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Steel Surface Defect Detection Using VGG Deep Learning Models

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Abstract

Recently deep learning has taken over the industry. Research is being carried out continuously to enhance the image recognition models for deep learning, with newer models being added to the directory every few years. Deep learning works by extracting the details from image sets and recognizing the differences in them. In this paper, with the help of VGG-16 and VGG 19, defects have been detected in steels. These defects may end up leading to various disasters if not taken care of in a timely manner. Defects were categorized into six different categories and segregated accordingly with the help of the models mentioned above. Comparisons have been studied in this paper amongst the models and their efficiency and optimality according to the user's need. Accuracy up to 97.2 % is obtained with the help of the VGG 19 model as compared to 93.3 % accuracy obtained using VGG 16 model. Adding this data to the pre-existing knowledge will help us tackle defects in a much more organized manner.

Keywords: Deep learning; VGG 16; VGG19; steel surface defects

1. Introduction

Steel has vast uses in various industries like marine, automobile, electronic, aerospace, etc. Assurance of the quality of steel is a must considering its use in important aspects of machinery and equipment. Even the tiniest defects might end up causing a lot of financial damage at times. The immediate need to classify these defects categorically so that they can be tackled in individual manner is very high. The defects on steel can be caused due to a variety of causes like temperature, corrosion manufacturing defects, stresses, wearing and solidification. These defects might cause issues like poor quality of structure, poor ductility, malleability overall leading to metal degradation.

S. Y. Jung et al. worked on defect detection on randomly textured surfaces using a Convolutional Neural Network (CNN) [1]. Here tree wood with different random textures is used for the automation of defect detection. Three different LeNet, DenseNet, and VGG 19 architectures were employed and trained using the wood images. Amongst which the Deep Convolutional Neural Networks gave an accuracy of 99.80%. Shengqi guan et al. worked on Steel Surface Defect Recognition Algorithm based improved deep learning neural networks using Quality Evaluation and Feature Visualization [2]. A pre-trained VGG19 model and DVGG 19 are used for feature extraction. SSIM and decision tree are used for adjusting parameters and for evaluating feature image quality. Later a VSD model is generated that is then used for classification. Xiang Wan et al. worked on an improved VGG 19 model for strip steel defect detection [3]. A set of various processes are proposed to improve the VGG 19 model. Overall accuracy of 97.8 % is achieved. Huohua Li et al. worked on surface defect detection of solar PV panels using an improved pre-trained VGG 19 model [4]. This paper aims at problems of sample size and also the complexity of various defects. The proposed model analyses the basics of CNN architecture and is inspired by pyramid networks. The results show it to be better than the classical VGG 19 model.

Jingwen Fu et al. worked on a pre-trained VGG 16 model for steel surface defect detection [5]. A pre-trained VGG 16 and CNN are used as feature extractor and classifier, respectively, to recognize defects using the feature maps. It aims to use this model in case of a scarcity of data. Xiaoyang Gai et al. used an improved VGG 16 model to surface detection, and it gave better accuracy and efficiency than the traditional methods [6]. Min Su Kim et al. worked on surface detection of steel when the available dataset is less than required for training purposes

[7]. Few Short Learning (FSL) is done by Siamese Neural Network using CNN. Wei Zeng et al. used the image processing data enhancement method for the dataset; later, this dataset was used to train and extract features using CNN [8]. The experiments gave satisfying accuracy in detecting the surface defects. Marco Vannocci et.al. worked on flatness defect detection and classification of steel [9]. Further traditional machine methods are compared with deep learning models, deep learning models showed better accuracy.

In this paper NEU dataset is used, which has been categorized into six different categories as follows: scratches, pitted, rolled, crazing, patches and inclusion. Over time a lot of work has been done to detect these defects and were successful. But with the introduction of deep learning, we get an edge over existing technologies and can get the work done sooner with more precision. State of art deep learning models like VGG 19 and VGG 16 are used to detect the steel surface defects. These models are tested based on the accuracies and the computational times.

1.1. *Dataset*

In this paper, defects images obtained from NEU Dataset sources are used to classify defects. The dataset has a test, train, and valid folders. Each folder has six classes, Crazing, Inclusion, Rolled, Scratches, Pitted, and Patches. 1656 images are present in the train folder, and the testing folder contains 72 images, i.e., 12 images each in the sub-folder. Fig. 1. Shows the sample images from each class of defects.

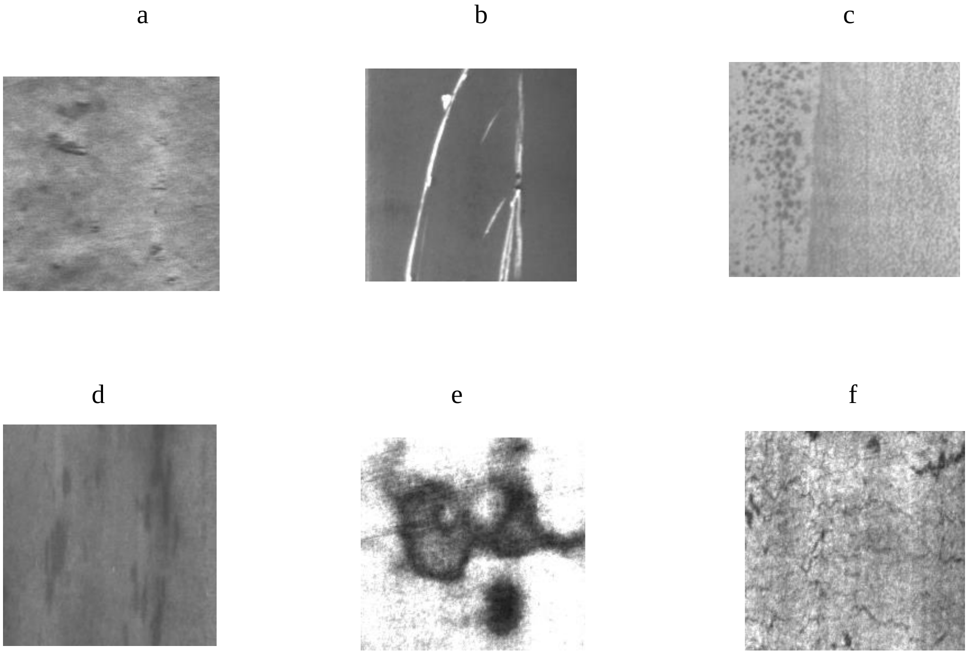

Fig. 1 (a) Rolled; (b) Scratches; (c) Pitted; (d) Inclusion; (e) Patches; (f) Crazing from NEU dataset [10]

2. VGG 16 and VGG 19 deep learning CNN models used

2.1 VGG 16

VGG 16 was developed by Andrew Zisserman and Karen Simonyan in 2014 [11]. VGG 16 has a total of 16 layers with an input image size (224× 224× 3). The arrangements with convolutional layers and pooling layers throughout the model are the basic architecture with the VGG 16 model. The first two layers have 64 kernels of 3 × 3 filter size and the same padding. As the same padding is used the output would be 224× 224. After that, a max-pooling layer has been used. After using the pooling layer, the outcome can be calculated using the formula:

$$[(IP+2p-k)/s] +1$$

where IP = input image size, k = size of the kernel = size of padding, s = stride. Thus, the output size will be (112× 112), and 64 filters, which is shown in Fig. 2. and similarly, for all the layers, the output size can be calculated using the above formula.

Use of pre-trained VGG 16 weights has been done which is imported from Keras library for the dataset classification purpose. Keras provided an applications interface for loading and using pre-trained models. Also use of pre-trained weights as a starting point, and then classification is done in the model.

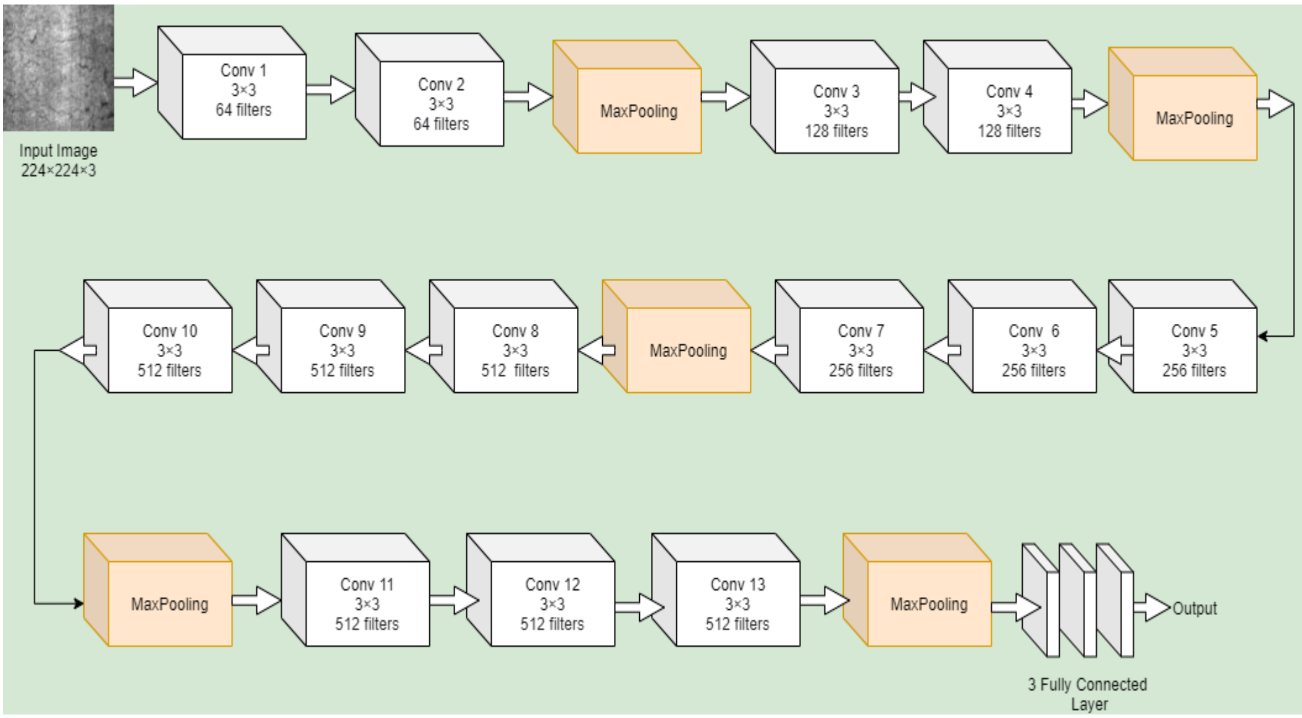

Fig. 2. VGG 16 Architecture

2.2 VGG 19

VGG 19 is a type of VGG model which has, 16 layers of convolution, 5 max-Pooling layers, 3 Fully Connected layers and a SoftMax layer. First of all, the default size of the RGB image (224 × 224) was given as input to this network which means the matrix was in size of (224× 224× 3). The only processing was to extract a mean RGB from every pixel that has to be calculated for training dataset. Kernel size of (3× 3) with a stride one is used. Padding has been used to maintain image location adjustment. Max Pooling was done over 2 × 2 pixels with a stride value 2. ReLu activation function is used because it helps to non-linearize the data, more the non-linearize data more is the accuracy. The last three fully connected layers are used followed by a final layer i.e., SoftMax function. The below Fig. 3. Shows the basic architecture of VGG 19.

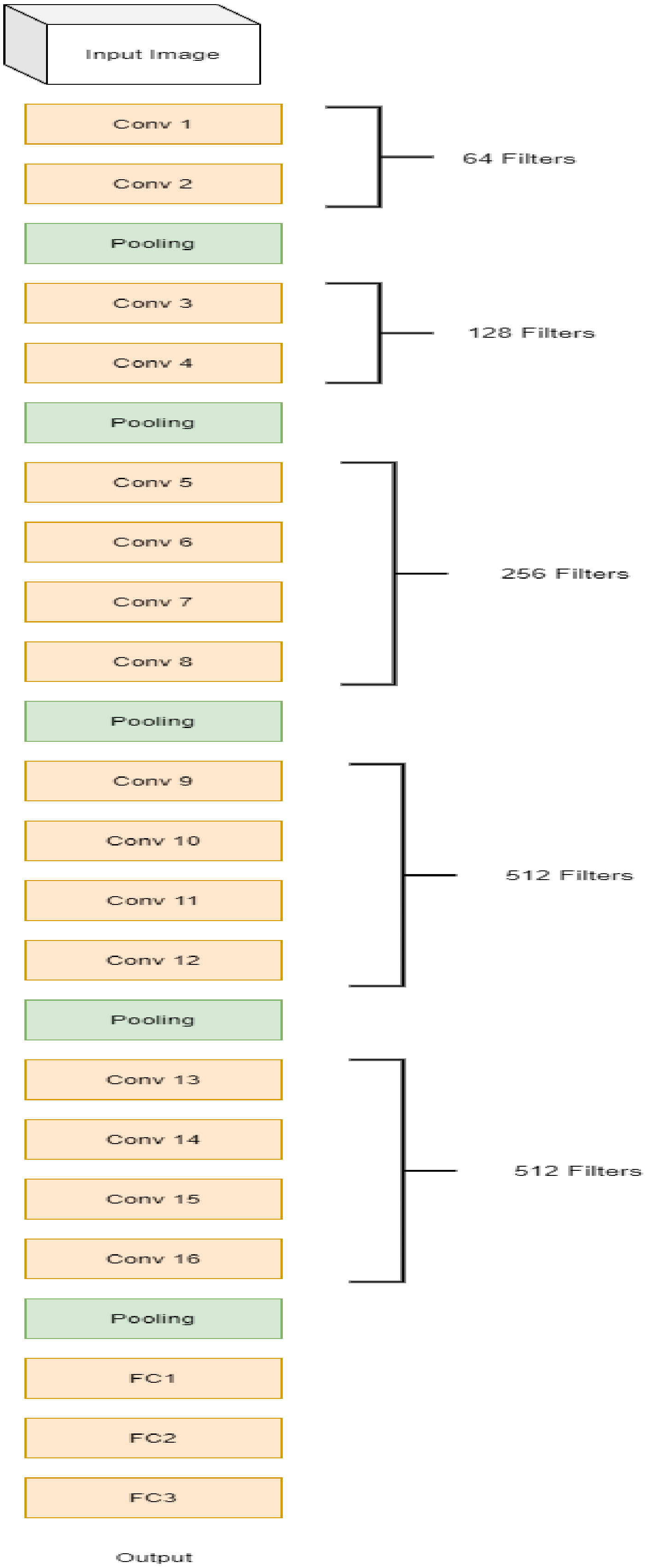

Fig. 3. VGG 19 Architecture

The use of VGG-19 trained network as a pre-trained model is been made. By adequately adapting the transfer method, pre-Training parameters model to extends the parameters of the convolution layer model. The parameters in VGG-19 are based on three FC layers. Parameters for the network was initially designed for 1000 divisions, but this paper focuses only on the format of division into six categories. Therefore, replacing the three fully integrated VGG-19 layers with one layer of Flatten and two fully connected layers is proposed. Since the convolution layer cannot be directly linked to the Dense layer, completely connected flatten layer is added.

3. **Result**

Dataset of metal surface defect consists of six categories: Rolling, Inclusion, Patches, Pitted, Crazing, and Scratches. VGG 16 and VGG 19 are the models used for identifying the steel defect. Table.1. shows the result obtained from VGG 16 and VGG 19 for five epochs.

Epochs Number	VGG 16 Accuracy (%)	VGG 19 Accuracy (%)
1	90.4	94.2
2	91.7	95.0
3	88.7	95.9
4	86.9	97.9
5	93.3	97.2

Table. 1. Accuracy comparison of VGG 16 and VGG 19

As shown in Table. 2. model summary VGG16 model consist of 16 layers. For our dataset VGG16 model, the first epoch gives an accuracy of 90%. As from Fig. 4. accuracy graph of epoch, three and four are the points where the model's accuracy is suffering. The accuracy at epoch three and epoch four is 88.9% and 86.9%, respectively. Similarly, from Fig. 4. loss graph, there is an increasing loss value at epoch 3 and 4. The final accuracy obtained by the VGG16 model is 93%.

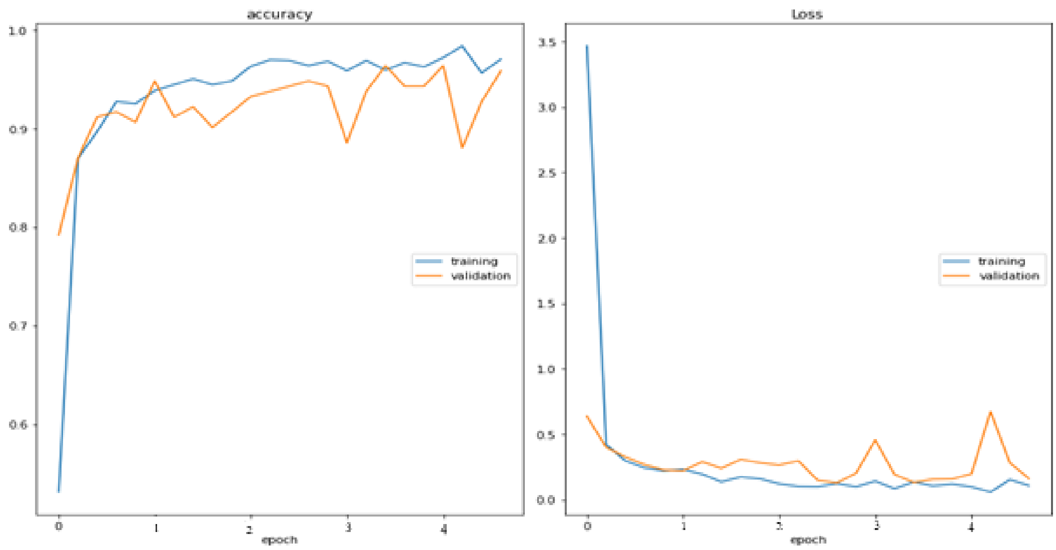

Fig. 4. Model accuracy and loss graph for VGG 16 model

Layer (type)	Output Shape	Parameter
conv2d (Conv2D)	(None, 224, 224, 64)	1792
conv2d_1 (Conv2D)	(None, 224, 224, 64)	36928
max_pooling2d (MaxPooling2D)	(None, 112, 112, 64)	0
conv2d_2 (Conv2D)	(None, 112, 112, 128)	73856
conv2d_3 (Conv2D)	(None, 112, 112, 128)	147584
max_pooling2d_1 (MaxPooling2	(None, 56, 56, 128)	0
conv2d_4 (Conv2D)	(None, 56, 56, 256)	295168
conv2d_5 (Conv2D)	(None, 56, 56, 256)	590080
conv2d_6 (Conv2D)	(None, 56, 56, 256)	590080
max_pooling2d_2 (MaxPooling2	(None, 28, 28, 256)	0
conv2d_7 (Conv2D)	(None, 28, 28, 512)	1180160
conv2d_8 (Conv2D)	(None, 28, 28, 512)	2359808
conv2d_9 (Conv2D)	(None, 28, 28, 512)	2359808
max_pooling2d_3 (MaxPooling2	(None, 14, 14, 512)	0
conv2d_10 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_11 (Conv2D)	(None, 14, 14, 512)	2359808
conv2d_12 (Conv2D)	(None, 14, 14, 512)	2359808
max_pooling2d_4 (MaxPooling2	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 4096)	102764544
dense_1 (Dense)	(None, 4096)	16781312
dense_2 (Dense)	(None, 6)	24582

Table. 2. Layers used in VGG 16

In Table. 3. all the 19 layers of VGG 19 are shown. The first epoch's accuracy of the VGG19 model is 94% greater than the final accuracy of the VGG 16 model using the surface defect dataset. Compared to VGG16, the plot of VGG19 shows an increasing pattern, and the computational time required for VGG19 is more than VGG16. Fig.5. shows that the highest accuracy was obtained at epoch 4. At epoch 4, accuracy reaches almost 98%. The final accuracy obtained by the VGG19 model is 97%

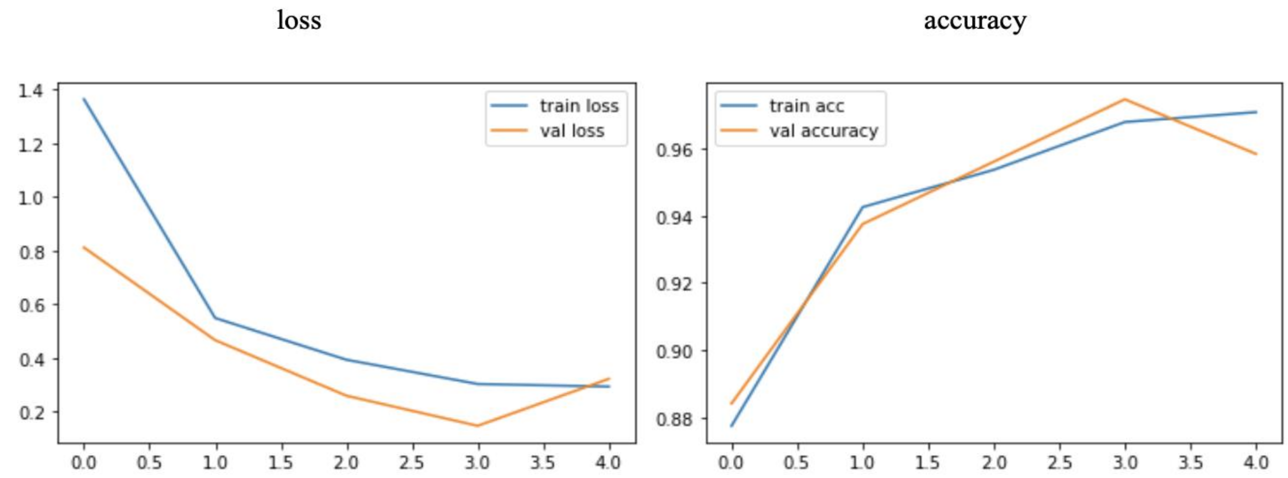

Fig. 5. Model accuracy and loss graph for VGG 19 model

Layer (type)	Output Shape	Parameter
input_2 (Input Layer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv4 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv4 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv4 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_1 (Flatten)	(None, 25088)	0
dense_1 (Dense)	(None, 6)	25089

Table. 3. Layers used in VGG 19

4. **Conclusion**

In this research paper, two deep learning models for image recognition of different types of surface defects are used. Deep learning is a powerful tool for image identification. The result obtained VGG19 proves that it goes deeper and gives maximum accuracy up to 97%. VGG19 and VGG16 both the models are precise and help to reduce loss of features. VGG 16 has less computational time which is approximately 1800 second for five epochs and gives the accuracy of 93%. Based on this model, it can conclude that VGG16 and VGG19 both models are suitable for metal surface defect detection in Mechanical parts, Machines, Steel industries, etc.

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