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METHODS FOR RECOGNIZING SURFACE DEFECTS ON THIN-SHEET MATERIALS FOR VISUAL TESTING AUTOMATION (REVIEW)

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ABSTRACT

The use of methods for recognizing surface defects in order to automate the process of visual non-destructive testing in production of rolled thin-sheet materials is becoming an increasingly urgent task. The use of automated systems for recognizing surface defects leads to early detection of damage and determination of their class and level of danger. After classifying a defect, the system makes a decision on further actions without the operator participation. The presence of such systems prevents the equipment downtime and reduces the impact of the human factor on production. The classifier performance rates were determined and analysis of the current techniques for determining surface defects was performed. The advantages and disadvantages of the methods are determined. The feasibility of using a method was analyzed depending on the type of surface and geometric characteristics of a defect. The expediency of using several methods to ensure more accurate recognition of surface defects is determined. Significant prospects for the application of machine learning methods based on neural networks are noted. The prospect of using neural networks in the systems for automated recognition of surface defects is predetermined by the possibility of automatic selection of features from the image, as well as processing of complex structures.

KEYWORDS: surface defects, defect detection methods, sheet materials, automated monitoring, defect recognition, image processing

INTRODUCTION

The intensive development of industry specifies the task of improving the quality of products. Due to this reason, automated monitoring of surface defects of thin-sheet materials is important in many industries [1–4]. The quality of thin-sheet products is determined by a number of mechanical characteristics and the presence of defects depending on the material from which it is made. The presence of defects leads to the downtime of production equipment due to the need in the shutdown of the forming machine, elimination of break or defect, which is negatively reflected in the efficiency of production. At the same time, modern computer technologies and methods of artificial intelligence make it possible to achieve a significant effect at improvement of control systems. Detection of minor defects in the early stages of production can prevent the appearance of rejection and ensure the compliance of products with the quality standards. The use of industrial cameras of GigE standard allows transmitting RAW images without compression to a server at a speed of up to 5 Gbps for further processing and analysis [5]. With the use of the methods for detection and recognition of surface defects based on statistic data, namely size, frequency of detection and type of defects, spectrum of brightness or color, as well as machine learning, it is possible to detect and classify defects by their degree of danger with high accuracy. The term “accuracy of detection” should imply the correct assessment of a defect, namely the ability of the method to detect whether a defect is present on the obtained image. In this case, the accuracy of the classification reflects how true the method determines the class of a detected defect. According to the classification results, the automated system takes a decision on further steps.

AIM OF THE WORK

is analyzing and systematizing the methods of automated recognition of surface defects on thin-sheet materials to determine their advantages, disadvantages and potential areas of application.

STATEMENT OF PROBLEM FOR RECOGNITION AND CLASSIFICATION OF DEFECTS

Two-dimensional color image of the thin-sheet material surface serves as the primary information in the problem of recognition and classification of defects. The images are obtained by scanning the surface with the use of the system of digital CCD cameras. The size and shape of defects typical for respective production can be significantly different. In the general case, automated systems for monitoring of the thin-sheet material surface are capable of detecting defects from 1–2 mm^2. To check the recognition quality of the methods, a magnified image of a through defect in a rolled paper web with a size of 5.8×30.9 mm was used. To detect defects in the sheet materials from their digital images, widespread methods were selected based on statistic data analysis, as well as methods based on spectral analysis were determined, that are less widespread in the solution of machine vision problems. Unlike the traditional recognition methods, the methods based on machine learning were chosen.

CLASSIFIER PERFORMANCE RATES

Assessment of the results of applying methods for detection of surface defects occurs on the basis of the following statistical categories (Figure 1):

- TP is a true positive, that indicates that a real defect is determined as a defect;
- TN is a true negative, that indicates that a real defect is determined as a background;
- FP is a false positive, that indicates that a background is mistakenly determined as a defect;
- FN is a false negative, that indicates that a real background is correctly determined as a background.

TP, FN, TN and FP categories are generally accepted and widely used in many fields of science, including machine learning and computer vision [7]. Therefore, for a high percentage of detecting surface defects, it is necessary that TP and FN categories prevail. If TN and FP prevail among the detection categories, the appropriate detection algorithms and/or methods should be improved. Based on the above-mentioned categories, the classifier performance rates can be calculated:

- True positive rate:

$$TPR=\frac{TP}{TP+FN}; \quad (1)$$

- True negative rate:

$$TNR=\frac{TN}{TN+FP}; \quad (2)$$

- False positive rate:

$$FPR=\frac{FP}{FP+TN}; \quad (3)$$

- False negative rate:

$$FNR=\frac{FN}{FN+TP}; \quad (4)$$

- Precision rate:

$$Precision=\frac{TP}{FP+TP}; \quad (5)$$

- Recall rate:

$$Recall=\frac{TP}{TN+TP}; \quad (6)$$

- Accuracy rate:

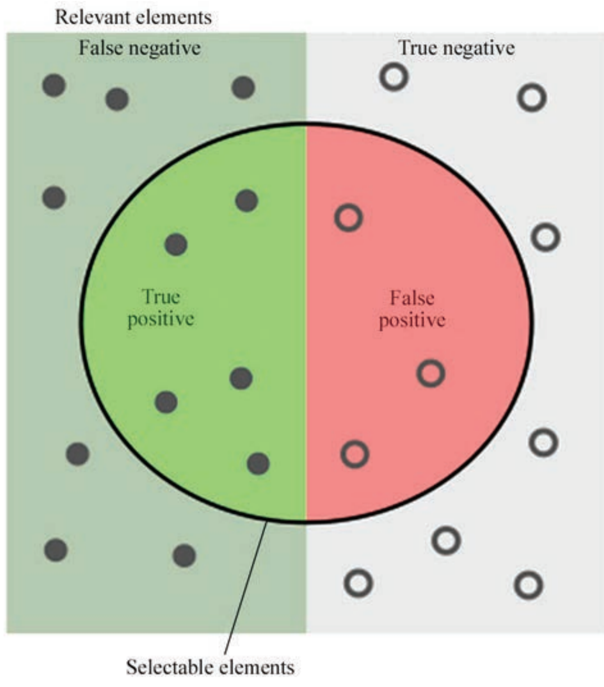

Figure 1. Confusion matrix [6]

$$Accuracy=\frac{TP+TN}{TN+TP+FP+FN}; \quad (7)$$

- G-mean:

$$G_{mean}=\sqrt{TPR \cdot TNR}; \quad (8)$$

- F-measure:

$$F_{measure}=\frac{2Precision \cdot Recall}{Precision \cdot Recall}. \quad (9)$$

Among these rates, G-mean and F-measure should be especially noted. G-mean is a value that estimates accuracy based on true positive and true negative rate. F-measure determines the overall efficiency of the process of detecting surface defects based on recall and precision parameters. The highest rate of F-measure is 1, which indicates the perfect precision and recall.

METHODS FOR RECOGNIZING SURFACE DEFECTS

The general classification of methods for recognizing surface defects is shown in Figure 2. In order to ensure the most effective level of recognizing defects, it is expedient to combine these methods and approaches depending on the task and production conditions.

1. STATISTICAL APPROACHES

The use of statistical approaches is justified in those cases, when the nature of defects is related to the surface texture. Therefore, the detection, description or classification of features on the base of textured surface characteristics, such as entropy, contrast, correla-

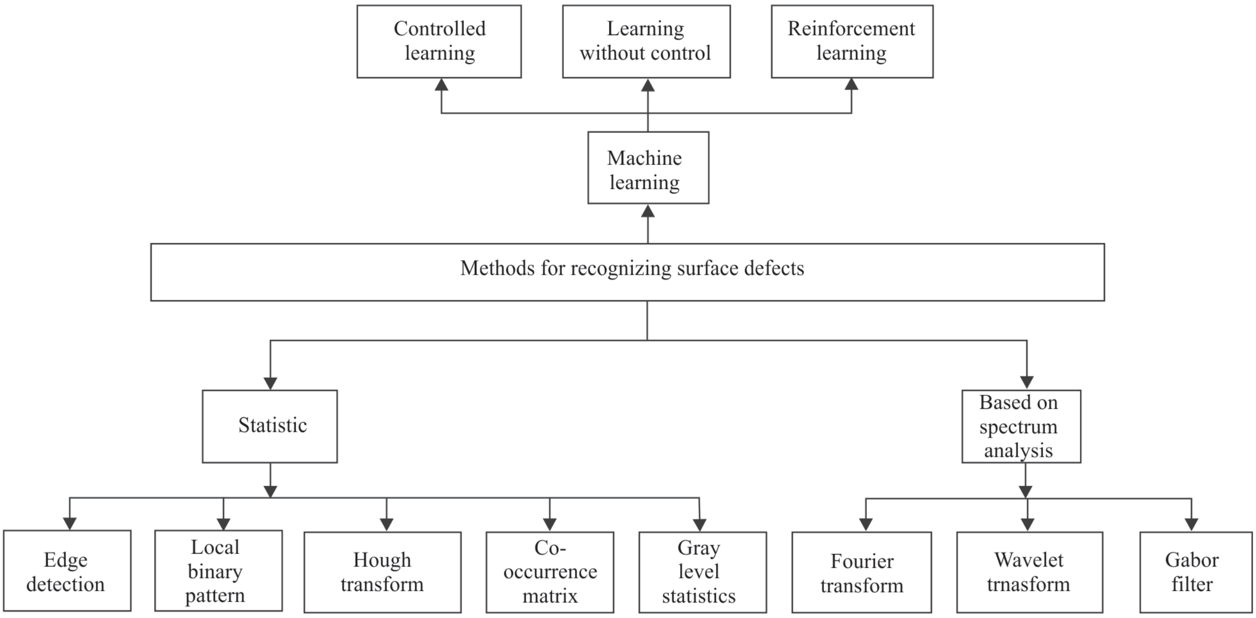

Figure 2. Classification of methods for recognizing surface defects

tion, etc., is an important element of the problem of recognizing surface defects [8].

1.1. METHOD OF EDGE DETECTION

An important step in recognizing defects on RAW images is the method of edge detection. There are several operators (Figure 3) to detect the edges of surface defects in the images.

Sobel operator is one of the most popular. To detect horizontal and vertical edges, it uses kernel convolution. Among the advantages of this operator, its simplicity of implementation, as well as a short time of performance should be attributed [9, 10]. However, the roughness of detection edges compared to the next operator should be noted, namely Canny operator [11]. At the first stage during its application, the

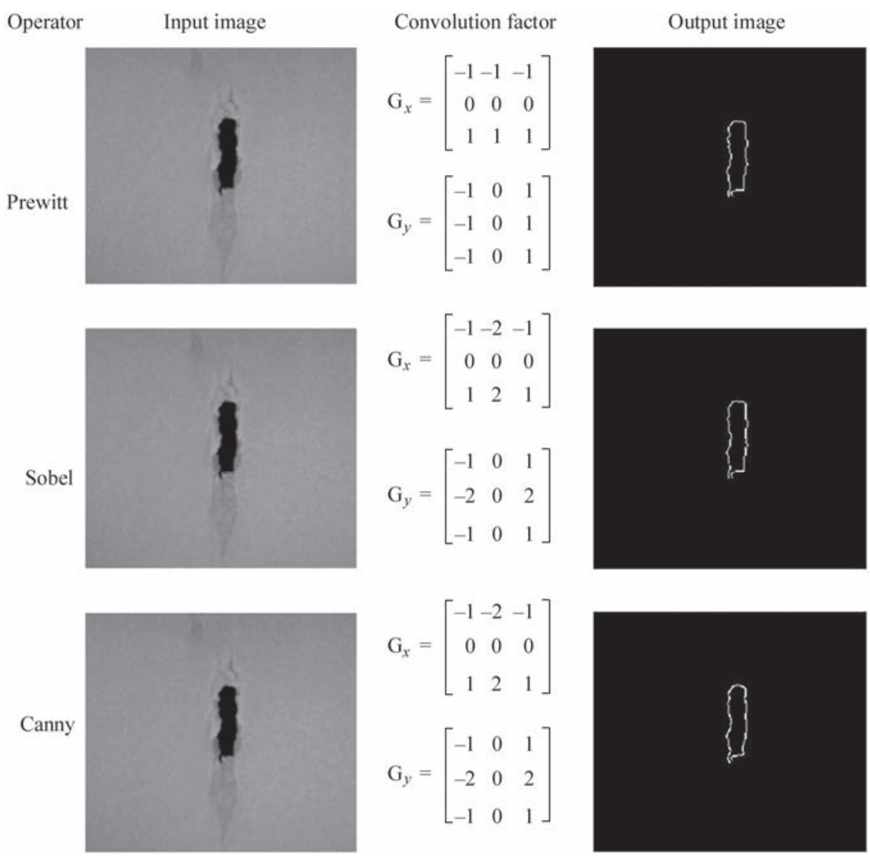

Figure 3. Result of using operators for edge detection

Table 1. Values of metrics for quality assessment of recognizing the considered methods

Number	Method	F-measure	Accuracy, %	Precision, %	Recall, %	Running time, ms
1	Edge detection					
	Canny operator	0.96	93.00	96.79	95.44	8.57
	Prewitt operator	0.92	92.34	92.34	90.83	4.12
	Sobel operator	0.86	81.00	85.41	86.67	5.36
2	Local binary pattern	0.83	82.00	84.51	81.70	21.41
3	Hough transform	0.78	72.00	75.57	80.18	27.49
4	Co-occurrence matrix	0.74	73.00	73.46	74.71	24.85
5	Gray level statistics	0.69	66.00	69.26	69.26	11.51
6	Fourier transform	0.65	63.00	65.77	64.72	36.21
7	Wavelet transform	0.85	82.00	88.85	80.69	67.32
8	Gabor filter	0.85	81.00	84.14	85.44	81.92
9	Supervised learning	0.94	93.00	95.00	93.58	12.38*

*Runnin time without taking into account the time for neural network learning.

image is smoothed. Then, a gradient of brightness is calculated for each image pixel. At the next stage, not maximum suppression and threshold value are used to obtain more smooth edges compared to Sobel operator. Among the disadvantages, the complexity of performance, as well as longer time for performance should be attributed. Sobel operator is similar to Prewitt operator. The use of a convolution to detect changes in brightness in the images is the same for these methods. Among differences, different characteristics of the kernel, less sensitivity to changes in intensity, as well as the smaller value of the Prewitt operator gradient can be attributed [12]. Sometimes, Roberts operator is also used, which is one of the simplest methods of detecting edges, Kirsch operator, as well as Laplace operator.

Quantitative characteristics of recognition quality using the method of highlighting edges is shown in the Table 1.

1.2. LOCAL BINARY PATTERN

The use of the local binary pattern (LBP) method has the most effective result of recognizing surface defects when they affect the textured characteristics of the surface. The essence of the method (Figure 4) is to determine a local surrounding context for each pixel of the image. In the next step, the brightness parameter of the central pixel is compared with the brightness of the pixels of the selected context. Next, a binary pattern is created for each pixel by setting the value "1" in the case when the brightness of the central pixel is less or equal to the brightness of the current value, as well as by setting "0" in other case. Next, for each image area, a histogram of LBP codes is created. This histogram reflects a number of each LBP code in the corresponding area [13–15]. The significant advantage of the LBP method is the ability to determine texture changes in the image. A high rate of calculations should also be noted.

Quantitative characteristics of recognition quality using the local binary pattern method are shown in the Table 1.

1.3. HOUGH TRANSFORM

This statistical approach is used to detect straight lines, round or ellipsoidal shapes in the image. The straight line detection algorithm is composed of the following steps. In the first step, each point of the image is transferred to the parametric space. In such a space, a straight line is represented by two values: an angle of inclination and a distance to the beginning of coordinates. In the second step, for each point of the image, a diagram is built in the parametric space. This diagram will display a hypothetical line crossing the current point. In the case when several points of the image lie on one straight line, their diagrams in the parametric space are intersected at one point. Programming of such an algorithm for highlighting of straight lines is based on the analysis of the above-mentioned intersections in the parametric space [16, 17]. To detect round shape objects in the image, a three-dimensional space for the mentioned algorithm

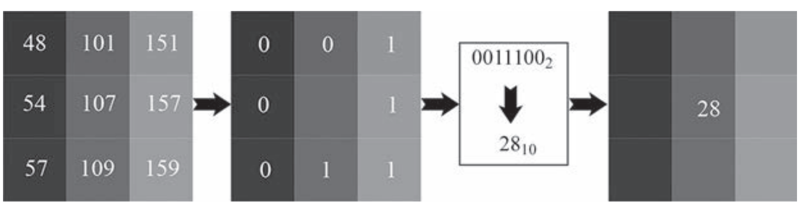

Figure 4. Principle of using LBP method

is used, in which objects to be detected will be represented by the coordinates of the center and the radius. Regarding the detection of ellipsoidal objects, in this case an object to be detected will be represented by the coordinates of the center, ellipse axis and angle of inclination.

Quantitative characteristics of recognition quality using the Hough transform method are shown in the Table 1.

1.4. CO-OCCURRENCE MATRIX

The co-occurrence matrix is a data structure used to assess the degree of similarity or coincidence between the areas or patterns of an image in the process of detecting surface defects. When applying this method, at first, textured characteristics, color information, shape, size and other attributes from images are distinguished, that may indicate surface defects. The selected features are compared with the features of reference patterns, which are created in advance on the basis of information about the types of defects. At the next step, a matrix for each image area is created, each cell of which contains comparison values. Next, the obtained matrix is analysed to detect coincidence with reference patterns [18]. Based on the analysis of the co-occurrence matrix, the system can make decisions on the presence of a defect and plan further actions.

Quantitative characteristics of recognition quality using the co-occurrence matrix are given in the Table 1.

1.5. GRAY LEVEL STATISTICS

The use of gray level statistics is justified in the case when the brightness and contrast of the defect zone is different from the surrounded area. Depending on the problem, this method can be used both independently as well as in combination with other methods for better results of detecting surface defects. One of the most popular methods is determination of the brightness threshold. By determining a threshold value of the gray level and highlighting all the pixels, the brightness of which exceeds this value, probable surface defects can be highlighted, the brightness of whose pixels is different from the surrounding pixels. At the next step, the obtained histograms for determination of texture features of the image are analyzed. Based on the results of the analysis, it is possible to determine textured features that may be superficial defects. To increase the probability of a defect based on the textured surface features, it is expedient to apply one of the methods of neural networks [19, 20]. Sometimes, the method of changing contrast is also used. The essence of this method consists in comparing the contrast of pixels of a probable defect and the surrounding area. A high level of contrast may indicate a surface defect. Quantitative characteristics of recognition quality using the gray statistics method are shown in the Table 1.

Among the disadvantages of statistical methods, unreliability in the case of light changes, as well as interference of pseudo-effects can be attributed.

2. METHODS BASED ON SPECTRUM ANALYSIS

These methods are used to determine and analyze the frequency characteristics of textured features of surface defects of thin-sheet materials.

2.1. FOURIER TRANSFORM

Fourier transform method is often used to analyze the frequency characteristics of textures and details on the images of surface defects. The essence of the method is the transition from the spatial representation of the image to the frequential representation. This transformation allows analyzing an image in the frequency range, as well as selecting the basic frequencies in the image that will be useful in highlighting edges and textures. As a result of this transformation, an image spectrum in the form of two-dimensional matrix is obtained, which contains information about the frequency components and their phase-frequency characteristics. The next step is highlighting and recognition of defects on the image by analyzing the frequency characteristics of the spectrum. Due to the fact that defects can change the frequential composition of the input image, i.e., contain high-frequency components or noise, it provides the visibility of probable defects in the spectrum. The use of this transformation makes it possible to detect defects or changes in the structure by suppressing undesired components or enhancing the required frequencies. After analyzing the frequency characteristics, it is possible to return to the spatial image representation by means of the inverse Fourier transform. The next step is the use of the threshold filtration method for detection and classification methods to determine the type of a defect [21, 22]. As a disadvantage of the Fourier transform method, the inability to describe the spatial model of information signal should be mentioned. That is the reason for ignorance of the most information of a local description.

Quantitative characteristics of the recognition quality using the Fourier transformation method are given in the Table 1.

2.2. WAVELET TRANSFORM

This method of image analysis is quite powerful, and therefore is often used for the recognition of surface defects of thin-sheet materials. The essence of the method consists in decomposition of the input image by scales and orientations with the use of the wavelet transformation. The result of the transformation are wavelet coefficients, presented in the form of scales and orientations of details of the input image. The filtration of the corresponding coefficients should be applied to highlight the required defects on the image. In the next step, the inverse wavelet transformation is performed to transform the image into a pixel system of coordinates. The result of the inverse transformation is an image with highlighted surface defects. In the case of insufficient intensity of highlighted defects, it is expedient to apply the method of threshold filtration. The final step is to apply the classification algorithms to determine the type and level of danger of a detected defect. This method makes it possible to recognize defects of different sizes by analyzing texture features, as well as localizing defects of different spatial frequency. The disadvantages of the method include sensitivity when choosing wavelets and decomposition parameters [23, 24]. The quantitative characteristics of recognition quality using wavelet transformation are shown in the Table 1.

2.3 GABOR FILTER

This method describes the spatial model of the information signal more effectively, compared to the method of Fourier transformation, by modulating the function of the Gaussian kernel with a sinusoidal wave of a certain frequency. In other words, Gabor filter is a mathematical filter that is used to analyze structural and textured surface defects. The essence of the method consists in determination of the filter parameters, such as frequency, orientation and size. On the basis of these parameters, the filter kernel is created, which is a two-dimensional function in the form of a sinusoidal wave limited by the Gaussian function. By means of the convolution operator, the obtained kernel of the function is applied to the image. This application helps to determine the texture and structural features by enhancing the textured details in the image corresponding to the filter frequency parameters. The use of the Gabor filter results in creation of a reaction map that reflects the degree of compliance of the textured features of each pixel of an image. Large values on this map can mean the presence of a surface defect. The reaction map is further processed using a threshold filtration method to highlight defect areas [25, 26]. Among the disadvantages of the method, its unortrogonality, resulting in excess components of features, which leads to a decrease in the efficiency of the textured image analysis, should be attributed. Quantitative characteristics of recognition quality using the Gabor filter are given in the Table 1.

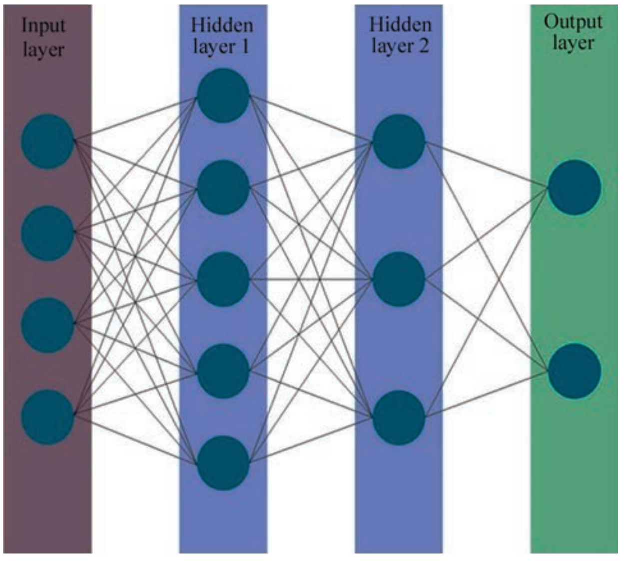

Figure 5. General structure of neural network [27]

3. APPROACHES BASED ON MACHINE LEARNING

Machine learning is a set of algorithms and methods of artificial intelligence (AI), by means of which a computer runs a self-learning process without direct instructions. To the main methods of machine learning, the following should be attributed:

- supervised learning or learning with a teacher;
- unsupervised learning;
- reinforcement learning.

The most used algorithm of machine learning is an artificial neural network. The use of a neural network requires a large amount of datasets for learning. Images with the required type of defects and without them serve as learning data. The required set of images with defects is selected depending on the material surface, on which recognition will be carried out. Typical defects for paper-cardboard production are web break, crumpling and defects of web edges, wandering crack, etc. In contrast to paper and cardboard production, typical defects for metal-rolled industries are scratches, corrosion and rust, exfoliation, traces of treatment, etc.

The neural network in the general case (Figure 5) consists of the input layer responsible for the normalization of data, a certain number of hidden layers that perform computing functions, as well as the output layer.

The methods of the neural network learning are divided into methods of direct and back error propagation. At the direct error propagation, the answer is directly predicted. At the back error propagation, the error between the answer and the prediction is minimized.

3.1. SUPERVISED LEARNING

The essence of the method consists in learning of a model with a teacher based on marked data, namely

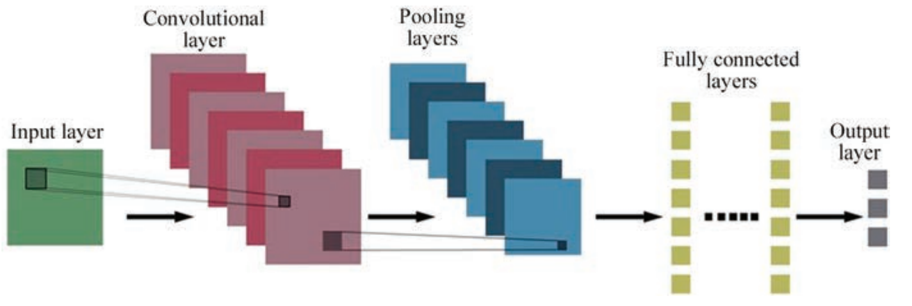

Figure 6. Typical architecture of CNN network [27]

samples having a known mark or class. Supervised machine learning is used to teach a model of surface defect classifier. At the first step, a database with images of product areas with typical defects indicating their type and coordinates (x, y) of the defect zone is created. At the second step, the selection of characteristic features from the images is carried out, that can be used to classify defects. The characteristic features include geometric or textured features, etc. Next, the appropriate model of machine learning is selected, namely CNN, SVM, RF, etc. After that, the process of model learning begins on the marked data using the extracted characteristic features of defects. During learning, a model of the neural network is adjusted to the characteristics of images that correspond to various classes of defects. Upon completion of the learning process, assessment of the accuracy of recognition is checked by means of a test dataset. In case of insufficient accuracy, repeated learning on another dataset is carried out until the required accuracy is achieved. The need in a large volume of quality data for learning can be attributed to the disadvantages of the method. Among the benefits, high accuracy at proper adjustment and learning should be mentioned [28, 29].

It should be noted that for the solution of computer vision problems, convolution neural networks (CNN) are best suited due to specialized architecture (Figure 6), scalability, as well as invariance to displacements and distortions. By means of the convolution layers, automatical selection of the features for detection of defects occurs. The next step is using subdiscretization layers to reduce data dimensions. To solve the problem of classification, pooling layers are used.

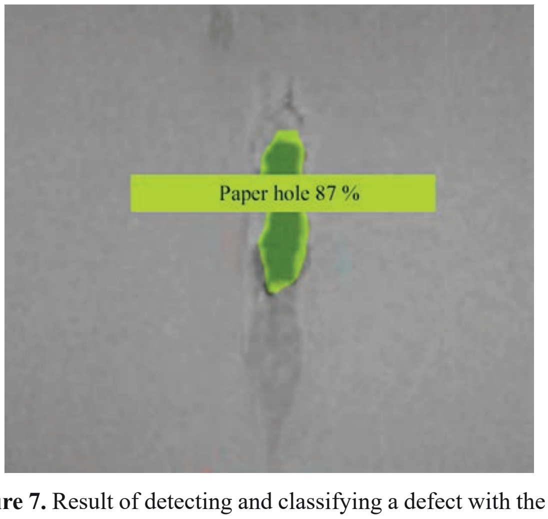

Figure 7. Result of detecting and classifying a defect with the use of the supervised learning method

Having selected a model of YOLOv4 neural network and having trained on a test sampling of images, containing typical defects of the paper web, the next result was achieved (Figure 7). The learning sampling of the marked data had 80 images. Test and validation samplings contained 10 images each. The availability of test and validation sampling is caused by the need in checking the adequacy of the learning process.

Quantitative characteristics of recognition quality using the supervised learning method are given in the Table 1.

3.2. UNSUPERVISED LEARNING

This method of machine learning accepts not marked data as input data. During learning, the model itself should find regularities or patterns without information about the classes of possible defects. The principle of clustering consists in seeking the model to independently group images by similar features without certain classes. The principle of reducing dimensions consists in preserving as much information as possible while reducing the dimensions of data. The use of the unsupervised method allows detecting hidden patterns or characteristics for further analysis or clustering of data, finding anomalies or associations. But there is a difficulty in determining the accuracy of detection due to the absence of "correct" answers [30].

3.3. REINFORCEMENT LEARNING

This method of machine learning consists in the interaction of the agent with the environment. The agent is a neural network that makes a decision based on input data. The agent receives a positive or negative assessment for made decisions. The main task of the agent is to maximize the positive assessments during learning and choose the optimal interaction strategy. The process of reinforcement learning of a neural network is based on the iterative interaction of the agent with the contacted environment. Thus, the agent learns at his actions and also on the gained experience of interaction with the environment. This method is the most suitable for learning robots and autonomous systems for control of unmanned vehicles [31, 32].

It should be noted that unsatisfactory quality assessment metrics were obtained with the help of machine learning methods, namely, unsupervised learning and reinforcement learning, because of the complexity of architecture and, as a consequence, complex adjustment. In turn, it should be noted that the supervised learning method showed a high result of the recognition quality. However, the “confidence” parameter (Figure 7) was at a level of 87 %, which can be explained by not sufficiently large set of learning data. Each of the above-mentioned machine learning methods can be used together for a more effective learning process on a limited input dataset.

Quantitative characteristics of defect quality recognition on digital images using the considered methods are shown in the Table 1.

CONCLUSIONS

Based on the results of the analysis of methods for recognizing surface defects, it can be concluded that machine learning methods, namely, convolution neural networks are the best suited for the use in the automated systems for testing the quality of thin-sheet material production. The use of machine learning methods is perspecitve due to the automatic separation of features from the image, as well as the ability to process complex data structures. Among the disadvantages of these methods, the need for a large amount of data for learning should be attributed. However, the correctly adjusted neural network on the ascending array of data for learning will only increase the accuracy of recognition. The considered statistical approach methods, as well as methods based on the spectrum analysis, are expedient for the use in combination with other methods to achieve greater accuracy of recognition. In some cases, the use of the methods for detection of edges, gray level statistics, local binary pattern, etc. is rationally to use as a preliminary processing for the formation of a learning database for machine learning methods. The cases and circumstances were also determined, in which the use of one or other method is more appropriate for a number of reasons. For example, it was determined that the Hough transform method shows the highest efficiency in the recognition of geometric shapes on images such as lines, circles and ellipses.

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