2023 4th International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE) | 979-8-3503-4361-8/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICBAIE59714.2023.10281351

Artificial Intelligence-based Recognition of Wear and Corrosion on Steel Surfaces

Wenxuan Nie
Sun Yat-sen University
Shenzhen, China
niewx3@mail2.sysu.edu.cn

***Abstract*—Based on the commonly used steel wear and tear identification method is limited by many factors and the accuracy is not high enough to be stable, this paper adopts a new artificial intelligence algorithm to improve the accuracy of steel wear and corrosion identification. In this paper, a total of six neural network models such as CNN, VGG, etc. are used to classify a total of 1,800 steel photos with six different degrees of wear and tear, and after the model construction and parameter debugging, we get the classification accuracy of CNN, InceptionResNetV2, and Xception models is higher, and MobileNetV2 model has higher sensitivity to the scratch category. The conclusion that the sensitivity of images is higher, using these emerging AI algorithms of deep learning is an effective way to improve the accuracy of steel wear and corrosion recognition.**

Keywords-Steel Wear Recognition; neural network model; Classification accuracy

I. INTRODUCTION

Based on the steel wear identification can determine the service life of the equipment and maintenance cycle, can effectively protect the normal operation of machinery and equipment, improve production efficiency, reduce production costs, steel wear accuracy and efficiency is increasingly important. The manual detection method, magnetic leakage detection method, eddy current detection method and laser detection method used in the past are limited by the subjective factors, the degree of defects, environmental factors, material and temperature, which leads to the defect detection is not accurate enough, and some of the artificial intelligence algorithms used previously also have the problems of low accuracy and easy to overfitting, etc. Therefore, we have introduced the emerging artificial intelligence algorithms of deep learning to improve the accuracy of steel wear and corrosion recognition accuracy.

After a literature review, the previously adopted methodologies for steel wear are the ANN-NSGA method [1], which uses an artificial neural network (ANN) to model the complex relationship between load, temperature, and relative humidity on the one hand and wear rate and COF on the other and uses a genetic algorithm (GA) to perform the optimization, and the response surface methodology [2], which treats the response of the system as a function of one or more factors, and employs graphic techniques to this functional relationship is displayed for us to select the optimization conditions in the experimental design by intuitive observation.

Among the applications of deep learning in steel wear, the results are also quite remarkable, such as the combination of artificial neural networks and genetic algorithms to model and optimize the tribological properties, as well as in the evaluation of the potential of remote process monitoring of tool wear in stainless steel stir friction welding [3], where a classification rate of 95.2% of the defined defective states was achieved through the evaluation and validation of the training of artificial neural networks, which proves to be the best solution in the case of a high melting point, high hardness material. melting point, high hardness materials for process monitoring of tool wear and weld quality in FSW, and impacts on the ability to remotely monitor nuclear repair welding in specific applications.

Regarding the previous image classification methods, we learned that there are image classification improvement methods based on convolutional neural networks and transfer learning ideas [4], multi-pose angle model SAR image classification methods [5], hyperspectral remote sensing image classification methods based on deep active learning [6], and weakly-supervised fine-grained image classification methods based on Bayesian algorithms [7], which each have their own advantages and disadvantages,. In this paper, six neural network models are used for classification, which are unfolded as follows.

II. CONVOLUTIONAL NEURAL NETWORK MODEL BUILDING

The first model tried in this paper is a CNN model, it is a kind of artificial neural network, which has become the current research hotspot in the field of speech analysis and image recognition. It has the advantage of enabling images to be used directly as input to the network, avoiding the complex process of feature extraction and data reconstruction in traditional recognition algorithms.

It utilizes spatial relationships to reduce the number of parameters that need to be learned in order to improve the training performance of general forward BP algorithms. A small portion of the image is used as input to the lowest layer of the hierarchical structure, and the information is then sequentially transferred to different layers, each of which passes through a digital filter to obtain the most salient features of the observed data. This method is able to obtain salient features for observations that are invariant to translation, scaling, and rotation because the local receptive region of the image allows neurons or processing units to access the most basic features, such as oriented edges or corners.

A. Experimental material organization

1800 photos of steel with six different levels of wear and tear were collected and a small convolutional neural network was implemented by building some convolutional, pooling, and fully connected layers, and the results of the steel picture organization are shown in Table 1.

Table 1: Picture Sorting

Image type	amount	Training Data	Testing Data	Size
crazing	295	207	88	200x200
inclusion	295	207	88	200x200
patches	295	207	88	200x200
pitted_surface	295	207	88	200x200
rolled-in_scale	295	207	88	200x200
scratches	295	207	88	200x200

B. Experimental details

The dataset comes from kaggle website, after adjusting the parameters such as pixel, filter depth and filter size, the accuracy of the test set rises to 92.5%. The process is as follows: first find out the five influencing factors of the accuracy rate as pixel, filter depth, filter size, pooling layer size, and number of hidden layers, then use the control variable method.

Next change only the pixels to 25*25, 50*50, and 100*100 on the original model, and measure the accuracy rate three times, as shown in Table 2, and find that the accuracy rate is already higher when the pixel reaches 50*50, and when the pixel continue to go up, the increase in accuracy is not obvious, but the speed decreases significantly, so 50*50 is more appropriate.

Table 2: Results of Pixel Variation in CNN model

Pixel	Train Acc	Test Acc
25*25	0.992	0.716
50*50	0.998	0.951
100*100	1.000	0.926

Then keep the pixel as 50*50, only change the filter depth to 16, 32, 64, the accuracy rate as shown in Table 3, found that the accuracy rate with the increase of filter depth shows the trend of increasing and then decreasing, higher at 32 layers.

Table 3: Results of Filter depth Variation in CNN model

Filter depth	Train Acc	Test Acc
16	0.998	0.925
32	0.998	0.931
64	1.000	0.898

After that keep the pixel as 25*25, the filter depth is 16, the pooling layer size is 3*3, and only change the filter size to 2*2, 3*3, 4*4, the accuracy rate as shown in Table 4, found that the accuracy rate is highest when the filter size is 2*2, followed by 3*3, and lowest when it is 4*4.

Table 4: Results of Filter size Variation in CNN model

Filter size	Train Acc	Test Acc
2*2	0.987	0.957
3*3	0.989	0.929
4*4	0.994	0.898

Later keep the pixel as 25*25, the filter depth as 32, the filter size as 3*3, and change only the pooling layer size as 2*2 and 3*3, as shown in Table 5, and it is found that the accuracy rate is not much different.

Table 5: Results of Pool layer size Variation in CNN model

Pool layer size	Train Acc	Test Acc
2*2	0.989	0.933
3*3	0.989	0.929

Finally, keep the pixel as 25*25, the filter depth as 16, the filter size as 3*3, and only change the filter size as 2*2, 3*3, 4*4 respectively, depth is 16, filter size is 3*3, pooling layer size is 3*3, change the number of implicit layers to 64, 128, 192, respectively, as shown in Table 6, and found that the number of implicit layers also has little effect on the accuracy rate.

Table 6: Results of Hidden layers Variation in CNN model

Hidden layers	Train Acc	Test Acc
64	1.000	0.920
128	1.000	0.918
192	0.998	0.922

C. Final model

Therefore, the synthesis concludes that when the pixel is taken as 50*50, the filter depth is 32 layers, and the filter size is 2*2, the accuracy rate is higher. And its built structure is shown in Table 7, which has three convolutional layers, two pooling layers, two fully connected layers.

Table 7: Network architecture

Layer	InputSize	OutputSize
Input Layer	50*50*3	
Conv2D	50*50*3	48*48*32
Conv2D	48*48*32	46*46*64
MaxPool2D	46*46*64	23*23*64
Conv2D	23*23*64	21*21*128
MaxPool2D	21*21*128	10*10*128
Flatten	10*10*128	12800
Dense	12800	128
Dense	128	6

In this case, the accuracy of the test set is obtained as 99.8%, and the accuracy of the training set is 92.5%, and the accuracy of the training set is slightly lower than that of the existing model, and the improvement method has the interval of parameter debugging can be narrowed down, so that the data points are more densely packed, then the accuracy of the tuned parameter will be further improved.

III. Migration Learning

In this paper, we tried five models, VGG, ResNet50, MobileNetV2, InceptionResNetV2, and Xception, and inputted six types of 295 photos each with 200*200 pixels of steel wear and tear, and outputted six kinds of classification results. Among them, InceptionResNetV2 and Xception have better results.

This is due to the characteristics of the model itself. VGG16 model is characterized by the ability to increase the nonlinear mapping, which can be used in place of full connectivity, and is able to effectively improve the performance by increasing the depth, and has only 3x3 convolution and 2x2 pooling from beginning to end, which is concise and graceful convolution; InceptionResNetV2 combines Inception and ResNet with residual connectivity, aiming to improve the performance and stability of the model; Inception module can extract features at multiple scales while residual connectivity can help the network better learn complex mapping relationships, preventing gradient disappearance when training deep networks; Xception is a further improvement of Inception_V3, mainly aiming to improve performance. After adding the residual connection mechanism, the experiments show that Xception improves both the convergence speed and the recognition rate.

The training accuracy results for the five migration models are as follows. The prediction results of model VGG for all six categories deviate in more than 30%, and the accuracy of the training set and the test set are basically the same; model ResNet50 has a very high accuracy in the training set but a lower accuracy in the test set, overfitting phenomenon occurs, and the model basically can only recognize one image of inclusion; model MobileNetV2 also has overfitting phenomenon but the recognition effect on the scratches; model InceptionResNetV2 and Xception have very high accuracy in both the training and test sets, and the recognition of each image is very good. The classification accuracies of the five classes of models are shown in Table 8:

Table 8: Results of Hidden layers Variation in CNN model

Model	Train Acc	Test Acc
VGG16	0.674	0.659
ResNet50	1.000	0.198
MobileNetV2	0.982	0.559
InceptionResNetV2	0.994	0.992
Xception	1.000	0.998

From the comparison of the results in the table, it can be seen that the InceptionResNetV2 and Xception models have a better fit, so these two models and the CNN model have the highest accuracy, Figures 1, 2, and 3 show the confusion matrices for these three models:

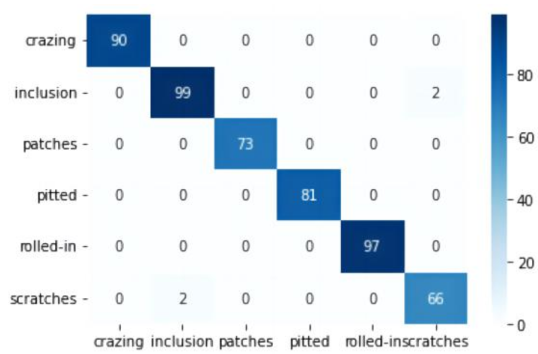

Figure 1: Confusion matrix for the InceptionResNetV2 model

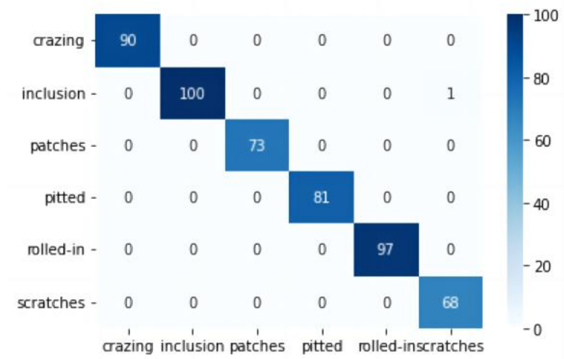

Figure 2: Confusion matrix for the Xception model

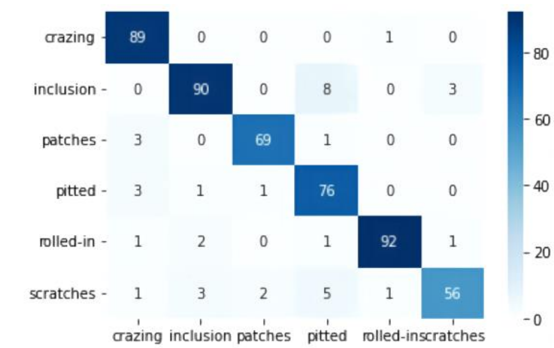

Figure 3: Confusion matrix for the CNN model

From the confusion matrix, it can be seen that Xception has the highest rate of checking completeness and accuracy among these three models, and in comparison CNN has a lower rate of checking completeness and accuracy, and they all have higher accuracy for the following reasons. Their checking completeness and accuracy are shown in Table 9,10,11:

Table 9: Completeness and accuracy of the InceptionResNetV2 model

InceptionResNetV2	Completeness rate/(%)	Accuracy rate/(%)
Crazing	100	100
Inclusion	98.0	98.0
Patches	100	100
Pitted	100	100
Rolled-in	100	100
Scratches	97.1	97.1
Average of the above	99.4	99.2

The InceptionResNetV2 network goes a little deeper than Inception V3 by incorporating residual-connected ResNet, where major portions of the repeating residual blocks have been compressed so that the whole network looks more intuitive and the InceptionResNetV2 architecture is more accurate than the previous optimal model.

Table 10: Completeness and accuracy of the Xception model

Xception	Completeness rate/(%)	Accuracy rate/(%)
Crazing	100	100
Inclusion	100	99.0
Patches	100	100
Pitted	100	100

Rolled-in	100	100
Scratches	98.6	98.6
Average of the above	100	99.8

Xception is based on Inception v3, replacing the Inception module with a deep separable convolution, and then combining it with ResNet's jump connections to propose a slightly higher accuracy than Inception-v3 on lmageNet, while the number of parameters decreases, and the addition of a ResNet-like residual connection mechanism to Xception also significantly speeds up the convergence process and achieves significantly higher accuracy. The ResNet-like residual joining mechanism added to Xception also significantly speeds up the convergence process of Xception and achieves significantly higher accuracy.

Table 11: Completeness and accuracy of the CNN model

CNN	Completeness rate/(%)	Accuracy rate/(%)
Crazing	91.8	98.9
Inclusion	93.8	89.1
Patches	95.8	93.2
Pitted	83.5	93.8
Rolled-in	97.9	94.8
Scratches	93.3	82.4
Average of the above	92.7	91.9

CNN has the following three advantages over general neural networks in image processing: firstly, the topology of the input image and the network can match well, secondly, the feature extraction and pattern classification are carried out at the same time and produced in the training at the same time, and finally, the sharing of the weights can reduce the network's training parameters, so that the final structure of neural network can become simpler and more adaptable.

It not only has good fault tolerance, parallel processing and self-learning ability, but also can obtain high accuracy rate after tuning the parameters such as pixels, filter depth, filter size, pooling layer size, and number of hidden layers.

IV. CONCLUSIONS

In this paper, six neural network models such as CNN and VGG were tried, and finally three models, CNN, InceptionResNetV2 and Xception, were obtained to have higher accuracy rate of more than 90%, as well as higher checking completeness and accuracy rate.

The reason for this is that this close relationship between inter-layer connections and null domain information in the CNN model makes it suitable for image processing and understanding. Moreover, it also shows a relatively superior performance in automatically extracting the salient features of an image, and it is continuously tuned to achieve the highest accuracy;

InceptionResNetV2 combines the Inception structure and residual connectivity to make the whole network look more intuitive and to improve the performance and stability of the model. And Xception is a further improvement of Inception_V3, with the main purpose of improving the performance, and the experiments after adding the residual The experiments after adding the residual connection mechanism show that Xception improves the convergence speed as well as the recognition rate. Also, the experiment gives the conclusion that MobileNetV2 model has higher sensitivity to the scratch category of pictures.

Deep learning using these emerging artificial intelligence algorithms such as convolutional neural network algorithms can effectively improve the accuracy of steel wear and corrosion identification, effectively guaranteeing the normal operation of machinery and equipment to improve productivity, and subsequently increase the number and type of images prior to testing and debugging to form a more standardized model with a wider scope of application.

REFERENCES

[1] Kumar A, Mukhopadhyay A. Investigation of reciprocating wear characteristics of carbon steel at varying load, relative humidity, and operating temperature using ANN-NSGA methodology. Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering. 2023;0(0). doi:10.1177/09544089221149404

[2] Kursuncu, B., Erdoğan, A., Özkan, D. et al. Investigation of Dry Sliding Wear Behavior of Different Diamond Segments with Response Surface Methodology. J. of Materi Eng and Perform (2023). https://doi.org/10.1007/s11665-023-07903-8

[3] Gibson, B. T., Tang, W., Peterson, A. G., Feng, Z., and Frederick, G. J. (December 18, 2017). "Evaluating the Potential for Remote In-Process Monitoring of Tool Wear in Friction Stir Welding of Stainless Steel." ASME. J. Manuf. Sci. Eng. February 2018; 140(2): 021012. https://doi.org/10.1115/1.4037242

[4] Shi Tengfei,Shang Jiaxiu,Wu Zonghang. Research on image classification improvement method based on convolutional neural network. Modern Information Technology,2023,7(05):109-112.DOI:10.19850/j.cnki.2096-4706.2023.05.026.

[5] LI Jiaqiang,HU Zhangyan,YANG Guangle et al. SAR image classification method based on multi-attitude angular model. Modern Radar,2022,44(12):63-69.DOI:10.16592/j.cnki.1004-7859.2022.12.009.

[6] FAN Yingying,ZHANG Shanshan. Classification method for hyperspectral remote sensing images based on deep active learning. Journal of Northeast Normal University (Natural Science Edition),2022,54(04):64-70.DOI:10.16163/j.cnki.dslkxb202108210001.

[7] Cui Xining,Sun Hongyu,Li Kelong. A weakly supervised fine-grained image classification method based on Bayesian algorithm. Computer Simulation,2022,39(09):467-470+512