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Research on metal image defect detection based on convolutional neural network, random forest model and support vector machine model

Yi Tao

School of Computer and Information Engineering, Henan University of Economics and Law Henan, Zhengzhou, 450016, China

ty15138636290@163.com

Abstract. Metal image defect detection is a very important task, which can help manufacturers to detect defects in metal products in time during the production process, so as to improve product quality and production efficiency. This paper presents a private dataset containing images of six different types of metal surface defects, including scratches, pits, indentations, bubbles, oil stains, and aluminum surface defects. The dataset contains 1800 images, 300 images for each defect type, each with a size of 200x200 pixels. The dataset is divided into training, validation and test sets in the ratio of 6:2:2. By using Support Vector Machine Model, Random Forest Model and Convolutional Neural Network Model for prediction, we obtained the following results: the Support Vector Machine Model has the best prediction ability with 89% accuracy; the Random Forest Model has 69% accuracy; and the Convolutional Neural Network Model has poor prediction ability with 26% accuracy. From these results, it can be seen that the support vector machine model is one of the most suitable models for defect detection in metal images. This model can effectively identify various defects on metal surfaces, thus helping manufacturers to better control the quality of their products. In comparison, the predictive power of the Random Forest model is weak, but it can still be used for some simple metal image defect detection tasks. The convolutional neural network model has the worst predictive ability, but it is widely used in other fields, such as image recognition and speech recognition. In conclusion, metal image defect detection is a very important task, which can help manufacturers find the defects of metal products in the production process in time, so as to improve product quality and production efficiency. In practical applications, we can choose different algorithms and models to realize metal image defect detection in order to get the best results.

Keywords: CNN, Machine learning algorithms, SVM.

1. Introduction

Metal image defect detection is a very important work, which can help manufacturers find the defects of metal products in the production process in time, so as to improve product quality and production efficiency [1]. With the continuous development of science and technology, the application of machine learning in metal defect detection has become more and more extensive, and has become a very effective means of detection [2].

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The traditional metal defect detection method mainly relies on manual visual inspection, which is not only inefficient, but also prone to problems such as leakage and misdetection [3]. Therefore, it is very important to study an automated, efficient and accurate metal defect detection method [4]. Machine learning, as a branch of artificial intelligence, can automatically identify and classify different image features by learning a large amount of data, thus realizing automated detection and greatly improving the efficiency and accuracy of detection [5,6].

The important role of machine learning in metal defect detection is not only reflected in automated detection, but also in multi-dimensional feature extraction and real-time monitoring [7]. Machine learning can analyze and identify metal images from different angles through multidimensional feature extraction, so as to detect different defect types more accurately [8,9]. At the same time, machine learning can improve product quality and production efficiency by monitoring the production process of metal products in real time and finding and dealing with defects in a timely manner.

In terms of applications, machine learning has been increasingly used in metal defect detection. For example, some researchers have used machine learning algorithms, which can analyze and identify the images of automotive parts, discover and deal with defects in a timely manner, and improve the quality and reliability of automotive parts [10]. In addition, machine learning can also monitor the images in the steel production process in real time, discover and deal with defects in time, and improve the quality and production efficiency of steel products. In conclusion, the application of machine learning in metal defect detection is promising and will play an increasingly important role in future manufacturing.

2. Introduction to the dataset

The Metal Defect Detection Dataset is a private dataset containing images of six different types of metal surface defects. These defects include scratches, pits, indentations, bubbles, oil stains, and aluminum surface defects. The dataset contains 1800 images with 300 images for each defect type. The size of each image is 200x200 pixels.

The purpose of this dataset is to help researchers and engineers develop image-based defect detection algorithms. These algorithms can be used in areas such as metal surface defect detection, quality control and automated production lines. The images in the dataset were taken by professional metal surface defect detection equipment and have high accuracy and reliability.

This dataset is labeled with the defect type of each image. There are 300 images for each defect type labeled with the numbers 1 to 6. This dataset can be used to train and test various image classification algorithms such as Convolutional Neural Networks, Support Vector Machines, and so on. By using this dataset, researchers and engineers can develop more accurate and reliable algorithms for detecting defects on metal surfaces, improving productivity and product quality. Some of the data is shown in Figure 1.

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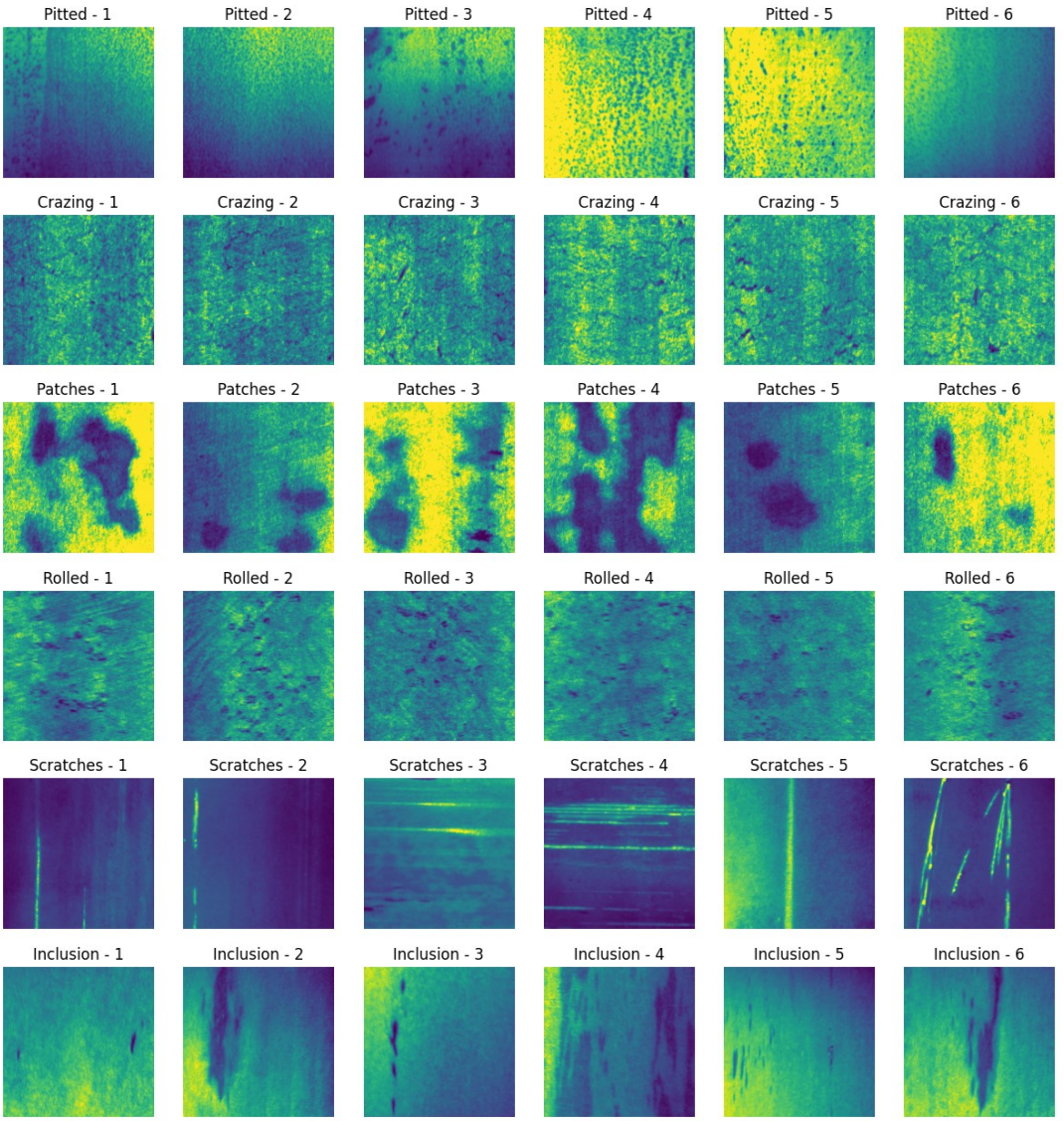


Figure 1. Partial data presentation.
(Photo credit: Original)

3. Machine learning model

3.1. Convolutional neural network model

CNN (Convolutional Neural Network) is a deep learning model commonly used in image recognition, speech recognition and other fields. Its core idea is to extract and classify the features of input data through the structure of convolutional layer, pooling layer, fully connected layer, etc. CNN has the characteristics of parameter sharing, sparse interaction, etc., which can effectively reduce the number of parameters of the model and the amount of computation, and improve the generalization performance of the model. In practice, CNN has been widely used in image classification, target detection, face recognition and other fields.

The structure of CNN model is mainly composed of three parts: convolutional layer, pooling layer and fully connected layer. Among them, the convolutional layer and pooling layer are the core components of the CNN model, and the fully connected layer is used to transform the feature maps output from the convolutional layer and pooling layer into classification results.

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The convolutional layer is the first layer of the CNN model, and its role is to extract the local features of the input data. The convolutional layer consists of multiple convolutional kernels, each of which can extract one feature from the input data. The convolution operation is to slide the convolution kernel over the input data and calculate the dot product of the convolution kernel and the input data to get the feature map. The convolution operation can effectively reduce the number of parameters and the amount of computation, while preserving the local features of the input data.

The pooling layer is the second layer of the CNN model, which serves to reduce the dimensionality of the feature map. The pooling layer includes multiple pooling kernels, each of which can perform pooling operations on a portion of the input data. The pooling operation can average or maximize a portion of the input data to obtain the pooling result. The pooling operation can effectively reduce the size and computation of the feature map while retaining the main features of the input data.

The fully connected layer is the last layer of the CNN model, which serves to transform the feature map into a classification result. The fully connected layer includes multiple neurons, each of which can compute a portion of the feature map. The fully connected layer can transform the feature maps into classification results while retaining the global features of the input data.

The training process of the CNN model mainly consists of two stages: forward propagation and back propagation. Forward propagation is the process of passing the input data through structures such as convolutional layers, pooling layers, and fully connected layers to obtain classification results. Backpropagation is the process of calculating the gradient of the model parameters based on the error between the classification result and the real label, and then updating the model parameters through the gradient descent algorithm.

3.2. Random forest model

Random Forest Modeling is an integrated learning method based on decision trees. Its core idea is to classify or regress the input data by constructing multiple decision trees. Random forest model has many advantages, such as easy to implement, insensitive to missing data, not easy to overfitting and so on. In practice, random forest model has been widely used in financial risk assessment, medical diagnosis, customer churn prediction and other fields.

The core component of the random forest model is the decision tree. Decision tree is a commonly used classification and regression model, and its core idea is to separate different categories of data by constructing a tree structure. Each node of the decision tree represents a feature, each branch represents a feature value, and each leaf node represents a category or a value. The decision tree construction process mainly includes steps such as feature selection, node division and pruning.

The random forest model classifies or regresses the input data by constructing multiple decision trees. The training process of random forest model mainly includes the following steps. First, a certain number of samples are randomly selected from the original dataset to construct a sub-dataset. Then, a certain number of features are randomly selected from the sub-dataset to construct a feature subset. Next, construct a decision tree based on the feature subset and the sample subset. Finally, repeat the above steps to construct multiple decision trees and merge them into a random forest model.

The random forest model has many advantages. First, the random forest model can handle high-dimensional data and is insensitive to missing data. Second, the random forest model can effectively avoid overfitting and has strong generalization ability. Finally, the random forest model can output the importance of features, which helps in feature selection and model interpretation.

3.3. Support vector machine model

Support vector machine model is a commonly used classification and regression model. Its core idea is to separate different classes of data by constructing an optimal hyperplane. Support vector machine model has many advantages, such as it can deal with high-dimensional data, it is insensitive to noisy data, and it has strong generalization ability. In practice, support vector machine models have been widely used in image classification, text classification, credit risk assessment and other fields.

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The core of the support vector machine model is the optimal hyperplane. An optimal hyperplane is a straight line or surface that can separate different categories of data. The goal of a support vector machine model is to find an optimal hyperplane such that it maximizes the distance to the nearest data point. The nearest data points are called support vectors because they have an important influence on the location and direction of the optimal hyperplane.

The training process of the support vector machine model consists of the following steps. First, the input data is mapped to a higher dimensional space, making it easier to separate the data in the higher dimensional space. This process is known as kernel function. Commonly used kernel functions are linear kernel function, polynomial kernel function, Gaussian kernel function and so on. Then, an optimal hyperplane is constructed based on the input data and labels. The position and direction of the optimal hyperplane are determined by the support vectors. Finally, the new data is classified or regressed according to the optimal hyperplane.

The support vector machine model has many advantages. First, the support vector machine model can handle high-dimensional data and is insensitive to noisy data. Secondly, support vector machine models can effectively avoid overfitting and have strong generalization ability. Finally, the support vector machine model can output the positions and directions of support vectors and optimal hyperplanes, which helps model interpretation and visualization.

Support vector machine models have a wide range of applications. In image classification, support vector machine models can be used in face recognition, target detection and other fields. In text classification, support vector machine models can be used in sentiment analysis, spam filtering and other fields. In credit risk assessment, support vector machine models can be used in areas such as credit rating, default prediction, and so on. Support vector machine model is a commonly used machine learning model with good classification and regression capabilities. It is very important for data scientists and machine learning engineers to be proficient in the principles and applications of support vector machine models.

4. Experiments and results

Divide the training set, validation set and test set according to 6:2:2, the training set is used for model training, the validation set is used for validation during model training, and the test set is used for testing after the model training is finished, plot the confusion matrices of the predictions of Convolutional Neural Networks, Support Vector Machines, and Random Forests, respectively as shown in Fig. 2, Fig. 3 and Fig. 4, and compute the accuracy, precision, and recall of predictions of the three models, as shown in Table 1.

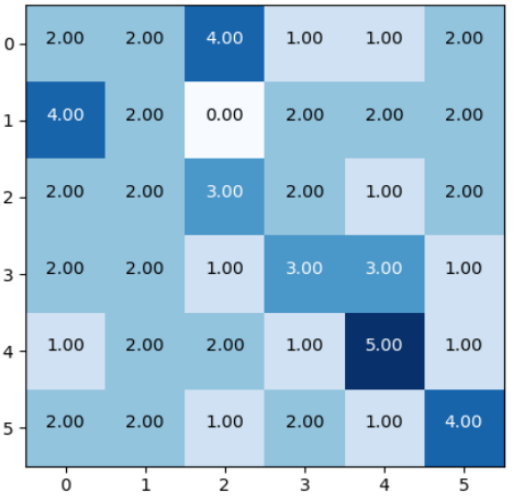


Figure 2. Convolutional Neural Network Confusion Matrix.
(Photo credit: Original)

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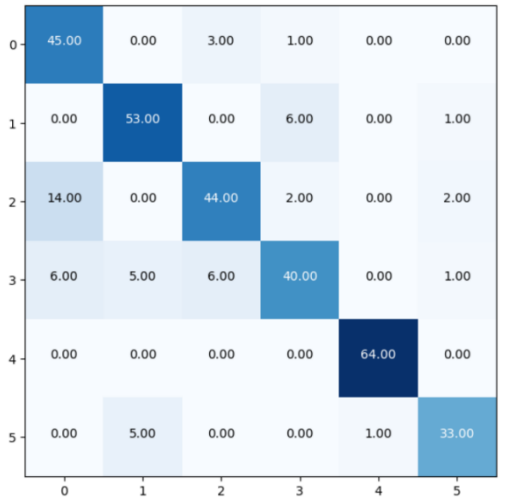


Figure 3. Support vector machine confusion matrix.
(Photo credit: Original)

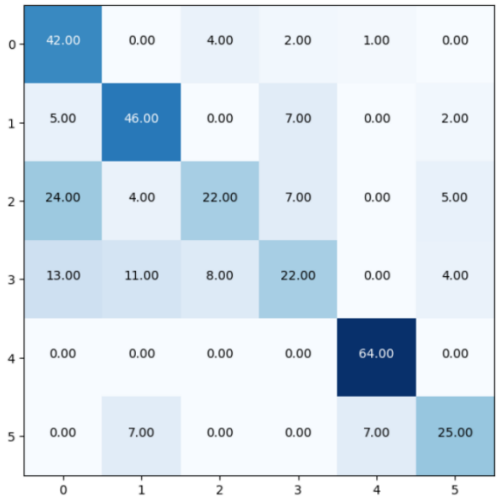


Figure 4. Random Forest Confusion Matrix.
(Photo credit: Original)

Table 1. Model evaluation.

model	precision	recall	f1-score
CNN	0.26	0.26	0.26
SVM	0.89	0.85	0.87
Random forest	0.69	0.64	0.67

From the results, it can be seen that the best prediction of defects in metal images is the Support Vector Machine model with 89% accuracy, followed by the Random Forest model with 69% accuracy, while the Convolutional Neural Network model has poor prediction ability with only 26% accuracy.

5. Conclusion

Metal image defect detection is a very important task, which can help manufacturers to find the defects of metal products in time during the production process, so as to improve the quality of products and production efficiency. In order to realize metal image defect detection, some advanced techniques and

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methods are needed, such as support vector machine model, random forest model and convolutional neural network model.

In this study, we used a private dataset containing six different types of metal surface defect images. These defects include scratches, pits, indentations, bubbles, oil stains and aluminum surface defects. The dataset contains 1800 images with 300 images for each defect type. The size of each image is 200x200 pixels. We have divided the dataset into training, validation and test sets in the ratio of 6:2:2.

After using three different models for prediction, we got the following results. The Support Vector Machine model has the best prediction ability with 89% accuracy. This is followed by the Random Forest model with an accuracy of 69%. Whereas, the Convolutional Neural Network model has a poor prediction ability with an accuracy of 26%.

From these results, it can be seen that the support vector machine model is one of the most suitable models for defect detection in metal images. This model can effectively identify various defects on metal surfaces, thus helping manufacturers to better control product quality. In comparison, the predictive power of the Random Forest model is weak, but it can still be used for some simple metal image defect detection tasks. The convolutional neural network model has the worst predictive ability, but it is widely used in other fields, such as image recognition and speech recognition. In practice, some other factors need to be considered for metal image defect detection. For example, the material of the metal, the surface treatment method and environmental factors need to be considered. In addition, appropriate algorithms and models need to be selected in order to get the best results in practical applications.

In conclusion, metal image defect detection is a very important work, which can help manufacturers find the defects of metal products in the production process in time, so as to improve product quality and production efficiency. In practical application, we can choose different algorithms and models to realize metal image defect detection in order to get the best results.

References

[1] Zhao L ,Zheng Y ,Peng T , et al.Metal Surface Defect Detection Based on a Transformer with Multi-Scale Mask Feature Fusion[J].Sensors,2023,23(23):

[2] Yiming G ,Yiyang S ,Jie W , et al.Superior Electromechanical Compatibility in Lead-Free Piezoceramics with Mobile Transition-Metal Defects.[J].ACS applied materials interfaces,2023,

[3] Meng S ,Lijian Y ,Songwei G , et al.Metal Surface Defect Detection Method Based on TE01 Mode Microwave[J].Sensors,2022,22(13):4848-4848.

[4] Ihor K ,Pavlo M ,Janette B , et al.Research of U-Net-Based CNN Architectures for Metal Surface Defect Detection[J].Machines,2022,10(5):327-327.

[5] Kun W ,Zixuan T ,Tengyue Z .Metal Defect Detection Based on Yolov5[J].Journal of Physics: Conference Series,2022,2218(1):

[6] V. V P ,S. E D .Testing for Defects in Pulsed Magnetic Field Transmitted Through Metal[J].Russian Journal of Nondestructive Testing,2022,57(10):856-864.

[7] Yiming X ,Kai Z ,Li W .Metal Surface Defect Detection Using Modified YOLO[J].Algorithms,2021,14(9):257-257.

[8] I N G ,A N K ,A A B , et al.Research of the occurrence and development of metal defects in sulfide stress cracking inducing environment[J].IOP Conference Series: Materials Science and Engineering,2021,1129(1):

[9] Chowdary D S ,Sudhakar M . Multi-objective Floorplanning optimization engaging dynamic programming for system on chip[J]. Microelectronics Journal,2023,140.

[10] JinPei D ,WenHua C ,HsienChang K , et al.Efficient small toxic gaseous molecule scavengers in metal-defective graphene: A density functional analysis[J].Journal of the Chinese Chemical Society,2021,68(3):517-521.