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Visual quality inspection using deep learning

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Abstract
In the modern industries, surface defects in metal sheets significantly affect the quality, safety, usability and aes-thetics of the products. The steel is the most important building material in many manufacturing firms. Detecting quality issues of steel products and classifying steel defects is a challenging task and time-consuming manual effort. Recent progress in AI makes it possible to use advanced deep learning technologies for visual quality inspection for defect classification. The proposed system automates steel surface defect classification using VGG16 as a feature extractor to correctly classify the defect present based on the mapped features. The correctly trained neural network for the system achieves an accuracy of 97% ensuring higher precision of quality management system.

Keywords: Deep Learning, Multilabel Image Classification, VGG16, Image Processing

1. Introduction
Surface quality of steel is essential for the steel industry as it is the most important building material in many manufacturing firms. Therefore, defect inspection during production is a necessary step to ensure product quality. To cope up with the standards of industry, quality inspectors in manufacturing companies generally check product quality manually after the product has been manufactured. This is a time-consuming manual effort, and a rejected product results in wasted up- stream factory capacity, labor and costs. Over manual inspection, automated visual inspection can effectively replace almost all manual labor on large-scale production lines, and is ubiquitous in the manufacturing of mechanical parts, auto parts, circuit boards, electronic parts, medicine and agricultural performance monitoring.

As manual defect detection takes too much time for defect inspection, the main task of the steel surface inspection system is to improve the defect recognition rate, which includes feature extraction and defect classification.

The traditional automated surface quality inspection system used three methods named the local binary pattern (LBP) and the completed local binary pattern (CLBP) and local ternary patterns (LTP) for feature extraction. But the drawback of thoes methods is their threshold schemes are sensitive to noise. In new method named AECLBP, an adjacent evaluation window is constructed to modify the threshold scheme of the completed local binary pattern (CLBP), to improve the recognition rate and get the more robust feature descriptor against noise. This method can also only achieve moderate recognition accuracy in the toughest scenarios.

In recent years, deep learning technology in the area of pattern recognition emerged and has already been widely used. It also overcomes the drawbacks of traditional methods effectively. Deep learning technology greatly improves the accuracy of image classification. Among these neural networks models most recent ones are VGG16, VGG19, Resnet50 which can help us to do the recognition of steel surface defects.

The proposed system uses the VGG16 deep learning model to extract the features and maps them to accurately classify the steel defect class.

2. Literature survey
Recently, numerous steel industries have adopted Automatic Optical Inspection (AOI) to detect the surface quality of steel products in order to improve their competitiveness. However, most AOI instruments are commercially busy and the details of their techniques are seldom presented for consideration of Intellectual property rights. In this paper [10], recently discovered new technologies, shows that the standard AOI tool supports two main functions: defect detection and defect classification. The defect detection function is to detect defects on the target material surface and the defect classification is used to classify the types of detected defects. In general, the detection process distinguishes defective regions from normal image of the vast surface without identifying what kinds of defects they are.

Further all uploaded images with suspicious defects are recognized and labelled with distinct defect types. From goal-oriented aspect, the primary defect detection is the foundation of the "quality drawback close loop," earlier defect review and location enable additional

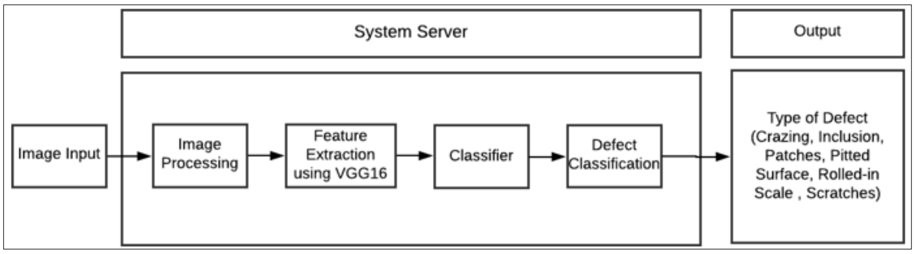

Fig 1: System Architecture

timely and fewer economic losses. The carefully observed defect classification is used for completing product inspection, which helps the relevant product pricing and distribution. A prominent obstacle to true online quality assurance is that it is difficult to achieve highly accurate defect detection and classification whilst remaining time efficient.

In [1] a three-dimensional inspection system was developed to obtain information about the sample height from the surface of high temperature steel products. A digital light processing projector was used to project the light from blue coded patterns, physical filtering and digital filtering methods were combined to obtain the images of the steel product. Stereo rectification and column-coded patterns were then used to obtain the final information on the height of the sample from the surface. Since this system is designed for a laboratory environment, it is not currently applicable to practical environments such as plate surface defects and smooth steel belts.

To improve the detection rate, the adjacent evaluation completed local binary patterns (AECLBP) method was proposed for defect detection [2]. In the proposed approach, an adjacent evaluation window that was around the neighbor was constructed to modify the closed-off local binary pattern (CLBP) threshold scheme to achieve an accuracy of 0.9893. The method uses knowledge of a particular area to extract properties, making the method complex for other steel products or other steel defects and even other areas.

A new CNN-based architecture was introduced to precisely perform both defect detection and classification tasks for a metal surface in complex industrial scenarios [3]. The proposed CASAE (Cascade Auto encoder) module can convert a defective image into a pixel prediction mask that contains only defective pixels and background pixels. However, the proposed method is that the training of a deep network requires manually labeled data, which takes a lot of time and expense.

At present, with newly developed techniques in pattern recognition and computer vision, the defect detection using both supervised manner [10, 11] and unsupervised manner [4, 5] has made impressive progress. The classification process is transformed into exploring a variety of accurate and efficient defect detectors for surface images.

3. System architecture

The system architecture is designed to classify the images of steel defects as shown in Fig.1

Image Input: The image is taken as input and fed to the system server.

Image Processing: The input image is then preprocessed. The input image will get resize to 200×200 if it is not in required dimensions. The image will get re-scaled using 1/255 is to transform every pixel value from range [0,255] to range [0,1].

Feature Extraction: The features of steel surface in an image are extracted using VGG16 network model. The VGG16 layer is a convolutional neural network model. The distinguished feature of VGG is that it uses a small 3×3 convolutional layer that will increase the network depth and effectively improves the models effect. The VGG16 model has 16 layers, 13 convolutional layers and 3 fully connected layers. After the primary 2 convolutions with 64 convolution kernels, one pooling is used, and the second time with 128 convolution kernels. Once that, pooling is used, and the three 512 convolution kernels are repeated twice, and then pooled, and at last 3 full connections are performed. The VGG16 pre-trained model is used for feature extraction. It is used for extracting defect features from the input image and also as base model in training. The features extracted by VGG16 are further useful in defect classification.

Classifier: Here, the features extracted are fed to the classifier. The main aim of the classifier is to identify defects based on feature map extracted by feature extractor. The proposed classifier is a sequential model as it has only one input tensor i.e. input image and one output tensor as defect classified. The classifier is built on a VGG16 pre-trained model by freezing its weights. The output from the final Pooling layer of VGG16 model is a three-dimensional matrix and to wrap all of its values into a vector, a flatten layer is added to top of base model. Three full Connection layers are added in the last part of the classifier. Dropout value of 0.5 is also used here to alleviate the over-fitting of the neural network.

Defect Classification: In this component, the given input image is classified into one the six classes of defects.

4. Dataset requirements

The training of neural network classifier is done using a dataset collected from related laboratories of NEU (North-East University). The NEU Metal Surface Defects dataset contains six types of typical surface defects of steel strips. It has 1800 grayscale images of 300 samples each of six different types of typical surface defects. The six types of defects are namely Crazing, Inclusion, Patches, Rolled-in Scale, Pitted Surface and Scratches.

The dataset is divided into 3 types - training, testing and validation sets where the training set contains 1656 images, testing set contains 72 images and validation set contains 72 images respectively.

The six types of defects are shown in Fig 2.

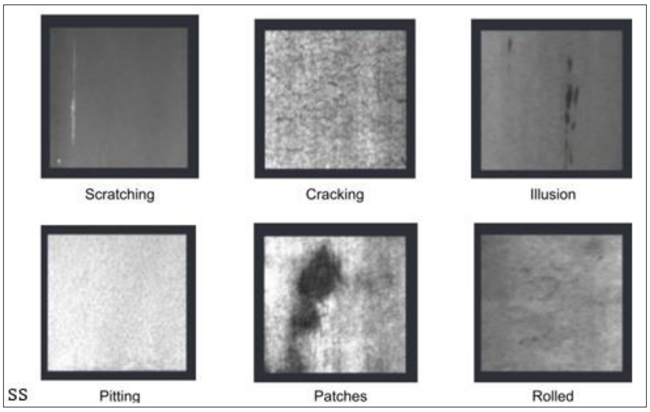

Fig 2: Types of Defects

5. Output

The Fig. 3 and 4 shows the output of defect classification.

Fig 3: Result for uploaded Test Image 1 of Pitted Surface is correctly classified to Pitted surface by the system

Fig 4: Result for uploaded Test Image 2 of Patches is correctly classified to Patches by the system

6. Testing results

For measuring the results, test dataset of 72 images are used where 12 images are of six types of steel defects namely Crazing, Inclusion, Patches, Rolled-in Scale, Pitted surface and Scratches are taken. The images are grayscale and of 200×200 dimensions in JPG format as shown in Fig. 5 Test Results. Test Results shows images with actual labels and predicted labels respectively.

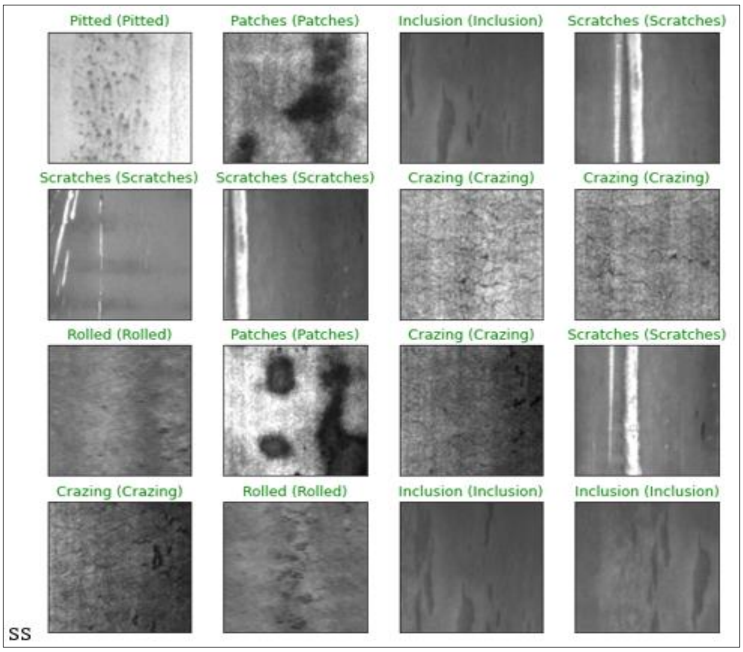

Fig 5: Test Results

- **Performance Parameters**

For evaluation of classification results, following parameters are used.

1. Accuracy
2. Precision
3. Recall
4. F1-Score
5. Support

Table 1: Result

	Precision	Recall	F1-Score	Support
Crazing	1.00	1.00	1.00	12
Inclusion	0.86	1.00	1.00	12
Patches	1.00	0.83	0.91	12
Pitted	1.00	1.00	1.00	12
Rolled-in	1.00	1.00	1.00	12
Scratches	1.00	1,00	1.00	12
Accuracy			0.97	72
Macro avg	0.98	0.97	0.97	72
Weighted avg	0.98	0.97	0.97	72

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- **Confusion Matrix**

Actual label: Number of images labelled as one of six defects.

Predicted label: Number of images classified and labelled same as to the actual label.

The confusion matrix for this model on the test images is shown below:

Table 2: Confusion Matrix

		Actual Label					
		Crazing	Inclusion	Patches	Pitted	Rolled-in	Scratches
Predicted Label	Crazing	12	0	0	0	0	0
	Inclusion	0	12	0	0	0	0
	Patches	0	0	12	0	0	0
	Pitted	0	2	0	10	0	0
	Rolled-in	0	0	0	0	12	0
	Scratches	0	0	0	0	0	12

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7. Conclusion

With the development of industrial automation, rapid and accurate quality inspection of industrial products is of great significance. As an important product of industrial production, steel products will have a variety of defects in the process of production and processing. The proposed system automates the classification of steel surface defects using deep learning. The model has been trained using the NEU steel surface dataset. On the basis of Tensor flow deep learning framework, the VGG16 model is customized to extract features and then the Convolutional neural network structure is implemented to classify steel surface defects.

8. Future scope

In future, identification of defect type will help to find solution to remove the defect which will lead re-usability of steel material. Also, by using different training dataset, this system can be implemented in textile industries, Plastic industries, etc.

9. References

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