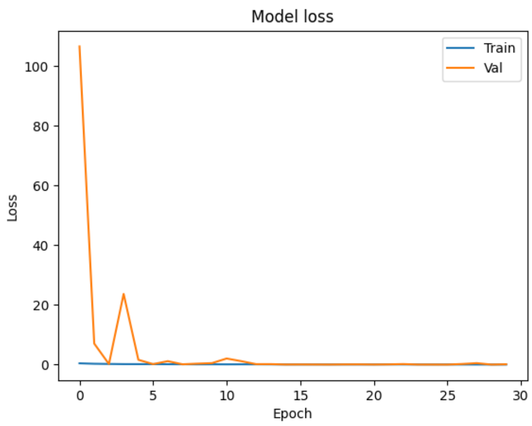


Fig. 9. Loss functions of the Xception model.

While conducting research, we put forward suggestions for future directions. First, it is necessary to increase the quality and quantity of training data to further improve the accuracy of detection and to improve and optimize the architecture of the neural network to better. It is also worth exploring to adapt to the special needs of the surface detection of the guide rail block. Finally, the combination with other technologies such as image processing and machine vision is studied to further improve the efficiency and accuracy of detection. Therefore, by applying the deep learning neural network to the linear slide rail surface detection of accessory rail blocks, this study achieved satisfactory results providing suggestions for future research directions. Future research will further improve and develop this field to provide better solutions such as improving the architecture of neural networks and the quality and quantity of data. Combining research with other technologies can be conducted to improve production efficiency and product quality.

The confusion matrixe of the test results is shown in the Table 2. There are 752 test pictures in total. The “good sample” has a recall rate of 95.1% and a true positive (TP) of 352. “Color defects” has a recall of 91.7% and a TP of 77. “Exposure defects” has a recall of 93.8% and a TP of 60. “Scratches defects” has a recall of 83.8% and a TP of 67. “Burrs defects” has a recall of 85.5% and a TP of 65. “Mark defects” has a recall of 88.5% and a TP of 69. The total test accuracy is (352 + 77 + 60 + 67 + 65 + 69)/752 = 91.8%. Therefore, the model for classifying the guide rail block is feasible with high accuracy. However, there are still some pictures that are misclassified by the model. For example, 5 “color defects” pictures were misclassified as “good sample”, 6 “mark defects” pictures were misclassified as “good sample”, and 10 “good sample” pictures were misclassified as “mark defects”. These misclassifications lead to reduced model accuracy and may need to be addressed through further model training or tuning the model’s hyperparameters. Overall, the model performed well in terms of recall, but there is still room for improvement in reducing misclassification.

Table 2. Confusion matrix table of testing results.

Label \ Predict	Good	Color	Exposure	Scratches	Burrs	Mark	Recall
Good	352	3	0	5	0	10	95.1%
Color	5	77	0	1	1	0	91.7%
Exposure	0	0	60	2	1	1	93.8%
Scratches	0	3	1	67	4	5	83.8%
Burrs	5	1	0	1	65	4	85.5%
Mark	6	0	1	2	0	69	88.5%
Total accuracy((352 + 77 + 60 + 67 + 65 + 69)/752)							91.8%

5. Conclusions

Based on the deep learning Xception model training, research on the surface detection of guide rail blocks was carried out. Through image preprocessing, training, verification and test samples, and comparison and evaluation, this model was proved to have a great impact on guide rail blocks. The Xception model was trained and tested using 5272 pitctures from the guide rail block image dataset. The results show that after 30 epochs, the training accuracy is about 98.7%, the validation accuracy is about 97.4%, and the test accuracy is about 91.8%. Therefore, it was concluded that the deep learning neural network is an effective method for the surface detection of the guide rail block of linear slide rail accessories. For the industry, labor costs can be greatly reduced and errors from human fatigue can be greatly reduced. Although the Xception model has excellent image classification capabilities, the recognition ability of the Xception model would not be fully recognized if the training data set is not sufficient. Therefore, it could not achieve excellent results in recognition. The accurate effect would be limited. In this case, the number of data samples needs to be increased, and the data set must be further expanded to improve the accuracy and further improve performance of the model. It is also necessary to explore the identification of different models for the surface detection of this guide rail block. In summary, the proposed research method using deep learning neural network is appropriate for the surface detection of linear slide rail accessories with the guide rail block. The application of machine learning in the field of the industry is inspirable. The research result of this study allows new thinking and inspiration to the industry. There will be more research in the future to further develop and promote this technology.

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