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Metal Surface Defect Inspection through Deep Neural Network

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ABSTRACT
Visual inspection of a metallic surface has taken thriving attention for the metal product quality control. Deep convolution neural networks have got impressive recommendation rates recently to effectively inspect defects for metallic products. Here, we proposed a deep neural network model to analyze the image data for inspecting metal surface defects and also their respective classes. The designed deep neural network was trained on 1800 images of six different kinds of typical surface defects of 200 × 200 pixel resolutions. The image datasets were obtained from North Eastern University (NEU) surface defect database. And to predict the model performance we had tested 17 images and found 64.7% accuracy. The results manifested that the proposed method gives a good outcome though we used small datasets and it can indeed trace metal surface defects in realistic situations.

Keywords: Metal surface inspection, deep neural network, defect classifier

1. Introduction
Quality is an important issue for industrial product and it's very important to look after the machine that associated with the production process. So for assuring the best quality of product machine should be in right kind and also if the product is metallic, it's also important to look after the metallic product. Actually metal quality more dependent on its surface first as well as its composition and another germane issue. Surface defect inspection is now have possessed great impact for assuring good quality for metallic product or machine. Now visual inspection system has got more attention for the measuring accuracy and correctness. Human visual inspection defends on the fatigue and stress level wherein vision system is fast enough.
As the technology growing fast the application of intelligence system grew more attention in manufacturing and quality consideration for a product [1, 2]. Visual system and other computer vision technology getting more popular for inspection base fields such as surface quality and textured surface [3, 16]. In molecular biology and genetics thousands of potential network architectures and parameter instantiations, screening object recognition performance can be solved now [10]. The Convolutional Neural Networks (CNN) Architecture is used now to determine the Automatic Localization Casting Defects inspection [16]. Image classification has got more attention at present and there have more methods that are classified the image into their relevant classes. Olivier Chappelle et.al introduced Support Vector Machines for Histogram-Based Image Classification [5] and Nearest-Neighbor Based Image Classification technique is used to classify image [4]. Convolution Neural Network (CNN) method shows the surprising result for classifying images because of short time requirements and the redundancy of data for feature learning[9, 6]. Backpropagation is used for learning the feature in CNN which has done by updating the weights and bias. CNN can extract features from the images automatically and need fewer connection compared to standard feedforward neural networks. K Jarrett and K Kavukcuoglu showed a Best Multi-Stage Architecture for Object Recognition [7]. High-dimensional images are difficult for computation, a hierarchical generative model [8] was developed which scales to realistic image sizes by convolutional deep belief network.For image defect inspection of the metallic surface, we used a Convolution neural network (CNN) as it's needed lesser time and computation.

2. CNN defect inspection method
The detection method consists of two part one is training the datasets by mapping with their relevant class and another process is testing a new image to find the relevant classesshown in the Fig.1. In training process images and their respective labels are set correctly as the procedure followed in a purely supervised learning manner.Then feature extraction process needed as CNN is a feature-based learning which the process is discussed briefly in 2.1 section. After feature extraction, the CNN algorithm finds the relationship between the input features and the output labels which is discussed in 2.2 section. Gradient descent algorithm used for updating weight and bias for minimizing the error. The training procedure works in an offline manner [12]. In the testing, procedure images need preprocessing and feature extraction also need for

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synchronizing with the classifier model. The classifier model predicts the output labels from the learning of training procedure.

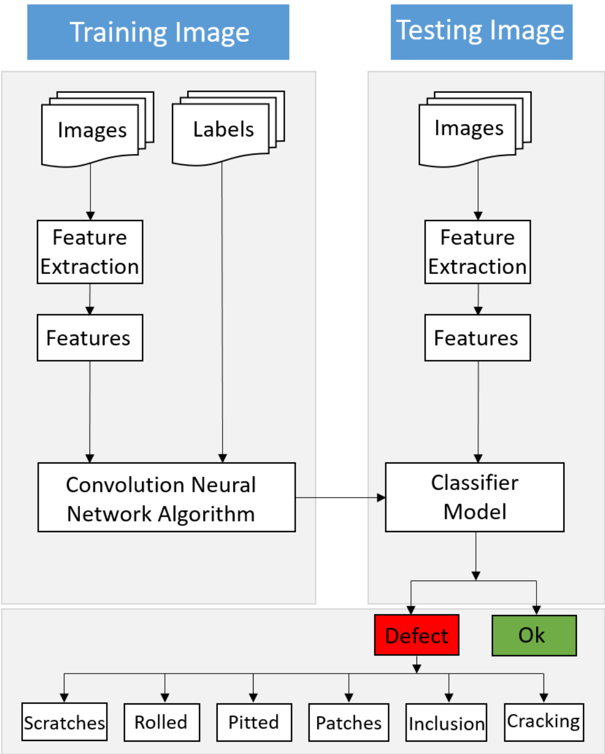

Fig.1 Classifier Model

2.1 Feature Extraction

The training images consider as a pixel value of the matrix and a filter is sliding over the matrix. The input image patch is convoluted by J_I^l number of maps with the size of $A_I^l \times A_I^l$ and is produced J_O^l number of outputmaps with the size of $A_O^l \times A_O^l$ where g^{l-1} and g^l are represent the input and output of the layer l and g^L is representing the output of the last layer L. The j^{th} feature maps of l^{th} convolution layer g_j^l, is calculated by:

$$g_j^l = \sum_{i=1}^{N^{l-1}} K_{ij}^l * g_i^{l-1} + r_j^l$$

Where $0 \leq i \leq J_I^{l-1}$, $0 \leq i \leq J_O^{l}$, K_{ij}^l is the convolution kernel corresponding to j^{th} map between l^{th} layer and i^{th} map in $(l-1)^{th}$ layer, r_j^l is the bias term of the above kernel. And the convolution process is indicated by symbol (*) [13, 14].And then it fed to an activation function which will decide which neuron should fire and also decides, given the inputs into the node.Here nonlinear activation function used as RELU:

$$f(x)=max(x,0)$$

And then Pooling operation is used to reduce the number of parameters and amount of computation in the network and it also controls the over fittings. Here we used mean pooling. Downsampling is performedfor pooling layer by mean pooling the (x, y) element output of feature map j of layer is expressed as:

$$z_j^l(x, y) = \frac{\sum_{m=0}^{s-1}\sum_{n=0}^{s-1} z_i^{l-1}(s \times x + m, s \times y + n)}{s^2}$$

Where $0 < x, y < c_i^l$ and s is expressed as Downsampling factor [14]. After pooling, the high-level reasoning in the neural network is done via fully connected layers. Neurons in a fully connected layer have connections to all activations in the previous layer, as seen in regular neural networks. Their activations can hence be computed with a matrix multiplication followed by a bias offset [13].

2.2 Classifier Model

Artificial Neural Network (ANN) which is formulated as:

$$a_j^l = \sum_{i=1}^{p^{l-1}} x_i^{l-1} * w_{ij}^l + r_{ij}^l$$

Where w_{ij}^l and r_{ij}^l are the weight vector and bias term of the i^{th} filter of the l^{th} layer. ANN is actually liable for predicting the output label for input data. Let o_k and y_k denote the output label and expected label for input samples individually. The Mean Squared Error (MSE) function is usually formulated as:

$$E = \frac{1}{2}\sum_{k=1}^{p^{l-1}} ||y_k - o_k||^2$$

The gradient descent method is used to minimize this error by updating weight vectors and bias term layer by layer. Softmax activation used to find the probability of the output of the ANN model which actually used at the last layer [13]. Softmax function is usually formulated as:

$$\sigma(a_j^l)_j = \frac{e^{z}}{\sum_{k=1}^{K} e^{z}}$$

It gives the probability form 0 to 1 and then from the best probability fraction relevant class can be detected [15].

3. Inspection analysis

3.1 Datasets

Datasets had collected from North Eastern University (NEU) Surface Defect Database. This database contains 1800 images of different types of defect of the metal surface defects shown in the Fig.2. Each image has 200x200 pixels and there have six types of defect images in this database. Each class has contained 300 Images and the classes are Scratches, Patches, Rolled, Pitted, Cracking and Inclusion.

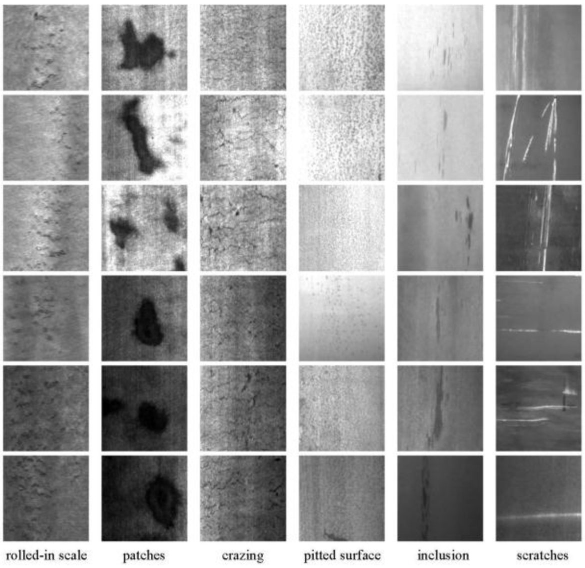

Fig.2 Six types of defect images.

3.2 Model implementation

To identify defect types of images we used two convolutions and pooling operation in our CNN model. Kernel striding through the images of 200x200 pixel values of the matrix is taken 3x3 and the pooling filter has taken 2x2. As our datasets labels contain more than two classes we used categorical cross-entropy as loss function. All 1800 images of different types defect use as training datasets but for validation 180 sample is taken by default by the program.

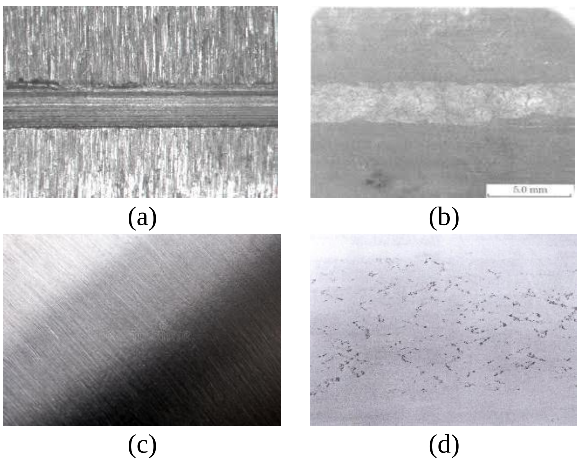

Fig.3 Test Images before implement to the model.

The batch size is chosen 90 and epoch taken 30 as having the low number of datasets. And for calculating the test image probability we used Softmax function which gives 0 to 1 probability. The output probabilities then compared to a specific threshold. Seventeen test images fed into the classifier model to find the relevant classes. And here four of them are shown in the Fig.3. Before implementing test images into the classifier model a preprocessing method is required where images resize to synchronize with the building model. And decided the test image as a defect of any types belonging or defect less.

3.3 Experimental result

The classifier model predicts the 17 test images based on probability and finds the relevant classes. Four of them shown in the Fig.4 along with the probability. Model classification accuracy for 17 images is 64.7% which is calculated from the confusion matrix.

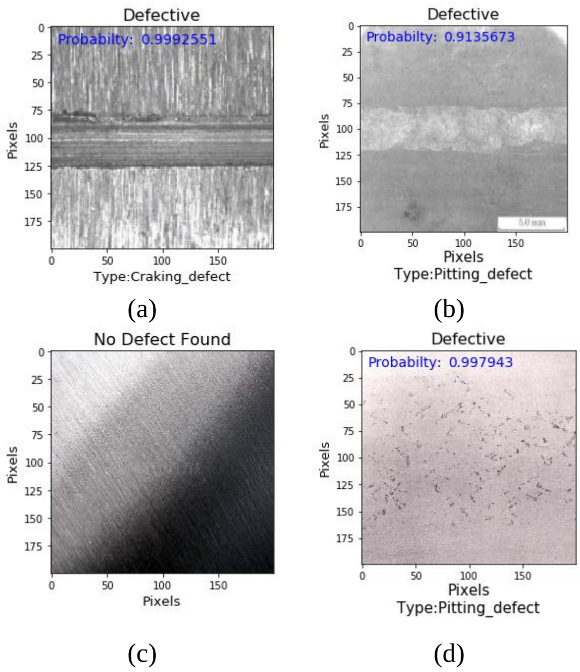

Fig.4 Test Images after implement to the model.

In the Confusion matrix for 17 images 11are found as TP (True Positive), 2 as TN (True Negative), 4 as FP (False Positive), and 1 as FN (False Negative). And the accuracy calculated by (TP+FN)/ (TP+TN+FP+FN) this equation.

3. Conclusion

In this work, we proposed a CNN architecture with two convolution layer for detecting the surface defect. We used categorical cross-entropy as loss function as our model output labels are six types. The result of the inspection is better that the proposed model expected. The model shows 64.7% accuracy which is best in sense of such small training datasets. The model evaluation will be more reliable if the model can be fed approximate 10,000 training datasets. In the future, the model will compare with other image classifier models like Nearest-Neighbor Based Image Classification technique or any other technique.

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