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Synthesis of the Artificial Intelligence and Model-Based and Statistical Algorithms in the Classification of the Metal Surface Defects

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Steel has played an indispensable role in numerous industries, particularly in architecture, aerospace, and the automotive sector, and has been one of the most crucial components in manufacturing. The possibility of defects in the steelmaking process has had a substantial impact on the quality and service life of the final product. With the objective of ensuring a timely response in steel production, this paper has presented a model for the classification, detection of defect regions, and visualization of spatial defects. The model has been founded on the synthesis of convolutional neural network, snake algorithms, and algorithms for generating spatial defects based on images. The convolutional neural network has been trained using images from the NEU Surface Defect database, and model evaluation has been carried out on previously unseen samples that have not been included in the training data. The convolutional neural network has achieved an overall accuracy of 88.4% with unseen samples from the NEU Surface Defect database, with predictive abilities ranging from 72.7% to 97.7%. Following the classification, a spatial representation of the damage has been generated, and defect segmentation on the material has been executed. The application of this model in modern industry has the potential to significantly enhance the performance and quality of high-risk manufacturing processes, mitigate unnecessary losses, and enable informed decision-making about future steps in a more insightful manner.

Keywords: Convolutional Neural Network, Active Contours, Steel, Defects, Spatial defect shape

1 Introduction

The fourth industrial revolution has fundamentally transformed global manufacturing and industrial processes. Its objective has been to enhance productivity and improve product quality. Many countries have adopted strategies to upgrade production technologies, incorporating sensors and communication devices for automation, improved quality, and cost reduction. This has encompassed the utilization of IoT and big data in smart factories within extensive production chains.[1, 2]

The utilization of cutting-edge technologies enables data collection from sensors in production lines, processing it into valuable information, all powered by artificial intelligence (AI), specifically deep learning. This technology, though relatively new, holds immense potential, with performance tied to data quality and quantity. Deep learning addresses data processing challenges seen in traditional AI by identifying complex patterns within unstructured data.[1-5]

Small and medium-sized enterprises have encountered obstacles while embracing these technologies, most often due to financial constraints and slow adoption of the need for digital transformation. Nonetheless, computer vision and deep learning have found versatile applications and have been constantly improving as productivity and product quality have enhanced. The industrial use of modern digital tech has expanded significantly, especially in high-risk manufacturing roles that have demanded precision and swift decision-making.[6] For instance, in steel manufacturing, timely defect detection has been crucial. Defects have significantly raised manufacturing costs and degraded product quality. Surface flaws on metals have detrimentally affected their properties, and metal has remained indispensable in production facilities.[7,8]

Metal surface defects have arisen under various conditions (e.g., during production, secondary rolling, cooling, external forces, etc.) and have had a significant impact on current or future production equipment. Consequently, substantial research has been dedicated to computer vision and deep learning for developing effective models to diagnose these issues. These models have primarily focused on assessing the extent of defect-affected areas and classifying defects.[6-9] Depending on the algorithmic nature, they have been categorized into the following

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groups: statistical methods (e.g., thresholding, clustering, edge-based, etc.), spectral techniques (e.g., Fourier transform, multiscale geometric analysis, etc.), model-based approaches (e.g., Weibull model, AC, etc.), and machine learning methods (e.g., supervised, unsupervised, CNN).[9-11] Given the need for classification model development and available resources, the performance of the proposed models has been satisfactory.

In line with current global research trends, this paper presented a model for metal surface defect classification, combining statistical, model-based, and AI algorithms.

2 Materials and Methods

2.1 Convolutional neural network

Traditional signal processing involved the application or creation of various filters. By using them, different types of information related to signals were obtained. The application of CNN in signal processing enabled the automatic creation of attributes that were relevant to a given problem.[12,13]

CNN required the existence of a convolutional layer, but in addition to it, it could also contain aggregation layers and fully connected layers. Each convolution operation was determined by the step, filter size, and zero padding. In computer vision problems, a convolutional layer was used to extract features from images. This was represented through a convolutional operation on the l-th convolutional layer:

$$A_j^l = \varphi\left(\sum_{i+1}^{c_m} w_{ij}^l \cdot F_i^l + b_j^l\right) \quad \ldots(1)$$

Convolutional layers and aggregation layers alternated with each other. Aggregation layers aimed to gradually reduce the dimensionality of the representation, which affected the number of parameters and the computational complexity of the model. One of the most popular aggregation methods was the rectified linear unit (ReLU), and it could be applied in various fields, such as image processing. A fully connected layer sat behind the last aggregation layer and learned using attributes constructed by previous layers.

In the output layer, there could be a softmax function that represented the normalized exponent of the output values. It was represented by the following expression:

$$o_i = \frac{e^{z_i}}{\sum_{i=1}^{M} e^{z_i}} \quad \ldots(2)$$

Jointly, CNN layers enabled proper signal processing, providing the required output, in this case, defect classification.

2.2 Active contours using the Chan-Vese model

Active contours were techniques that allowed the segmentation of the area of interest in the image based on a contour that evolved over time. In other words, an active contour was a curve defined in the image domain with the property of changing its shape, size, and topology during its evolution, as defined by the energy functional. At the beginning of this process, an initial curve was set, which could be of arbitrary shape and position, while at the end of the process, the curve assumed its final position by encompassing the desired object in the image. The energy functional depended on the image configuration and had a minimum value when the curve was in the target position. Its essential role was to control the direction of movement and the shape of the curve.[14]

When traditional methods of active contours were applied, a problem could arise in detecting objects with smooth boundaries or in cases where there was no clear boundary between objects in the image. To overcome this problem, the Chan-Vese model was developed. This model divided the relevant image into inner and outer regions with a contour curve. The initial curve evolved to the desired limits based on the following energy functional:[15]

$$E^{CV} = \lambda_1 \int_{C_{in}} |I(x) - c_1|^2 dx + \lambda_2 \int_{C_{out}} |I(x) - c_{12}|^2 dx + v|C| \quad \ldots(3)$$

The minimization of the energy functional was performed according to the following expression:

$$\frac{\partial \Phi}{\partial t} = \delta(\Phi)\left[-\lambda_1\big((x) - c_1\big)^2 + \lambda_2 (I(x) - c_2)^2 + v \cdot div\left(\frac{\nabla \Phi}{|\nabla \Phi|}\right)\right] \quad \ldots(4)$$

$$c_i = \frac{\int I(x) H_i(\Phi(x)) dx}{\int H_i(\Phi(x)) dx}, i = 1,2 \quad \ldots(5)$$

Considering the homogeneity of the image, the differences between c_1 and c_2 were required to be large enough for the curve to follow the desired contours.

2.3 Dataset

The database used to train the network was the NEU Surface Defect Database, which consisted of six kinds of typical surface defects of the hot-rolled steel strip, namely RS, Pa, Cr, PS, In, and Sc. Each of these categories contained about 300 samples. Images were sized at 200×200 pixels.[16]

2.4 The architecture of the CNN

CNNs proved to be extremely practical networks in the classification of various types of images. The proposed architecture of our model was given in Fig. 1.

Our model consisted of three parts:

a) *CNN/prediction*. The network trained based on a database of images that were divided into six categories. The images passed through a series of convolutional layers responsible for extracting features. The convolution and aggregation layers alternated. Faster training of the network was ensured by introducing non-linearity into the model using the ReLU function. The normalization of activations and gradients was achieved through the batch normalization layer. The last layer, which was fully connected, performed the analysis of the sampled characteristics and the categorization of images. The essence of CNN application was that the dimensions of the image were compressed as they passed through layers by discarding unnecessary information from the initial full-resolution image, retaining only the essentials. In the last layer, the number of neurons corresponded to the number of classes to which the images could belong;

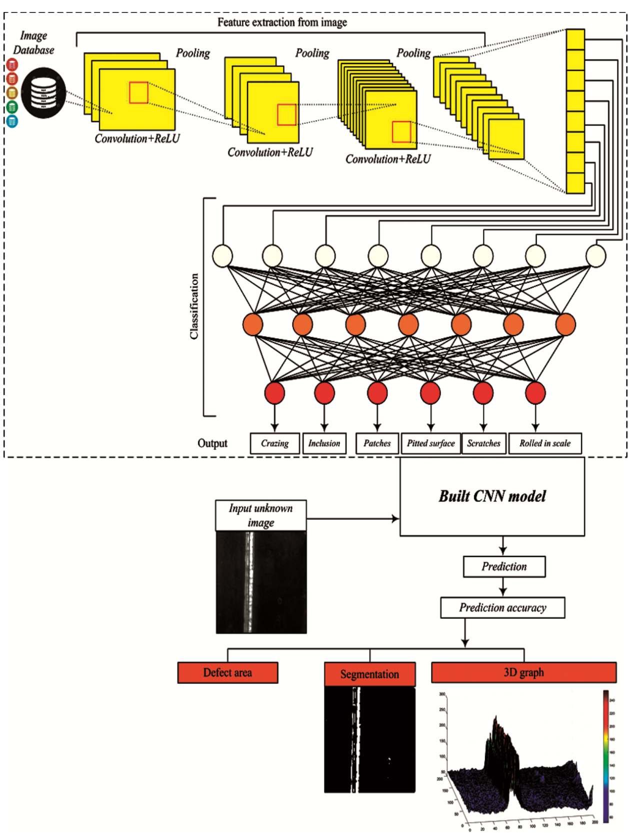


Fig. 1 — The architecture of the CNN

b) *Generation of a spatial representation of the defect*. Based on the 2D image and the grayscale image, a spatial representation of the defect was formed, enabling a better understanding of the nature of the defect; and

c) *The segmentation of defect and the calculation of the surface affected by the defect*. The segmentation was performed using AC, whereby any irregular shape of the defect was isolated, and based on the separated part, it was possible to determine the surface affected by the defect.

3 Results and Discussion

The proposed model showed satisfactory results in terms of the following essential features of the model: convergence of the accuracy and loss curves during the training process of the neural network (Fig. 2), the confusion matrix (Table 1), the generated spatial surfaces of the defects in the images, as well as the segmentation of the damage (Table 2).

Figure 2 showed the training process of the neural network and monitored the change in accuracy and loss. It could be observed that in the first 20 epochs, the training accuracy amounted to about 40%. This was accompanied by high values of the Loss (around 12%). With an increase in the number of epochs, i.e. iterations, the precision reached a higher value, while simultaneously, the Loss decreased. In other words, the values of the precision curve continuously increased until about 120 epochs, where they assumed an approximately constant value. This was followed by a continuous decline of the Loss curve; its constancy occurred approximately continuously around the 120^{th} epoch.

After training the network, the performance of the network, as well as the classification performance by individual groups, were shown in the confusion matrix (Table 1).

Generally, the overall accuracy was 88.4%. In other words, it was demonstrated that the proposed model performed the classification correctly in 88.4% of cases. The best predictive ability of the network was shown for the Cr category (97.7%), while the worst predictive ability was shown for the Sc category (72.7%). The percentage of prediction for other categories ranged from 86.7% to 93.3%.

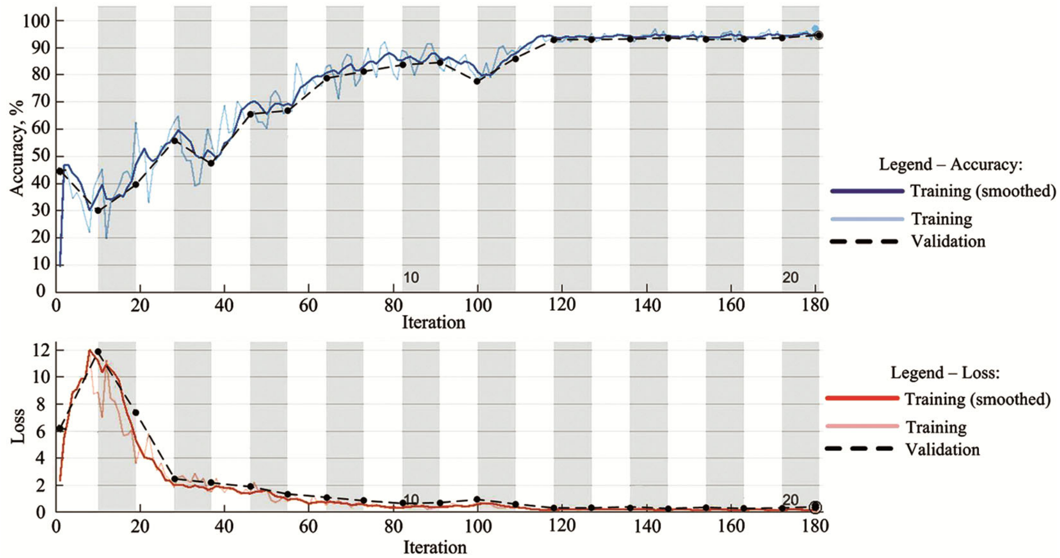


Fig. 2 — The training process of the CNN

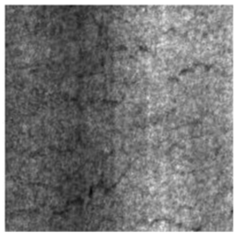
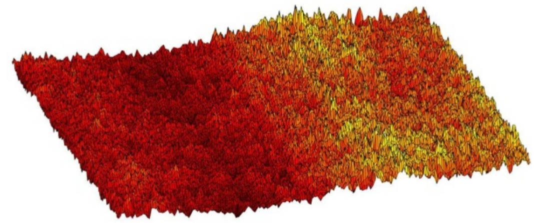
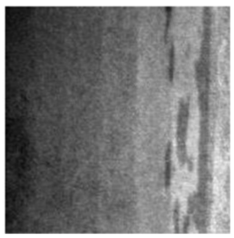
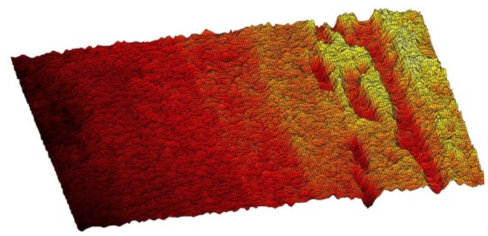
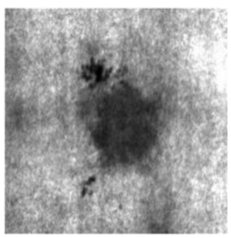
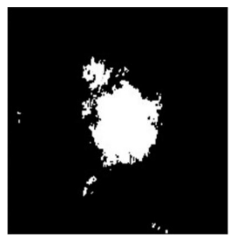
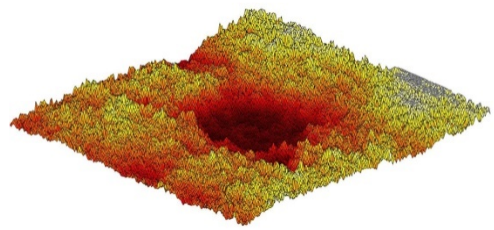
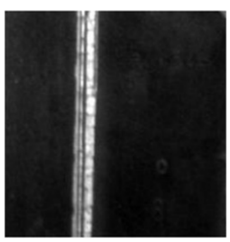
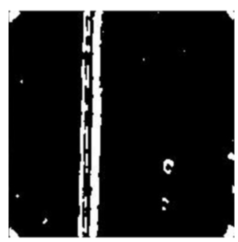
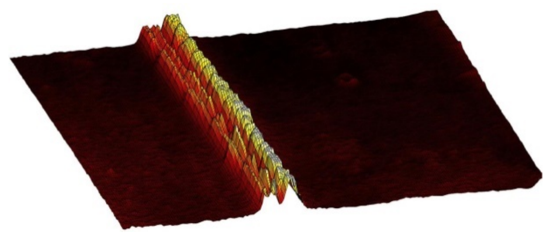
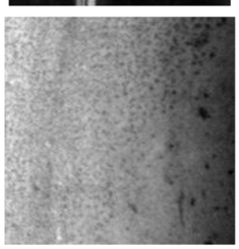
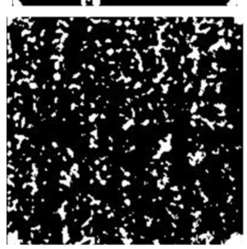
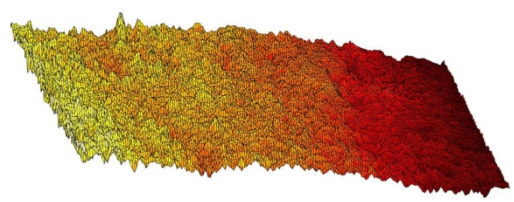
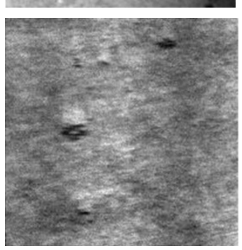
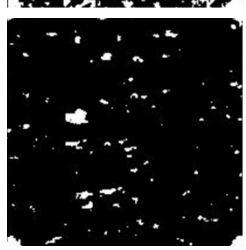
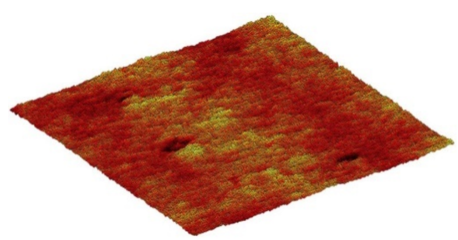
Table 1 — Confusion matrix

	C	I	P	PS	RIS	S	Prec.
C	93,5%	0	2.4%	0	0	0	97.7% 2.3%
I	0	71.4%	0	4.4%	0	5.55%	90.9% 9.1%
P	6.5%	0	97.6%	0	0	5.55%	88.9% 11.1%
PS	0	10.7%	0	84.8%	0	0	86.7% 13.3%
RIS	0	1.8%	0	4.4%	100%	0	93.3% 6.7%
S	0	16.1%	0	6.4%	0	88.9%	72.7% 27.3%
Rec.	93.5% 6.5%	71.4% 28.6%	97.6% 2.4%	84.8% 15.2%	100% 0%	88.9% 11.1%	88.4% 11.6%

In 93.5% of cases, the network classified the sample from the Cr category correctly, while in 6.5% of cases, it misclassified the sample from the Cr category and potentially replaced it with the Pa category. A high correct classification of the samples was observed in the event of the Rs category (in 100% of cases, samples were classified correctly) and in the event of the Pa category (in 97.6% of cases, samples were classified correctly; in 2.4% of cases, the sample was misclassified as Pa). A satisfactory level of accuracy was observed in the network in the event of the Sc category (in 88.9% of cases, samples were classified correctly; in 11.1% of cases, they might have been replaced with the In or Pa category). We obtained similar results for the Ps category, where in 84.8% of cases, the sample was classified correctly, while in 15.2% of cases, the sample in the Ps category was misclassified and might have been replaced with the In, Rs, or Sc categories. The worst-case performance of the network was observed during the classification of the In category, where in 71.4% of cases, the sample was classified correctly, and in 28.6% of cases, it might have been replaced with the Ps, Rs, or Sc categories.

After training the network, the verification was performed on the samples that were not selected for training the network. First, a prediction was made and the precision of the prediction was determined, then spatial surfaces were generated for the given cases and the defect segmentation was performed, on the basis of which it was possible to determine the area affected by the defect (Table 2).

Table 2 — Visualization of the original sample, defect segmentation and spatial surface for categories: Crazing, Inclusion, Patches, Scratches, Pitted surface and Rolled in the Scale

	Original sample	Defect segmentation	Spatial surface
Crazing			
Inclusion			
Patches			
Scratches			
Pitted surface			
Rolled in scale			

Steel is an extremely important material in the metal industry. Having high-quality steel is essential for the normal operation of the production equipment. Surface defects can significantly affect the lifetime of production equipment.[7,8,16,17] The aim of this paper was to demonstrate the application of CNN for the classification of defects on metals, to create a spatial representation of the defect, and to locate it in the image.

The database used for training and testing the CNN was the NEU dataset, which contained six categories of the most common metal defects.[7,8,16] In general, the main challenge for defect detection was to accurately separate the defect from the metal surface pattern. One complicating factor in using the aforementioned dataset was the lighting, which was not uniform and often varied.[17] Samples were taken from the database for independent verification of the classification.

The application of CNN for the classification of various metal defects could be found in many papers.[3,8,11] That being the case, in this paper, we presented a model for defect detection, the main algorithm of which was CNN with 6 convolutional layers and one fully connected layer Y. He *et al*. proposed a defect detection network using DL.[16] By combining features at multiple levels, they enabled defect detection, obtained important quality parameters related to the quantity, category, complexity, and the area of the defect. Their system produced extremely high accuracy. Besides them, Lv X. *et al*. proposed a defect detection network based on Single Shot MultiBox Detector.[17] Performance evaluation was carried out by analyzing the parameters of the confusion matrix. The results for recall were approximately the same, but the algorithm Lv X. *et al*. developed performed better classification for I, PS, and P, while the algorithm we developed performed better classification for RS. The accuracy obtained by using our algorithm was superior. In addition to the development of new models for defect detection, the existing CNN algorithms were often improved. For example, Wang S. *et al*. examined the performance of the existing CNN algorithms (ResNet50) and improved them. By improving them, they managed to increase the accuracy of detection.[18]

The accuracy of the complete model, i.e. the training time, was influenced by several factors, the number of selected epochs is among many others. In our case, the training was performed in 20 epochs. At the beginning of the training process, we observed a high value of the Loss, which entailed a low value of accuracy. However, already in the second epoch, the Loss started decreasing, and after the tenth epoch, it assumed a value approximately equal to 0 and became stable. This indicated that the learning rate was optimally selected.[18,19]

Rapid defect classification was of utmost importance, but it was also important to locate the defect in the image. For this purpose, many algorithms for image segmentation could be applied. As already observed in various research papers, AC algorithms proved to be one of the best performers.[14,20] Therefore, after the classification of the images, defect segmentation was performed using the AC algorithm, and the area of the damaged area was calculated.

Lee S.I. *et al.* extended their CNN algorithm with class activation maps,[7] while we extended our CNN algorithm by generating a spatial surface and calculating the area affected by the defect. Their network showed a slightly better performance. However, the spatial representation of the defect gave a clearer picture of the localized regions and helped in better understanding of the defect's nature and decision-making.

4 Conclusion

This paper has presented a model for the detection, classification, and reconstruction of defects on metal surfaces. The model has been designed as a synthesis of statistical, model-based, and AI algorithms. Considering the constant development of the industry, the application of this model has significantly sped up and simplified the process of detecting possible defects as well as the decision-making process. The presented model has made an essential contribution, especially in high-risk jobs, as well as for users without the necessary specialized software skills. Further research will be aimed at improving the model for detecting imperfections in metal microstructures, generating spatial models of the microstructure, and towards the prediction of the possible formation of defects on the surface layers of the material, depending on the microstructure.

References

1 Wang J, Ma Y, Zhang L, Gao R X & Wu D, *J Manuf Syst*, 48 (2018) 144

2 Jung W-K, Kim D-R, Lee H, Lee T-H, Yang I, Youn B D, Zontar D, Brockmann M, Brecher C & Ahn S-H, *Int J Precis Eng and Manuf*, 22 (2021) 201.

3 Essien A & Giannetti C, *IEEE Trans Industr Inform*, 16(9) (2020), 6069.

4 Dave V, Singh S & Vakhaira V, *Indian J Eng Mater Sci*, 27 (2020) 878.

5 Kandavel T K, Kumar T A & Varamban E, *Indian J Eng Mater Sci*, 27 (2020) 503.

6 Svinth C N, Walace S, Stephenson D B, Kim D, Shin K, Kim H-Y, Lee S W & Kim T-G, *Int J Precis Eng and Manuf*, 23 (2022) 609.

7 Lee S Y, Tama B A, Moon S J & Lee S, *Appl Sci*, 9(24) (2019) 5449.

8 Hao R, Lu B, Cheng Y, Li X & Huang B, *J Intell Manuf*, 32 (2021) 1833.

9 Luo Q, Fang X, Liu L & Sun Y, *IEEE Trans Instrum Meas*, 69(3) (2020), 626.

10 Czimmerann T, Ciuti G, Milazzo M, Chiurazzi M, Roccella S, Oddo C M & Dario P, *Sensors*, 20(5) (2020) 1459.
11 Tao X, Zhang D, Ma W, Liu X & Xu D, *Appl Sci*, 8(9) (2018) 1575.
12 Albawi S, Bayat O, Al-Azawi S & Ucan O N, *Comput Intell Neurosci*, 2018 (2018) 6973103.
13 O'Shea K & Nash R, *Neural and Evolutionary Computing*, (2015) 1511.08458.
14 Gur S, Wolf L, Golgher L & Blinder P, *Unsupervised Microvascular Image Segmentation Using an Active Contours Mimicking Neural Network,* in 2019 IEEE/CVF International Conference on Computer Vision (ICCV), Seoul, Korea (South), 2019, 10721.
15 Wang L, Chang Y, Wang H, Wu Z, Pu J & Yang X, *Inf Sci*, 418-419 (2017) 61.
16 He Y, Song K, Meng Q & Yan Y, *IEEE Trans Instrum Meas*, 69(4) (2020) 1493.
17 Lv X, Duan F, Jiang J-J, Fu X & Gan L, *Sensors*, 20(6) (2020) 1562.
18 Wang S, Xia X, Ye L & Yang B, *Metals*, 11(3) (2021) 388.
19 Deshpande A M, Minai A A & Kumar M, *Procedia Manuf*, 48 (2020) 1064.
20 Bumrungkun P, *J Phys Conf Ser*, 1195(1) (2018) .