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Deep Learning Framework for Steel Surface Defects Classification

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ABSTRACT: Deep learning has offered new avenues in the field of industrial management. Traditional methods of quality inspection such as Acceptance Sampling relies on a probabilistic measure derived from inspecting a sample of finished products. Evaluating a fixed number of products to derive the quality level for the complete batch is not a robust approach. Visual inspection solutions based on deep learning can be employed in the large manufacturing units to improve the quality inspection units for steel surface defect detection. This leads to optimization of the human capital due to reduction in manual intervention and turnaround time in the overall supply chain of the industry. Consequently, the sample size in the Acceptance sampling can be increased with minimal effort vis-à-vis an increase in the overall accuracy of the inspection. The learning curve of this work is supported by Convolutional Neural Network which has been used to extract feature representations from grayscale images to classify the inputs into six types of surface defects. The neural network architecture is compiled in Keras framework using Tensor flow backend with state of the art Adam RMS Prop with Nesterov Momentum (NADAM) optimizer. The proposed classification algorithm holds the potential to identify the dominant flaws in the manufacturing system responsible for leaking costs.

Keywords: Deep Learning, Industrial Management, Quality Inspection, Turnaround Time, Neural Networks, Surface Defects, NADAM

I INTRODUCTON

Quality inspection systems in steel industries typically consist of two parts: defect segmentation and defect processing. Defect processing encompasses feature extraction and defect classification. In recent years, abundant research targeted towards feature extraction and defect classification[1] has yielded many cutting edge frameworks for classifying steel surface defects.
For this paper, we have considered six types of surface defects[2] ubiquitous in the steel industry namely:

1) Crazing: Crazing is the phenomenon that produces a network of fine cracks on the surface of a material, for example in a glaze layer. Crazing frequently precedes fracture in some glassy thermoplastic polymers. As it only takes place under tensile stress, the plane of the crazing corresponds to the stress direction. The effect is visibly distinguishable from other types of fine cracking because the crazing region has different refractive indices from surrounding material.[3]
2) Inclusions: Inclusions are chemical compounds and nonmetals that are present in steel and alloys. They are the product of chemical reactions, physical effects, and contamination that occurs during the melting and pouring process. These inclusions are categorized by origin as either endogenous or exogenous.[4].

3) Scratches: Scratches on the rolled surface represent mechanical defects parallel to rolling direction caused by friction between the rolled product and parts of the equipment such as worn or broken guides. The scale form and shape of the defect area indicate that the bar was likely hot when damaged.

4) Rolled-in Scale: When an oxide scale is formed on steel surfaces during hot rolling, this defect occurs. It significantly affects the surface quality of the products. To prevent this, scale is usually removed with high-pressure water immediately before the steel goes into mill stands.

5) Pitted Surface: Pitting corrosion, or pitting, is a form of extremely localized corrosion that leads to the creation of small holes in the metal. The corrosion penetrates the mass of the metal, with a limited diffusion of ions.

6) Patches: They occur on Galvanized steel. The galvanized layer falls off (leakage plating) easily resulting in dark spots.

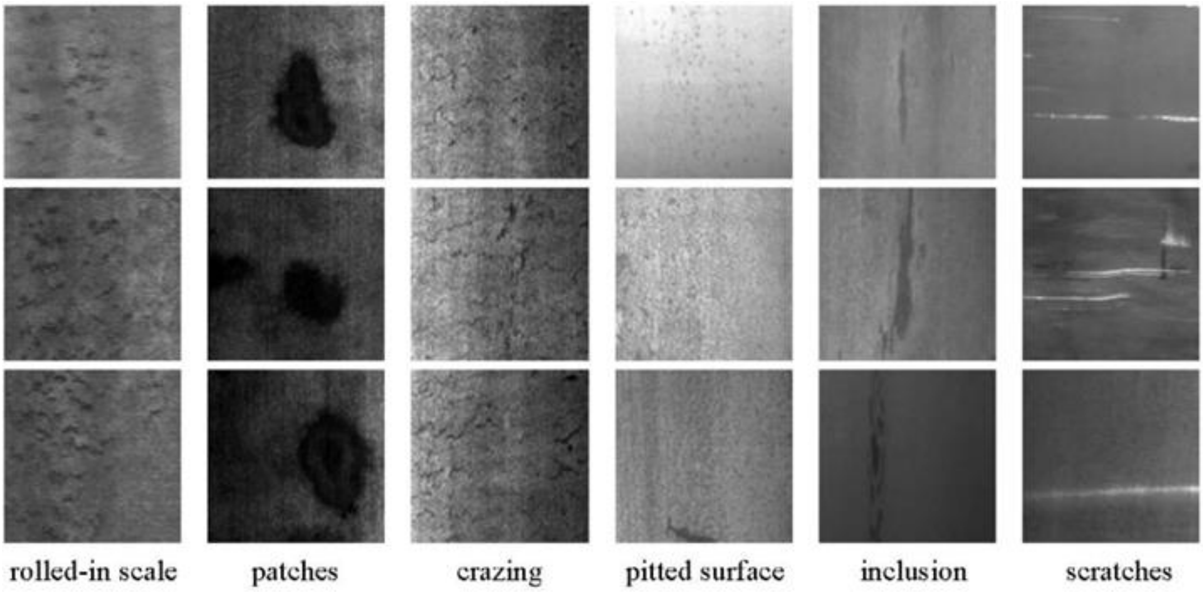

Figure 1 Types of Steel Surface Defects [5]

Computer vision has been disrupted by the use of convolutional neural networks (CNNs). CNNs are a class of deep neural networks that have been widely gaining traction and are deployed to give incredible result and record-breaking performance on many challenging problems.

Classification accuracy is the evaluation metric in the inspection systems, which has also been the criteria of evaluation of the proposed algorithm, while a discriminative feature representation of surface defects is the cornerstone.

This paper builds an image classifier using artificial neural network by breaking down theraw pixels of the image into a large number of feature representations of surface defects. Technically, deep learning[6] CNN models to train and test, each input image will be passed through a series of convolution layers with Kernels, Pooling, fully connected layers (FC) and apply Softmax[7] function to classify an object with probabilistic values between 0 and 1. Figure 2 shows a typical architecture of a convolutional neural network for image classification

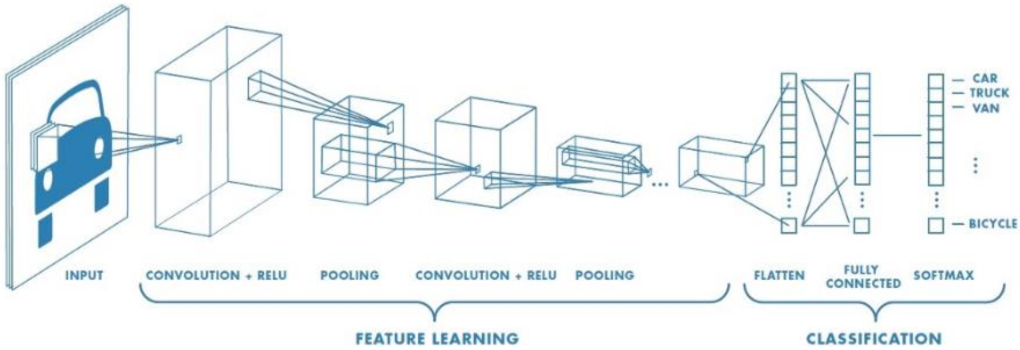

Figure 2 CNN Architecture [8]

II LITERATURE REVIEW

A lot of methods about feature extraction and classification for image have been developed,
M. X. Chu [9] extracted features of geometry, gray, projection, texture and frequency-domain of defect in steel, then an enhanced twin support vector machine was adopted to realize the classification.
A. Cord [10] proposed a classification method of statistical learning based on a textural feature for defect of metallic surface.
S. Ghorai [11] derived a set of good-quality defect descriptors from wavelet feature set and applied support vector machine to the classification and detection of the defects.
These traditional methods usually use handcrafted features, such as geometrical shape, grayscale, texture, local binary pattern, wavelet transform or their combinations, followed by a trainable classifier, such as artificial neural networks, support vector machine and so on.
They mainly include three stages:
1) Locating the position of surface defects (Detection).
2) Computing a large number of feature representations of surface defects.
3) Training a classifier via optimized feature vector and then predicting a new pattern by the trained classifier (Classification). CNNs have been shown to give incredible result and record-breaking performance on some challenging problems.
J. Masci [12] presented the max-pooling convolutional neural networks for the classification of steel defects.
Z. Q. Zhao [13] introduced the growing of convolutional neural networks for plant-leaf identification.
K. Xu [14] exploited the unsupervised convolutional neural networks for vehicle-type classification. As the availability of large datasets, fast growth in computing power such as availability of GPU and efficient algorithms such as dropout.
CNNs are inspired by the concept of biological visual cortex. Visual cortex in living beings contains some cells that are only sensitive to a local receptive field. In contrast to traditional feed forward ANNs, neurons or units in CNNs are arranged for a squared feature map, and each neuron of the feature map in each layer is only partially connected to a small set of neurons in the previous layer. They are an end-to-end self-learning model with a minimal need for human draft. It constructs a trainable architecture that combinations of feature extractor and classifier and operates on image's pixels of two-dimensional image directly. The extensive use of shared weight in CNNs can reduce the number of parameters.

III RESEARCH METHODOLOGY

The proposed model has the below mentioned structure. There are four 2D convolutional layers, four relu activation layers, two pooling layers, three dropout layers with 0.2 dropout rate. The model architecture is represented below in table 1.

As shown in Figure 3, there are many kinds of activation functions, such as sigmoid (a), hyperbolic tangent (b) and rectified linear units (ReLUs) (c). ReLUs are only bound by their minimum value zero and represent any non-negative real value. At the same time, ReLUs have good sparsity properties, since having a zero activation value, as well as limiting the saturation of the output and diffusion of the gradient during the training process.

TABLE 1 Proposed CNN Framework[16]

Layer (Type)	Output Shape
conv2D_1 (Con2D)	(None, 64, 64, 32)
activation_1 (Activation)	(None, 64, 64, 32)
conv2D_2 (Con2D)	(None, 64, 64, 32)
activation_2 (Activation)	(None, 64, 64, 32)
max_polling2d_1 (Maxpolling2)	(None, 31, 31, 32)
dropout_1 (Dropout)	(None, 31, 31, 32)
conv2D_3 (Con2D)	(None, 29, 29, 64)
activation_3 (Activation)	(None, 29, 29, 64)
max_polling2d_2 (Maxpolling2)	(None, 14, 14, 64)
dropout_2 (Dropout)	(None, 14, 14, 32)
Flatten_1 (Flatten)	(None, 12544)
dense_1 (Dense)	(None, 64)
activation_4 (Activation)	(None, 64)
dropout_3 (Dropout)	(None, 64)
dense_2 (Dense)	(None, 6)
activation_5 (Activation)	(None, 6)

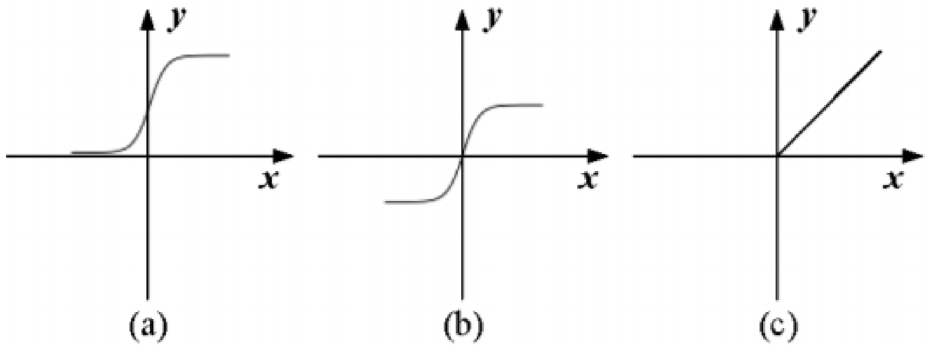

Figure 3 Graphical Representation of Activation Functions [15]

For CNN[16] the dataset comprised of 6531 images spread across 6 surface defects and for training purpose the dataset was split in the ratio of 80:20 i.e 20% of the dataset has been used for validation.Pooling has been for dimensionality reduction and nonlinearity. Feature pooling makes the feature map less vulnerable to the exact location of the pixel of an image and the specific structure of the model. Feature pooling allows feature representations of a higher layer to preserve the most critical feature information and reduce the computational burden without losing critical information. The output feature maps of the subsampling layer are given by a certain activation of the non-overlapping or overlapping square regions. For this algorithm max pooling is employed. [17]

The last hidden layer or classification layer (figure 4) employs a softmax function or normalized exponential function. This produces a probability score over the output classes and ensures each output can be assigned a probability of an input belonging to a certain class. For a given test input image, the label corresponding to the maximum output probability corresponds to its predicted class.

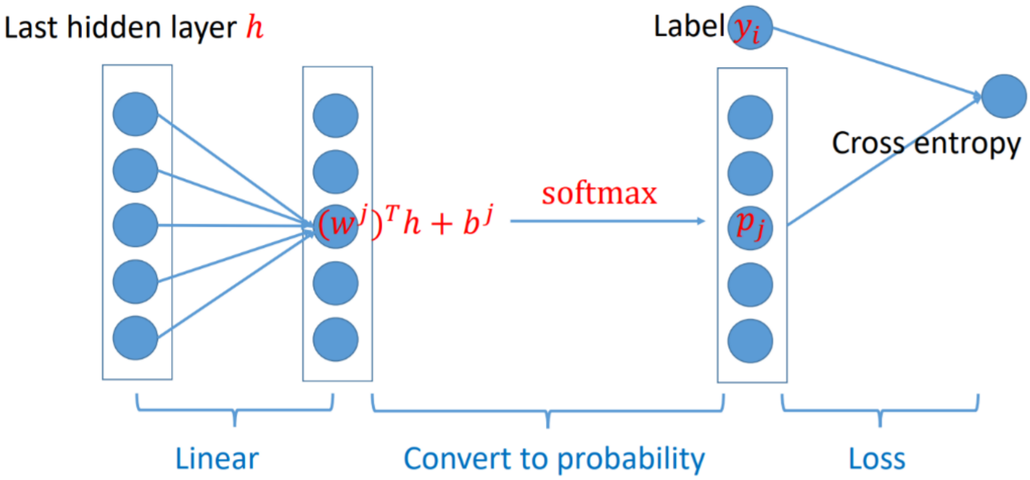

Figure 4 Softmax Activation

IV NUMERICAL&GRAPHICAL ANALYSIS

The neural network was compiled by incorporating nesterov momentum in ADAM optimizer, which outperformed the current state of the art ADAM optimizer over 30 epochs [18] by 95.63% accuracy on the validation set.

Employing a batch size of 32, the algorithm performance in terms of multi-categorical entropy loss and overall accuracy at every epoch is listed in the table 2 below:

Table 2 CNN results across Training and Validation Sets

Epoch	Training Loss	Validation Loss	Training Accuracy	Validation Accuracy
1	1.8789	1.514	0.3228	0.5187
2	1.4172	1.2924	0.4976	0.5104
3	1.2859	1.555	0.4524	0.5698
4	1.1207	0.8572	0.6002	0.7172
5	0.8755	0.6525	0.6891	0.7649
6	0.7279	0.7329	0.7401	0.7953
7	0.6281	0.5697	0.7735	0.8128
8	0.5424	0.4334	0.7979	0.8638
9	0.4728	0.429	0.8235	0.8444
10	0.4218	0.3497	0.841	0.8979
11	0.3947	0.3953	0.851	0.8672
12	0.3728	0.4019	0.8626	0.8548
13	0.3239	0.3339	0.8766	0.888
14	0.3178	0.3812	0.8798	0.8534
15	0.3036	0.8573	0.8875	0.7599
16	0.3094	0.3587	0.8879	0.8845
17	0.2952	0.3137	0.8884	0.8976
18	0.2558	0.3418	0.9066	0.9011
19	0.2441	0.4044	0.9088	0.8935
20	0.237	0.3461	0.918	0.8978
21	0.2132	0.3291	0.9122	0.8883
22	0.2108	0.3076	0.9253	0.899
23	0.2204	0.2965	0.9215	0.9011
24	0.2008	0.2854	0.934	0.9128
25	0.191	0.2768	0.9409	0.9209
26	0.1803	0.254	0.9564	0.9317
27	0.1786	0.2228	0.9671	0.9349
28	0.1713	0.2188	0.9699	0.9419
29	0.1651	0.2176	0.9789	0.9467
30	**0.1541**	**0.1999**	**0.9818**	**0.9563**

The plot for training loss and validation loss over 30 epochs is shown in the figure 5, which represents a good model fit with minimal overfitting.

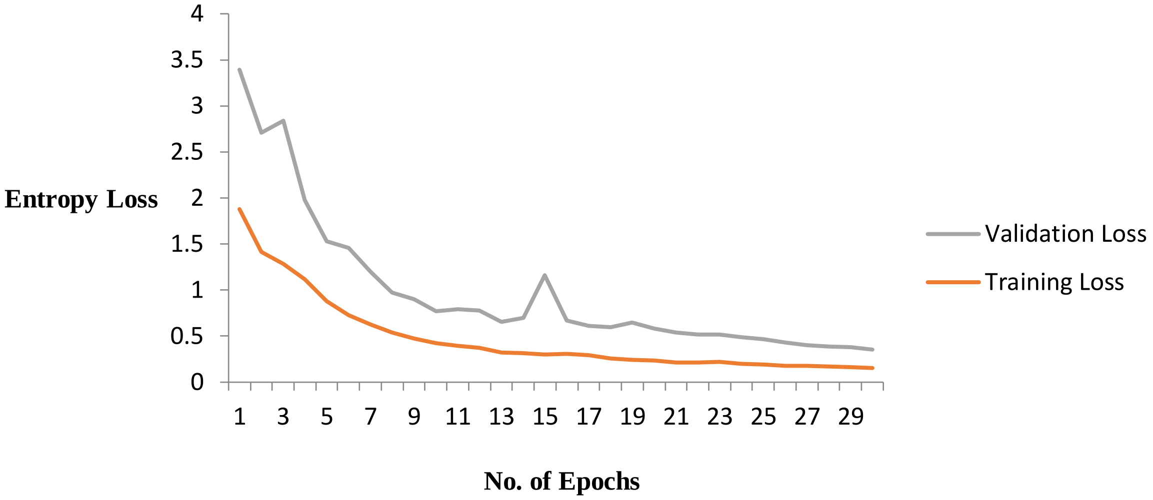

Figure 5 Entropy Loss on Training and Validation with 30 epochs

The plot for training accuracy and validation accuracy over 30 epochs is shown in the figure 6.

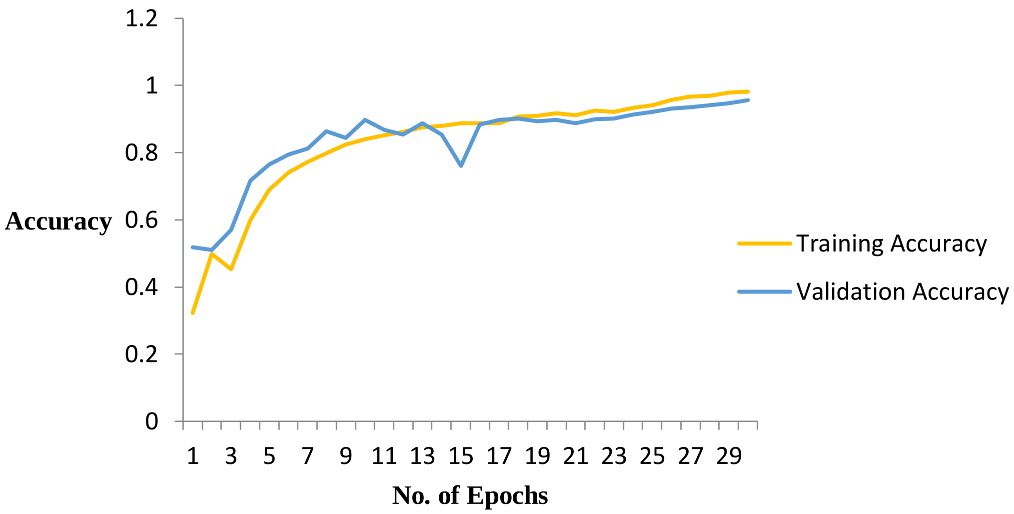

Figure 6 Accuracy Plot with 30 Epochs

V RESULT

The proposed framework is giving an accuracy of 95.63% in classification of defects on the surface of the steel after 30 epochs. THE entropy loss curve (figure 5) is close to its ideal state and therefore it authenticates the learning curve of the proposed framework. These accuracies results speaks volumes about the scope of the proposed algorithm for the industry where it can help to increase the sample size for the inspection of the lot with a decrease in the capital employed for the same.

VI CONCLUSION

The implementation of deep learning framework for the problem of steel classification has been successfully employed. Since deep learning is ever expanding with multi-level opportunities, one can often broaden the scope of the concerned area relating to steel industry. Classification is just the beginning. We can also predict the severity of the problem. Tolerance limits can be set up so as to discard the production batch that falls outside the tolerance limits. Certain patterns and causes of defects can be observed from the discarded lot so as to improve the process. We can similarly extend and apply our framework in the concerned area to uncover the hidden layers of the problem.

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