Advanced Structural Mechanics 1 (2023) 71-80

Advanced Structural Mechanics

journal homepage: http://asm.sku.ac.ir

A novel method for detecting the type of surface defects of hot rolled steel strip using the convolutional neural network

Seyed Mohammad Hossein Sharifi[a,*], Farhad Hamidi[b], Sajad Chabokrou[c]

[a] *Associate Professor, Department of Mechanical Engineering, Petroleum University of Technology, Abadan, Iran*
[b] *MS.c. Student in Mechanical Engineering, Department of Mechanical Engineering, Shahid Beheshti University, Tehran, Iran*
[c] *BS.c. in Mechanical Engineering, Department of Mechanical Engineering, Petroleum University of Technology, Abadan, Iran*

Article received:2023/ 01/ 01, Article revised: 2023/ 05/ 01, Article accepted: 2023/ 05/ 02

ABSTRACT

Steel production is essential in today's world. The classification of surface defects of steel strips in the steel industry is essential for their diagnosis because it is closely related to the quality of the final product. In this study, classification is considered to identify six types of defects from the North Eastern University dataset on hot rolled steel strip surfaces using artificial intelligence (AI). The proposed method is a kind of architecture based on a convolutional neural network. The 200 × 200 images enter the convolutional neural network, changing to 32 × 32 in the first layer, 64 × 64 in the second layer, and 128 × 128 in the third layer. The test results show that this architecture achieves 93.54% accuracy in the test set, which is much more than the comparable architectures. To evaluate the results of the proposed architecture, the criteria of accuracy, precision, and recall have been used.
Keywords: Surface defects, Hot-rolled steel strip, Convolutional neural network, Deep learning, Artificial intelligence

1. Introduction

Steel production is essential in today's world. Steel is widely used in many industries such as automotive, electronics, furniture, weapons, shipbuilding, etc. [1]. Product quality control is vital and unavoidable. The high quality of the final product results in the high quality of our lives [2]. Defects in the steel produced can reduce the properties of the final products, and in addition, harm us. Hot rolled steel is a common type of steel that is

* Corresponding author at: Department of Mechanical Engineering, Petroleum University of Technology, Abadan, Iran.
E-mail address: sharifi@put.ac.ir
DOI: 10.22034/asm.2023.14202.1010: https://asm.sku.ac.ir/article_11456.html

pressurized at temperatures above 1700 ° F, which is much higher than recrystallization temperature for most steels. This action includes flexibility and ease of working with it. In the steel production process, surface, internal and geometric defects occur according to the production conditions. Surface defects include longitudinal and transverse cracks in the corners, reticular hairs, longitudinal and transverse dimples, superficial flaking, etc. Diagonal cracks, star cracks, separation and central cracks are among internal defects, and indentation defects and curvature are among geometric ones. Usually, steel strip quality control inspection is done manually. Manual inspection of steel strip defects can lead to delays in the production process, and this in itself can be a problem. Due to the many different types of defects in the production processes of steel and steel strips, the accuracy of defects identification in steel strips depends on the experience of inspectors. Manual inspection is a difficult and time consuming process. The time consuming of this process reduces the production rate. Reducing steel production rates leads to shortages of industrial raw materials such as those mentioned above. These events result in significant economic losses for industries and manufacturing companies [2].

Finding a solution to these problems has led to the creation of a method for automatic detection of defects in the steel strip. These machine vision-based methods have been developed to solve manual inspection inefficiencies, such as low accuracy, time consuming, high labor demand and waste of resources [3]. Over the past decade, many researchers have studied machine learning techniques for diagnosis of defects, which are not just for steel defects diagnosis. There are many ways to teach neural network models in machine vision applications such as object tracking, face recognition, and quality assessment of fruits and vegetables. With the popularity of computer-aided learning methods based on deep learning, most researchers have used deep learning methods to detect superficial defects and have replaced traditional methods and machine learning over recent years. Deep learning is now one of the new topics among industries and academics [4]. This method of automatic fault detection is based on deep learning and can significantly improve product quality and production efficiency. This algorithm can also automatically extract the deep and powerful features of the image and get the results and perform the defect detection work efficiently and accurately. Several tasks have been performed to diagnose steel defects using in-depth learning. These works used various deep learning models such as convolutional neural network[1] [5], deep automatic encryption network [6] and Yolo [7]. Based on these studies, deep learning shows promising results for diagnosing steel defects.

The CNN-based method can be divided into three sub-sections: image classification, image division, and object recognition. Surface defect detection algorithms based on object detection can be divided into two categories: one-stage and two-stage. Single-stage object detection algorithms mainly include Yolo. For example, Lee et al. [7] have improved the Yolo algorithm, which includes 27 convolutional layers and can provide end-to-end solutions. Two-stage object detection algorithms mainly include faster R-CNN[2] [7].

As mentioned above, various algorithms have been proposed with the development of machine learning and computer vision [8] and all of them have their own strengths and weaknesses. Traditional machine-based learning methods are usually sensitive to scale and noise and are easily influenced. In addition, the accuracy of this algorithm cannot meet the real needs of automatic fault detection. Some features have to be designed manually, and the scope of application is very limited. The deep learning-based classification method can classify images, but it cannot determine the location and size of the defect. This has an important effect on data analysis. It is very difficult to teach a stable and accurate model based on conflict-generating networks and reinforcement learning. More accuracy and stability are required to automatically detect the location of the steel strip surface defect.

Comparing CNN to other methods for image classification depends on the specific method you are comparing it to. However, in general, CNNs have become the state-of-the-art method for image classification due to their ability to automatically learn features from raw image data. Before the emergence of CNNs, traditional methods for image classification relied on hand-engineered features such as SIFT, HOG, or LBP, which were often sensitive to changes

[1] CNN
[2] Region-based Convolutional Neural Networks

in scale, rotation, and illumination, and required extensive pre-processing steps. In contrast, CNNs are capable of learning high-level features directly from raw images, without the need for extensive pre-processing, and are robust to variations in scale, rotation, and illumination. This ability to automatically learn features has led to significant improvements in image classification accuracy, and CNNs have become the go-to method for tasks such as object recognition, face recognition, and scene recognition. There are still other methods for image classification, such as decision trees, support vector machines, and random forests, which can perform well on some datasets. However, they often require hand-engineered features and extensive pre-processing steps, which can be time-consuming and limit their applicability to large-scale datasets.

In summary, while there are other methods for image classification, CNNs have become the state-of-the-art method due to their ability to automatically learn features from raw image data, without the need for extensive pre-processing, and their robustness to variations in scale, rotation, and illumination. In this study, we will investigate the detection of surface defects of hot rolled steel strips using CNN.

2. Design of CNN structure

2.1. CNN

The origins of artificial neural networks[1] go back to the biological neural system, which is a special type of learning model for data processing. The simplest type of ANNs is feed neural networks in which the direction of information movement is only forward [9]. A feed neural network is defined in such a way that there is no cycle. To understand more, consider a three-layer network. Layer 1 is the input layer and layer 3 is the output layer. Layer 1 feeds Layer 2, Layer 2 feeds Layer 3, and Layer 3 is created. The neural network receives input in layer 1 and feeds layer 2. If layer 2 feeds layer 1, a cycle occurs, but in this type of neural network (feed) no cycle is formed and layer 2 feeds layer 3. The process of optimizing parameters is called training, which is done to reduce the difference between the outputs through an optimization algorithm called post-diffusion. During feed network training, data is transferred to the network and the resulting classification is compared with a known training sample. If the classification of the network is incorrect, the weights are reversed from the post-diffusion method and the correct classification is created. A set of feed neural networks that include at least three layers (input layer, hidden layer and output layer) [4] and use the post-diffusion algorithm to train the layers, form multilayer perceptron networks. Deep neural networks are used for defect classification in hot rolled steel strips. CNNs are a special type of deep feed neural networks that have been designed with modifications to the classical multilayer perceptron networks and are a good choice for processing two-dimensional data such as images.

As shown in Fig. 1, a CNN consists of convolutional, pooling and fully connected layers. The task of feature extraction is the responsibility of convolutional and cumulative layers, while the third layer, the fully connected layer, draws the extracted features at the final output. The purpose of drawing the final output in this paper is to classify the defects of hot rolled steel strips. The convolutional layer plays an essential role in the CNN. This layer consists of a set of mathematical operations [10]. In digital images, pixel values are stored in a two-dimensional grid.

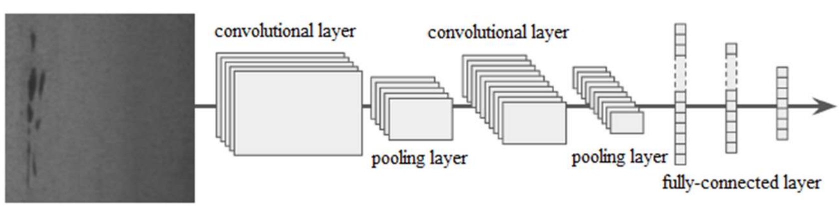

Fig. 1. General structure of a convolutional neural network[10].

[1] ANN

2.2. Dataset

In this study, a dataset for hot rolled steel strip defects was taken from the North Eastern University Metal Surface Defects dataset. This dataset, as shown in Table 1, includes six types of surface defects in hot-rolled steel strips, including recesses, patches, corrosions, cavities, inclusions, and scratches. The dataset contains 1,800 images on a gray scale with 300 samples from each of the six types of surface defects. For analysis, the dataset is divided into 3 parts. This section contains 276 images out of 300 images to teach each type of defect. The remaining 24 images of each defect also belong to the categories of tests and validation data. So the data are divided into three categories of training, testing and validation according to the table below.

Hot-rolled strips can be subject to a variety of surface defects during the manufacturing process. Some of the most common defects include inclusion, crazing, patches, pitted surface, rolled-in scale, and scratches. Let's take a closer look at each of these defects and the reasons for their occurrence:

2.2.1. Inclusion

Inclusion is a type of defect that occurs when foreign material is embedded in the steel. This can happen during the melting and casting process or during the rolling process. Inclusions can be caused by a variety of factors, including poor quality raw materials, inadequate cleaning of the melt, or poor handling of the steel during the manufacturing process. Inclusions can cause weakness in the steel, leading to failure under stress.

2.2.2. Crazing

Crazing is a surface defect that appears as a network of fine cracks on the surface of the steel. This can occur during the cooling process when the steel is still hot and is exposed to air. Crazing is usually caused by rapid cooling, leading to thermal stresses in the steel.

2.2.3. Patches

Patches are areas of the surface that have a different texture or appearance from the surrounding steel. Patches can be caused by a variety of factors, including variations in the thickness of the steel, uneven cooling, or changes in the chemical composition of the steel.

2.2.4. Pitted surface

A pitted surface is a type of defect that appears as small depressions or pits on the surface of the steel. Pitting can be caused by a variety of factors, including exposure to corrosive substances, improper cleaning of the steel, or damage to the surface of the steel during the rolling process.

2.2.5. Rolled-in scale

Rolled-in scale is a type of defect that occurs when scale, a layer of oxides that forms on the surface of the steel during the manufacturing process, is not removed properly during the rolling process. The rolled-in scale can weaken the steel and cause it to fail under stress.

2.2.6. Scratches

Scratches are a common surface defect occurring during the handling and transportation of the steel. Scratches can weaken the steel and cause it to fail under stress.

In conclusion, the occurrence of these defects may have a significant impact on the quality of the hot-rolled strip. Manufacturers must take care to minimize these defects by using high-quality raw materials, maintaining proper temperature and pressure during the manufacturing process, and using appropriate handling and transportation procedures.

Table 1. Dataset information.

Defect type	Train	Test	Validation	Sum
Rolled-in Scale	376	12	12	300
Patches	376	12	12	300
Crazing	376	12	12	300
Pitted Surface	376	12	12	300
Inclusion	376	12	12	300
Scratches	376	12	12	300
Sum	1656	72	72	1800

3. The proposed CNN structure

There are several ways to efficiently teach a model in a small dataset, including data enhancement and transition learning. Transitional learning is a common and effective strategy for network training in a small dataset, where a network in a very large dataset such as ImageNet that contains 1.4 million images with 1000 classes is pre-trained, then used, and is applied for the given task. The basic premise of transitional learning is that general features learned on a sufficiently large dataset can be shared among seemingly different datasets. This ability to move learned general features is a unique advantage in in-depth learning that finds itself useful in a variety of domain tasks with small datasets. Architectures such as AlexNet, VGG[1], ResNet, and Inception are open to the public and have many uses.

One form of transitional learning is its limitations in input dimensions. The input image must be two-dimensional and have three RGB channels (red, green and blue), while gray scale images have only one channel (gray level).

Although the mentioned architectures have a high functionality, in this article we do not use them and we use the proposed architecture. According to Table 2, 3 models of CNN have been used, each of which has used one more layer than the previous one. The models are as follows:

1- CNN with 1 convolutional layer

2- CNN with 2 convolutional layers

3- CNN with 3 convolutional layers

In the all data in the dataset, 1656 images are dedicated to training, 72 images to testing and 72 images to validation. These data are equally divided into six categories: depression, patch, corrosion, perforated surface, incision and scratch. Each category has 12 test images, 12 validation images and 276 images for training, and each category has 300 images, and the total data of the 6 categories together includes 1800 images.

This model is formulated for 20 courses with batch size of 32, with *categorical_crossentropy*[2] cost function and *rmsprop* optimizer.

RMSprop is a gradient-based optimization method used in neural network training. Gradient functions are very complex, such as neural networks that tend to disappear or expand as data are transmitted through functions.

The purpose of the cost functions is to calculate the amount that a model should seek to minimize during training, we form the model for one layer, two layers and three convolutional layers. The maximum integration size and number of filters per layer is specified. We create convolutional, pooling and fully connected layers according to Table 2.

Here as shown in Fig.2 is the CNN architecture with 3 convolutional layers, 3 pooling layers, flatten layer, and one fully connected layer:

---

[1] Visual Geometry Group

[2] All words in italics are Python programming language functions

Table 2. Proposed network structure.

Block	Layer type	Description
Block 1	Convolution	32 filter 2 × 2 and correct layering
	max pooling	Size 2 × 2
Block 2	Convolution	64 filter 2 × 2 and correct layering
	max pooling	Size 64 × 64
Block 3	Convolution	128 filter 2 × 2 and correct layering
	max pooling	Size 2 × 2
Block 4	Fully connected	Neurons with dimensions of 6 × 256

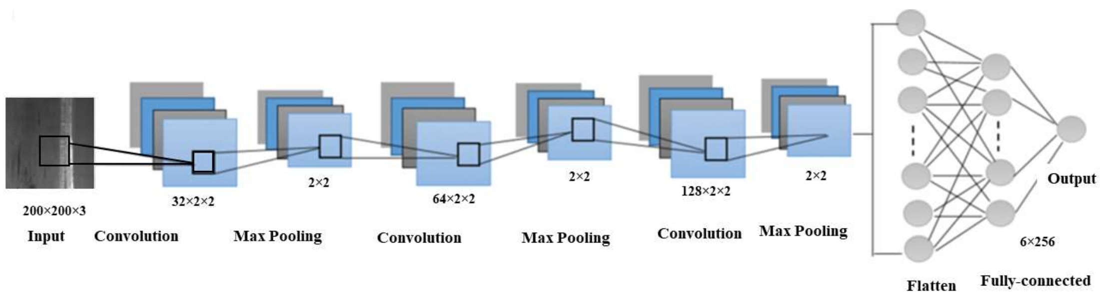

Fig. 2. Structure of proposed convolutional neural network.

Now, let's explain the architecture of the CNN:
Input Layer: The input layer is the first layer of the CNN that accepts the input image.

Convolutional Layer 1: The first block consists of a convolutional layer with 32 filters of size 2x2. The filters are applied to the input image to extract important features. The output of the convolutional layer is passed through a ReLU activation function, which introduces non-linearity into the network.

Max Pooling Layer 1: After the first convolutional layer, a max pooling layer with a size of 2x2 is applied to reduce the spatial dimensions of the output.

Convolutional Layer 2: The second block consists of a convolutional layer with 64 filters of size 2x2. The output of the first max pooling layer is passed through this convolutional layer, which extracts more complex features. The output is then passed through a ReLU activation function.

Max Pooling Layer 2: After the second convolutional layer, a max pooling layer with a size of 2x2 is applied to further reduce the spatial dimensions of the output.

Convolutional Layer 3: The third block consists of a convolutional layer with 128 filters of size 2x2. The output of the second max pooling layer is passed through this convolutional layer, which extracts even more complex features. The output is then passed through a ReLU activation function.

Max Pooling Layer 3: After the third convolutional layer, a max pooling layer with a size of 2x2 is applied to further reduce the spatial dimensions of the output.

Flatten Layer: After the third max pooling layer, the output is flattened into a 1D vector to be passed to the fully connected layer.

Fully Connected Layer 1: The flattened output is passed through a fully connected layer with 256 neurons. This layer performs classification or regression on the input.

Output Layer: The output layer is the final layer of the CNN. It consists of neurons, which correspond to the number of classes in the classification task.

In summary, this CNN with 3 convolutional layers, 3 pooling layers, and one fully connected layer consists of 3 blocks, each of which consists of a convolutional layer, a ReLU activation function, and max pooling. The output of the third block is then flattened and passed through a fully connected layer to perform the final classification task.

4. Results and discussion

To accurately evaluate the proposed model, quantitative criteria of accuracy, precision and recall have been used. Accuracy means how accurately the trained model predicts output. Accuracy indicates the degree of trust in the output of the category, and the call indicates the efficiency of the classification according to the number of events in a particular category[5].

$$Acc = \frac{TP+TN}{TP+TN+FP+F} \tag{1}$$

$$Pr = \frac{TP}{TP+FP} \tag{2}$$

$$Re = \frac{TP}{TP+FN} \tag{3}$$

Acc: Accuracy
Pr: Precision
Re: Recall
TP: The number of images that are correctly assigned to a category by the algorithm.
TN: The number of images that, although not belonging to a category, were not correctly predicted in that category.
FN: The number of images that belong to other categories, even though they belong to one category.
FP: The number of images predicted in that category, although not in groups.

The confusion matrix of the proposed model shown in Table 3 indicates the classification results for the six categories in the dataset. The categories of corrosion, depression and patch have a higher degree of correct classification than the rest. This is due to the apparent differences in the samples within the categories. The predicted category is less accurate for classes that have similar aspects in appearance.

In this proposed model, the types of defects in the sample images are correctly and incorrectly identified in Fig. 3 and Fig. 4, respectively.

Table 3. The proposed model confusion matrix for 72 test samples.

Predicated type / Real type	Rolled-in scale	Patches	Crazing	Pitted	Inclusion	Scratches
Rolled-in scale	11	0	1	0	0	0
Patches	0	11	1	0	0	0
Crazing	0	0	12	0	0	0
Pitted	1	0	1	9	0	1
Inclusion	4	0	0	0	5	3
Scratches	0	1	0	1	0	10

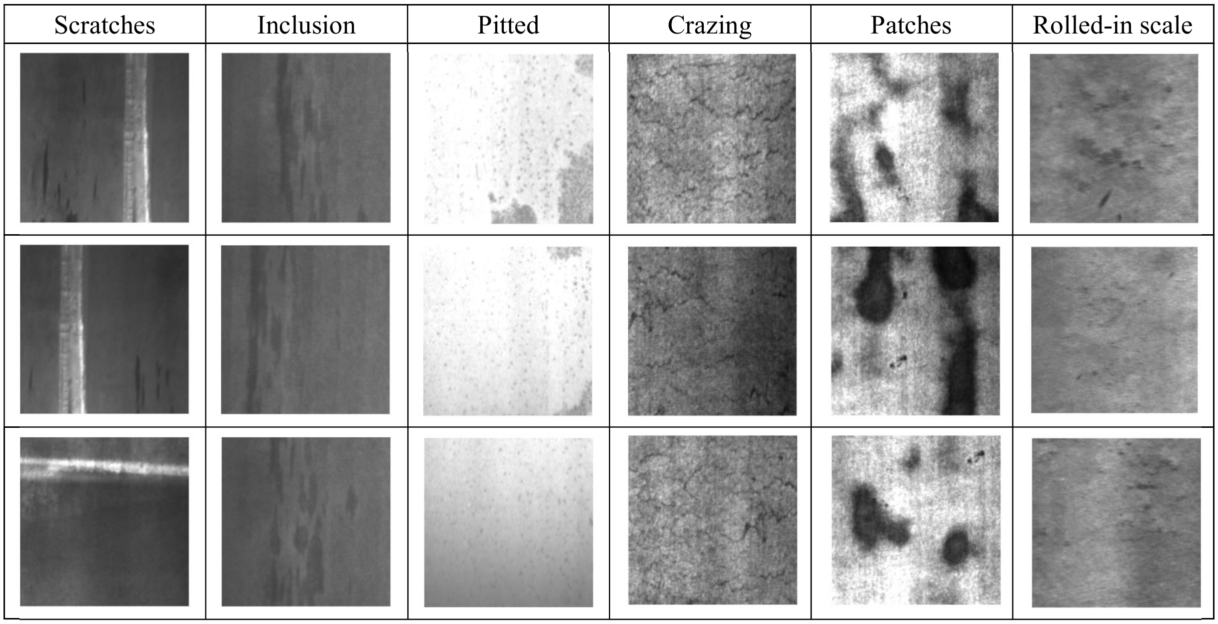

Fig. 3. An example of images predicted correctly by the model.

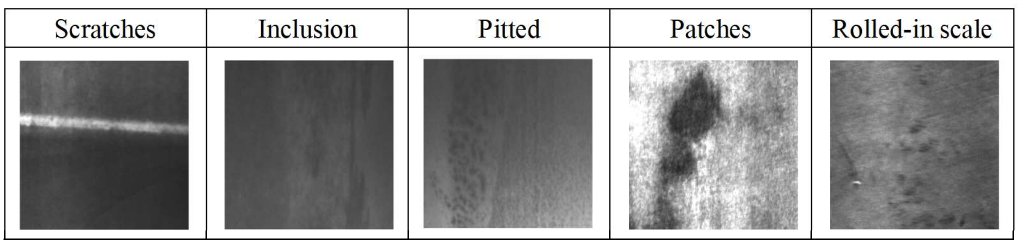

Fig. 4. An example of images predicted wrongly by the model.

Course changes in accuracy and cost functions when teaching the proposed models are shown in Fig. 5 and Fig. 6, respectively. In several periods, the models have reached the maximum degree of generalization, and higher accuracy can be achieved by increasing the period. In the 3-layer model, better accuracy was obtained in validation data.

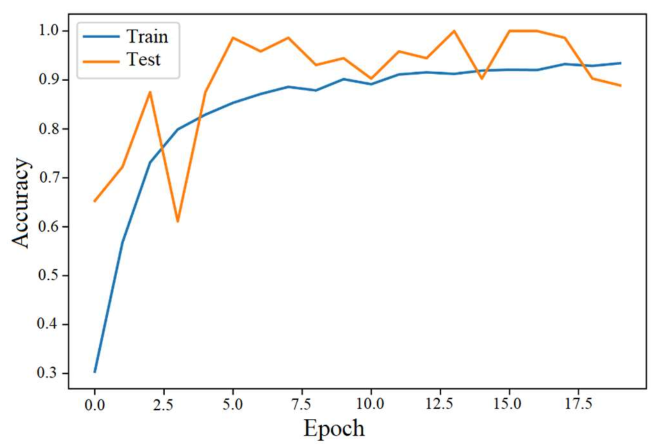

Fig. 5. Accuracy chart by epoch.

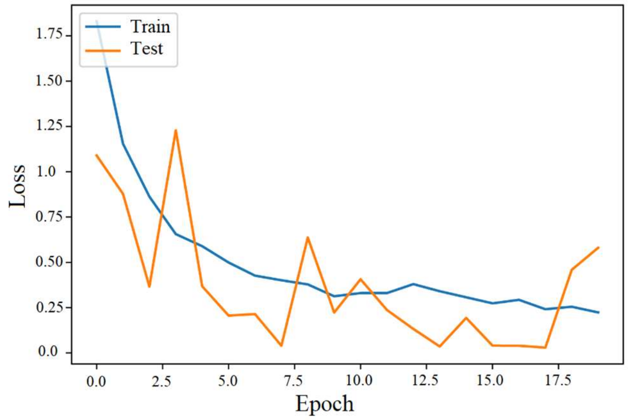

Fig. 6. Loss chart by epoch.

5. Conclusion

In recent decades, a large number of researchers have researched the surface defects of steel[11]. In addition, various algorithms are proposed with the development of machine learning. Traditional machine learning-based methods are usually sensitive to the scale of defects and are easily influenced. In addition, the accuracy of this algorithm cannot meet the real needs of automatic fault detection. Some features have to be designed manually and have a very limited range of applications. The deep learning-based classification method can only classify images, but it cannot determine the location and size of the defect. This has a great impact on the analysis of subsequent data. It is very difficult to teach a stable and accurate model based on the desired architecture.

The result of this study is the evaluation of the performance of the proposed learning model for classifying the surface defects of the hot rolled steel strip in the North Eastern University dataset. Image size affects the model's training capability. For this dataset, images with a size of 200 × 200 enter the CNN and then in the first layer the size of the images changes to 32 × 32, in the second layer to 64 × 64 and in the third layer to 128 × 128. Other important issues are the size of the handle and the period during which the appropriate values must be selected. Our proposed method for detecting surface defects of hot-rolled steel strip can reach the desired accuracy of 93.54%.

References

[1] Luo, Q., Fang, X., Liu, L., Yang, C., Sun, Y., 2020. Automated visual defect detection for flat steel surface: A survey. IEEE Transactions on Instrumentation and Measurement. 69, 626-644.

[2] Martynenko, V., Martínez Krahmer, D., Nápoles Alberro, A., Cabo, A., Pérez, D., Zayas Figueras, E.E., Gonzalez Rojas, H.A., Sánchez Egea, A.J., 2020. Surface damaging of brass and steel pins when sliding over nitrided samples cut by finishing and roughing EDM conditions. Materials. 13, 3199-3215.

[3] Li, X., Tso, S. K., Guan, X. P., Huang, Q., 2006. Improving automatic detection of defects in castings by applying wavelet technique. IEEE Transactions on Industrial Electronics. 53, 1927-1934.

[4] Dong, H., Song, K., He, Y., Xu, J., Yan, Y., Meng, Q., 2020. PGA-Net: Pyramid feature fusion and global context attention network for automated surface defect detection. IEEE Transactions on Industrial Informatics. 16, 7448-7458.

[5] Tao, X., Zhang, D., Ma, W., Liu, X., Xu, D., 2018. Automatic metallic surface defect detection and recognition with convolutional neural networks. Applied Sciences. 8, 1575-1584.

[6] Kholief, E.A., 2017. Detection of steel surface defect based on machine learning using deep auto-encoder network. 7th International Conference on Industrial Engineering and Operations Management (IEOM).

[7] Li, J., Su, Z., Geng, J., Yin, Y., 2018. Real-time detection of steel strip surface defects based on improved yolo detection network. International federation of automatic control (IFAC-PapersOnLine). 51, 76-81.

[8] Martins, L.A.O., Pádua, F.L.C., Almeida, P.E.M., 2010. Automatic detection of surface defects on rolled steel using computer vision and artificial neural networks. IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society. 10, 1081-1086.

[9] Gardner, M.W., Dorling, S.R., 1998. Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. Atmospheric Environment. 32, 2627-2636.

[10] Scherer, D., Müller, A.C., Behnke, S., 2010. Evaluation of pooling operations in convolutional architectures for object recognition. Internet Corporation for Assigned Names and Numbers (ICANN).

[11] Yousef, N., Parmar, C., Sata, A., 2022. Intelligent inspection of surface defects in metal castings using machine learning. Materials

Today: Proceedings. 67, 517-522.