Automated Visual Defect Classification for Flat Steel Surface: A Survey

Qiwu Luo, *Member, IEEE*, Xiaoxin Fang, Jiaojiao Su, Jian Zhou, Bingxing Zhou, Chunhua Yang, *Senior Member, IEEE*, Li Liu, *Senior Member, IEEE*, Weihua Gui, *Member, IEEE*, and Lu Tian

***Abstract*—For a typical surface automated visual inspection (AVI) instrument of planar materials, defect classification is an indispensable part after defect detection, which acts as a crucial precondition for achieving the on-line quality inspection of end products. In the industrial environment of manufacturing flat steels, this task is awfully difficult due to diverse defect appearances, ambiguous intraclass and interclass distances. This paper attempts to present a focused but systematic review of the traditional and emerging automated computer-vision-based defect classification methods by investigating approximately 140 studies on *three* specific flat steel products of con-casting slabs, hot-rolled steel strips and cold-rolled steel strips. According to the natural image processing procedure of defect recognition, the diverse approaches are grouped into *five* successive parts: image acquisition, image preprocessing, feature extraction, feature selection and defect classifier. Recent literature has been reviewed from an industrial goal-oriented perspective to provide some guidelines for future studies, as well as to recommend suitable methods for boosting the surface quality inspection level of AVI instruments.**

***Index Terms*—Automated visual inspection (AVI), automated optical inspection (AOI), surface defect classification, flat steel, survey.**

I. INTRODUCTION

FLAT STEEL acts as a vital and fundamental material for steelmaking industry, as well as the related planar material industries. Any surface defects not treated in time will threaten the steel product quality, which might cause substantial economic and reputation cost to both the steel manufacturers and end customers [1-5]. In-situ surface defect inspection is attracting increasing attention from flat steel industries. This task is mainly handled by automated visual inspection (AVI) instruments [6-9].

A typical AVI instrument mainly realizes the two fundamental functions of defect detection and classification, whose results are used to adjust the relevant configurations of the production line to guarantee the quality of final steel product [5, 10, 11]. It is to be observed that the main distinction between defect detection and classification is that the former cannot identify the specific defect types after extracting and selecting the features of defect images. The primary target of defect detection is to differentiate defective and defect-free regions, and the task of identifying and labelling concrete types of defects is left to the classification process. To declare the twin problems clearly, a survey of the framework of the defect inspection was raised in [12] by separately reviewing the defect detection (Part-I) and defect classification (Part-II), in which Part-I has already been reviewed. Thus, this paper will review Part-II from *five* successive components: image acquisition, image pre-processing, feature extraction, feature selection and defect classifier.

In general, as shown in Fig. 1, surface image frames of flat steel are collected by image acquisition components. Only through image pre-processing, feature extraction, feature selection and classifier selection, can the potential defects in the continuously acquired image streams be finally recognized and assigned with the closest defect labels. Essentially, feature extraction and feature selection are dedicated to learning the temporal, spatial [13-15] and spectral features [16, 17] in images and even the intrinsic priors in the production line [18] to narrow the intraclass variation and expand the interclass distance. In defect classification, excellent learning features favor pattern recognition. Compared with defect detection, which mainly affects the time-efficiency and missed detection rate of the AVI instrument, defect classification directly determines its final user experience, as the cognitive performance of defect patterns represents the troubleshooting ability of the AVI instrument. Fortunately, advanced imaging techniques and emerging machine learning methods jointly resist the challenges of unsatisfactory imaging environments and quasi real-time requirements [5], forcefully driving the progress of defect recognition, especially in learning classification [8]. To further the work in [12], this survey concentrates on the up-to-date theoretical and technological progress of automated visual defect classification in the recent twenty years to provide a reference for researchers in this field. In particular, the literature over the last ten years accounts for approximately 75% of the abovementioned advancements.

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Q. Luo, J. Su, J. Zhou, B. Zhou, C. Yang and W. Gui are with the School of Automation, Central South University, Changsha 410083, China. (*Corresponding Author, Chunhua Yang, Email: ychh@csu.edu.cn*).

X. Fang is with the School of Electrical and Automation Engineering, Hefei University of Technology, Hefei 230009, China.

Li Liu is with the College of System Engineering, National University of Defense Technology, Changsha 410073, China, and is also with the Center for Machine Vision and Signal analysis, University of Oulu 90014, Finland.

L. Tian is with the Powder Metallurgy Research Institute, Central South University, Changsha 410083, China, and also with the RAMON Beijing Research Institute, RAMON Science and Technology Company Ltd., Beijing 100190, China.

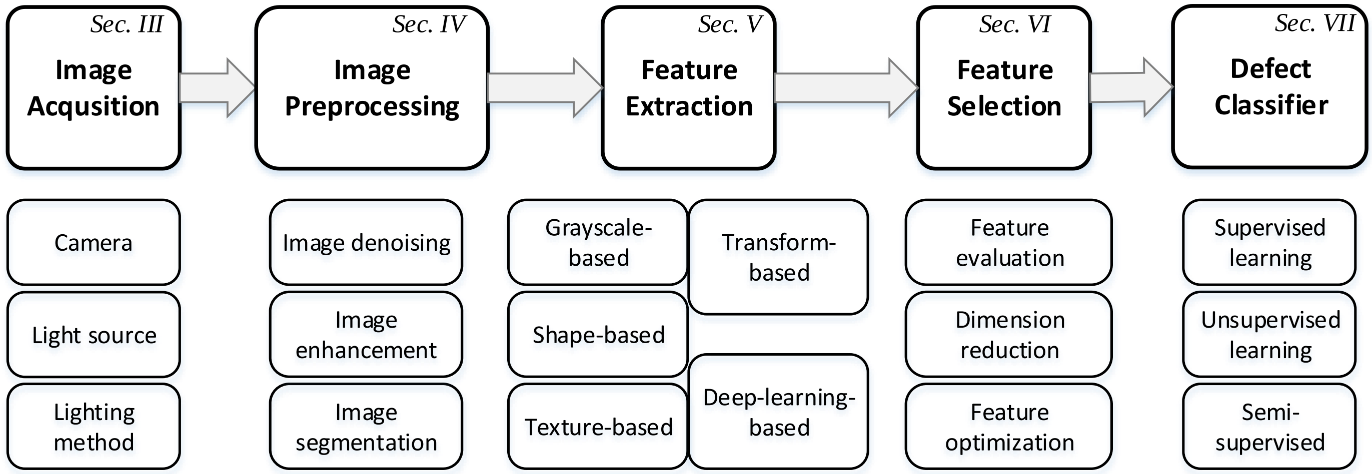

Fig.1. Overall paper organization of surface defect recognition for flat steel.

The composition of this paper is organized as follows. Following the introduction section, several relevant surveys are reviewed in Section II. Image acquisition, image preprocessing, feature extraction, feature selection and defect classifier are successively detailed from Section III to Section VII. Section VIII concludes this paper with summaries and comments on future trends. The overall organization of this paper is illustrated in Fig. 1.

II. Prior Literature Review

In automated inspection, defect detection and defect classification are regarded as pre- and post- relationships; the latter is to identify the specific types of defects based on the detection results of the former. Both of these steps play important roles in ensuring the quality of industrial products. Due to the low cost, high quality and easy-of-use of visual sensing technologies, the development of computer vision methods for industrial applications has been grown exponentially, and some AVI surveys (such as [19-21]) with a wide range of objects have been conducted. However, these surveys are insufficiently updated, and the methods involved do not reflect the latest level of algorithms in contemporary development. Gradually, researchers began to focus on specific planar materials such as asphalt pavement [22, 23], fabric [24-26], timber [27] and semiconductors [28]. Notably, in 2014, a comprehensive AVI review reporting both defect detection and classification methods for diverse types of steel products of slab, billet, plate, hot strip, cold strip and rod/bar by Neogi [29]. Sun *et al.* [30] offered a supplement to Neogi [29]. Recently, Czimmermann *et al.* [31] reviewed the latest development of visual-based automatic defect detection and classification methods for various materials such as metals, ceramics and textiles. However, these surveys paid more attention to the detection methods, and they simply summarized the research progress of the classification methods through supervised and unsupervised classifiers. In addition to the performance of the classifiers, the characteristic of the extracted features is another important factor influencing the precision of classification methods. This article overviews the latest algorithm and achievements from image acquisition, image preprocessing, feature extraction, feature selection and classifier selection. In response to previous work [12], this paper tries to present a twin survey on defect classification to support AVI development for relevant industrial manufacturing jointly.

III. Image Acquisition

Image acquisition occurs during the first step of defect classification, and the quality of the acquired images directly affects the performance of the subsequent processing. At present, the commonly used imaging methods are based on range imaging and intensity imaging. Pernkopf and O'Leary conducted an summary of these two image acquisition ways for the AVI on metallic surfaces in [32]. Because the former is limited to surface defects with three-dimensional properties, e.g. cavities, scratches, and nicks, and it is not competitive with the latter in terms of spatial resolution and acquisition speed, intensity imaging is most commonly used in real-world flat steel production lines. Sun *et al.* [30] surveyed intensity imaging acquisition technologies in detail from three aspects: camera, light source and lighting method. According to the characteristics of the industrial environment of different steel production lines, this chapter will briefly summarize and supplement these three aspects.

A. Camera

Industrial camera is a core component of flat steel surface automated visual inspection equipment. Its working principle can be briefly summarized as the conversion of continuous optical signals on the photosensitive sensors into digital signals. The commonly used industrial camera sensors are complementary metal-oxide-semiconductor (CMOS) and charge-coupled devices (CCDs). The main distinction between CCD and CMOS is their readout architecture. The charge information stored in CCD sensors needs to be transmitted to the readout register in sequence under the control of synchronous signal. On the contrary, CMOS can directly select each row to readout through the row and column select circuits. Compared with CCD, CMOS has fewer components, less power consumption and faster readout speed. Although the development of CCD is relatively mature, CMOS is comparable in most aspects. According to the arrangement of the photosensitive unit, cameras can be divided into area array cameras [1, 3, 4, 7] and linear array cameras [33-36]. The area array camera can take a two-dimensional image only once triggered outside. It is easy to operate and the result is intuitive but it is not suitable for the scenes that require large field of view and high resolution. The linear array camera with wide dynamic range and fast data transmission is suitable for application in the industry field with high-precision requirements. However, when capturing 2D images, it requires the motion control system to perform progressive scanning at a constant speed.

B. Light Source and Lighting Method

High-quality lighting reduces the computational burden of image processing, and the light source and lighting method play an important role in image acquisition. Some classical light devices for flat steel surface inspection illumination are incandescent lights, halogen lamps, light-emitting diode (LED) lamps and fluorescent lamps. Among them, LED is the most widely used luminaire in machine vision applications due to its advantages of longevity and low heat production [35, 37, 38]. The basic lighting methods include diffuse, bright field and dark field illumination. Diffuse illumination is a non-directional uniform lighting method, and it can realize the captured images with few shadows or highlights. Diffuse lighting can be appropriately applied for the surfaces with complex angles (e.g. non-Lambertian surfaces). In bright field illumination, the illumination direction is roughly perpendicular to the surface to be inspected and the surface appears bright. In contrast, in dark field illumination, the illuminated surface appears dark due to the large angle between the incident light and the surface normal vector. Combining these three illumination methods can greatly benefit defect detection and classification. For example, the composite of bright and dark domains mainly depends on each other as supplements; thus, the surface images have continuous gray-level and the edge details are greatly protected [5, 39-42].

C. Brief Summary of Image Acquisition

Generally, the challenges that image acquisition faces are the greatest in all parts of flat steel surface defect classification. Intensity imaging technology is largely dependent on the illumination condition, which is the most vulnerable to interference in production. The pollution and jitter of the CCD camera lens are also deeply troubling. Therefore, optimization of image acquisition equipment is urgently needed to overcome these problems. For instance, Tao *et al.* [43]used an ion air gun to clean surface dust and fibers caused by the effect of electrostatic adsorption. In view of the limitation of intensity imaging techniques, Zhao *et al.* [44]combined the traditional line array scanning and laser three-dimensional scanning strategies to suppress the respective imaging system's limitation. Beyond that, it is important to note that the intensity imaging techniques still rely on the reflection property of the entire surface, so it is necessary to explore imaging methods that are less sensitive to the changes in reflection factors.

D. Quick Glance of Defect Types

Fig. 2 (a) shows *six* types of defects on continuous casting slabs, including cracks, scratches, scales, nonuniform lighting effects, burrs, and slag marks (part of the defect samples come from the application of the system proposed in [5] in the on-line inspection of the surface quality of a continuous casting slab [45]). Cracks, scratches and burrs are natural defects, and the remaining three samples belong to pseudo-defects. The natural defects may lead to accidents due to the poor quality of the slabs. However, cracks are challenging to detect because of the interference of scales, slag marks, and uneven illumination, which are similar to the appearance of cracks. The most critical goal of defect classification for continuous casting slabs is to distinguish cracks from the other three similar pseudo-defects. Fig. 2 (b) shows *eighteen* types of image samples of hot-rolled steel strips, because the surfaces usually covered with many scales, which increase the possibility of misclassifying other types of defects. Fig. 3 (c) shows *twelve* types of image defects of cold-rolled steel strips, including hole, macular, emulsion rust, under picked, ripple, stain, corrosion, longitudinal scratch, wrinkle, scale, pit and transverse crack. The surface quality of the cold-rolled strip is usually better than the other two flat steel. Therefore, the number, size and degree of defects are also the most demanding.

IV. Image Preprocessing

Weak correlation information and strong interference information influence the reliability of feature extraction and defect classification. The primary purpose of image preprocessing is to solve this problem. This section will introduce this from three sub-steps of image denoising, image enhancement and image segmentation.

A. Image Denoising

In the process of acquiring and transmitting flat steel images in industrial automated visual inspection, several kinds of noise can be caused by the influence of unstable sensor attributes, poor industrial environments and transmission decoding processing errors. For example, if the image sensor runs for a long time and the temperature is too high, or the field of view is not bright enough and the brightness is lacking when acquiring images, Gaussian noise will be generated; if there is a strong interference in the image signal of the transmission channel of the image sensor, the transmission errors will result in some random white points or black points, which are known as salt and pepper noise (pulse noise). This noise is not related to the research object (i.e., defects) and disturbs the observable information of the image.

To reduce the impact of the noise on the obtained flat steel surface images, *filters* such as the median filter [46-48] (for impulsive noise), Gaussian smoothing filter [49-51] (for Gaussian white noise), mean filter [52], bilateral filter [45, 53, 54] and Wiener filter [55] are widely used. Among them, it is proved that the median filters have the best performance on the suppression of salt and pepper noise, and the Gaussian filter and Wiener filter have better effects on Gaussian noise. However, a

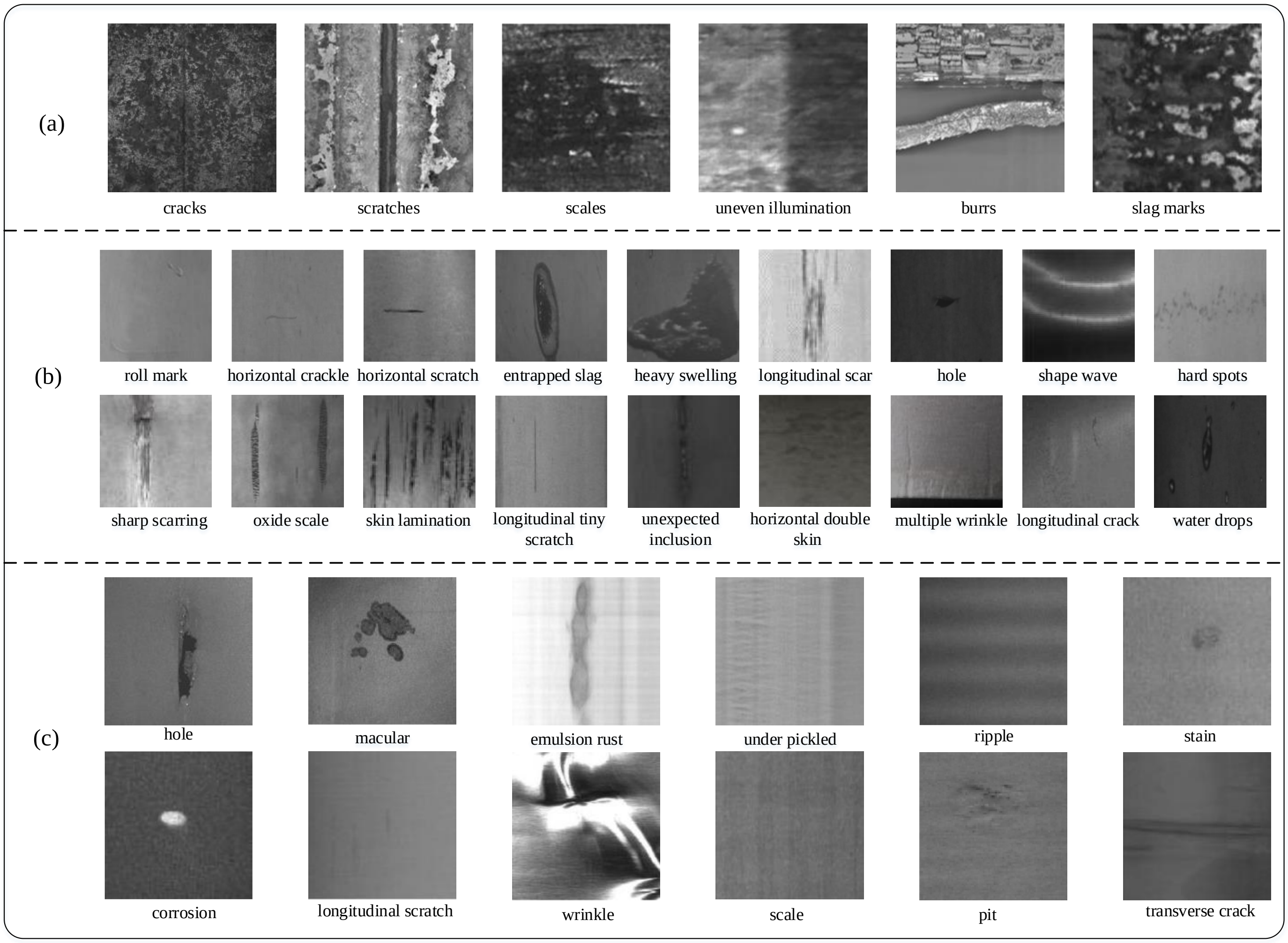

Fig. 2. Typical defect image samples. (a) Continuous casting slabs, (b) hot-rolled steel strips and (c) cold-rolled steel strips.

single filter may not only smooth the image but also miss the details of the image. To solve this problem, scholars have attempted to combine multiple filters to suppress noise. Li *et al.* [56] used a median filter to smooth the casting images first and then applied Wiener filter to improve these images and reduce the noise effects. Chu *et al.* [39, 57] improved the median filter and bilateral filter to remove salt-and-pepper noise and Gaussian noise, respectively. The optimized filters have been very effective not only in filtering mixed noise, but also in maintaining edge details. In addition to the filtering methods, *wavelet transform* methods based on the frequency domain are also often utilized to suppress noise [58-61]. The wavelet smoothing calculation is based on multilevel 2D discrete wavelet transform, which modifies the decomposed detail coefficients, and then uses the approximation coefficients to reconstruct the real signal. Wavelet smoothing can sharpen an object's edges and restrain noise; moreover, it can enhance the positioning precision of the edges and the depiction of the images.

B. Image Enhancement

Image enhancement is to enhance the global or local effective information of the test image. Reasonable image enhancement technologies can enhance the features of useful in the image and suppress the redundant ones. This approach can usefully improve the appreciation and enhance the characteristics of the image to meet the needs of subsequent analysis (i.e., defect detection and defect classification). The two basic image enhancement methods are based on spatial domain and frequency domain, respectively. For spatial domain methods, histogram equalization makes the image clearer by equalizing the histogram of the original image [55, 61, 62]. In addition, the grayscale intensity transformation enhances the image contrast by changing (i.e., stretching, compressing or transforming) the grayscale dynamic range of the image [18, 48, 63]. For frequency domain methods, 2-D Fourier Transform (FT) transforms the test images into the frequency domain, and then the low-pass or high-pass filter is used to filter the signals, which can achieve the effects of noise removal and edge enhancement, respectively [64]. Furthermore, homomorphic filtering associates frequency filtering with grayscale transformation. It conducts frequency domain processing based on the illuminance/reflectivity of the image and eliminates the uneven illumination on test images by shrinking the brightness range and strengthening the contrast [65]. Because the global gray value of steel surface images is ordinarily low but the dynamic range is large, the effect of histogram equalization is not as good as that of homomorphic filtering.

It is worth emphasizing that image enhancement should not take too much time and resources as the pre-processing work of the defect classification task. Furthermore, some intrinsic priors in production lines that are easily ignored should be utilized effectively. The resource-saving algorithm of dynamic homogenizing compensation (DHC) [5] explores the intrinsic prior that the image intensity is varying actively but horizontal intensity distribution is extremely stable, which helped the DHC algorithm win a competition against other image enhancement methods.

C. Image Segmentation

Image segmentation is crucial from image processing to image analysis. The goal of segmentation is to remove redundant information and represent the image as concisely and effectively as possible, making it easier to analyze in subsequent operations. Some scholars utilized a fixed threshold to binarize the test image to highlight the defect area [61, 66, 67]. Although this method is simple and efficient, in many cases, the contrast between the defect and the background is not the same everywhere in the image, so it is challenging to separate the abnormal area and the background with a unified threshold. At this time, different thresholds can be used to segment the image according to its local characteristics [39, 49, 68], which is called the adaptive threshold method. Otsu is a classical adaptive threshold method for separating defects from the background in flat steel images [59, 69, 70], which obtains a threshold value based on the characteristic of the large variance between the background and foreground. Different from the threshold methods, the methods based on edge detection use the first or second derivative to detect edge points by taking advantage of the property of discontinuous pixel values in adjacent regions, such as Robert [71], Sobel [72, 73], Prewitt [74], Canny [55] and Kirsch [52, 53]. The grayscale of steel strip images is ordinarily nonuniform, the gray value variation cross the background and the defect is sometimes gradual, and the size of defect area is very small, not easy to be recognized by the computer. Operators such as Sobel and Roberts have difficulty detecting unclear and tiny defects due to their relatively small weighting factor. The Laplacian operator is of poor robust to noise and has a large amount of calculation. Kirsch operator has a good effect in maintaining details and anti-noise, but it depends on the edge direction and cannot guarantee the continuity and closure of the edge, which make it difficult to form a large region. At the basis of topological theory, the watershed algorithm is acting as a mathematical morphology segmentation method and its core concept is to represent each point’s gray value in the image to the altitude of the pixel. The influence domain of each local minimum is slowly spread outward, and the boundary of the influence domain is the edge. Chu *et al.* utilized the watershed algorithm to segment the defects and background of the steel surface in [45, 54]. The watershed algorithm can well detect weak edges, even though the noise in an image may cause over-segmentation, it can still ensure a closed continuous edge. In contrast, threshold-based methods are simple and efficient, but the selection of the optimal threshold value is usually labor-intensive. Edge-based operators can locate edges accurately but cannot guarantee the continuity and closure of edges. The watershed algorithm is able to detect weak edges but is still sensitive to noise. Therefore, searching for better combinational solutions may be a wise choice to give full play to their respective advantages and obtain better segmentation results. For example, the genetic algorithm is applied to threshold screening to select the threshold that can best segment the image [75]. The differential matrix of the image is obtained by using a differential calculation, and then the double threshold is selected to segment the defect area [76].

V. FEATURE EXTRACTION

Feature extraction aims to extract the significant information from images through the use of computers. To meet the requirements of validity, less computation and better robustness of target segmentation and classification in the flat steel surface, the input image preprocessed first, and certain features are extracted by a variety of feature extraction methods which will be described as follows.

A. Grayscale-based Methods

The grayscale feature of the steel image is the most fundamental feature, which is the statistics of the gray value distribution of the image. An image histogram is the graphic depiction of the gray distribution in the gray image.

The first-order statistical characteristics of gray information can be calculated by formula (1):

$$P(b) = P\left\{g(x,y) = b\right\}, (0 \le b \le L-1) \tag{1}$$

where b is the gray value, L ($1 \le L \le 256$) means the total amounts of gray levels, and $g(x, y)$ is the gray value of the point with coordinate (x, y) in the image. Therefore, the corresponding first-order grayscale histogram of an image can be obtained by formula (2):

$$P(b) = \frac{N(b)}{M}, b = 0,1,\ldots,L-1 \tag{2}$$

where M is the total amounts of image pixels and $N(b)$ is the amounts of image pixels with gray value b.

The typical histogram coefficients, including the mean, standard deviation, skewness, kurtosis, energy and entropy, can be calculated by formulas (3) to (8). They are often used to describe the grayscale features of steel defect images [52, 67, 77].

$$Mean = \sum_{b=0}^{L-1} bP(b) \tag{3}$$

$$Standard\ deviation = \sqrt{\sum_{b=0}^{L-1}(b-\bar{b})^2 P(b)} \tag{4}$$

$$Skewness = \frac{1}{Variance^3}\sum_{b=0}^{L-1}(b-\bar{b})^3 P(b) \tag{5}$$

$$Kurtosis = \frac{1}{Variance^4}\sum_{b=0}^{L-1}(b-\bar{b})^4 P(b) - 3 \tag{6}$$

$$Energy = \sum_{b=0}^{L-1} P(b)^2 \tag{7}$$

$$Entropy = -\sum_{b=0}^{L-1} P(b)\log_2\left[P(b)\right] \tag{8}$$

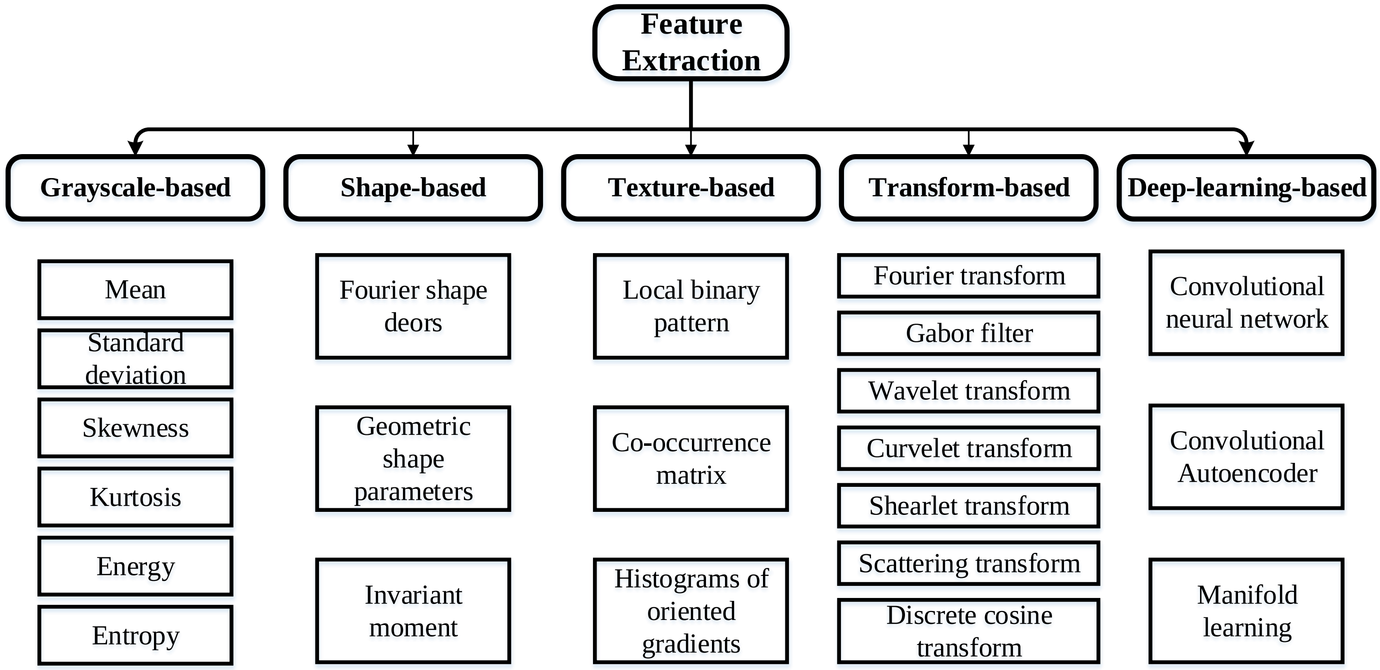

Fig.3. The overall architecture of feature extraction

B. Shape-based Methods

Shape features also play an essential role in image description. The outline shape and the regional shape are two typical shape features that depict the outer boundary and the overall object area, respectively. The fundamental task of shape feature extraction and representation is to find efficient and effective shape descriptors. For the description of outline features, Fourier shape descriptors are the most popular [67, 77, 78]. The core concept is to use the FT of the target boundary as the shape depiction, and use the closeness and periodicity of the region boundary to transform the 2D problem into a 1D problem. For regional shape features, the geometric shape parameters method based on the quantitative measure of the shape (such as length, breadth, elongation, compactness, and area ratio) is a simple method to express the shape [47, 79]. In addition, moments, especially geometric moments, centric moments and orthogonal invariant moments are more dependable for shapes with complex boundaries. The Hu invariant moment [80] is the most classical method and is often used to describe the regional shape of steel surface defects [67, 77]. In addition to the above typical shape feature description methods, some scholars have proposed new shape feature extraction methods. For example, Chu *et al.* [11] proposed a type of statistical feature used with the shape distance (SD-SFs) to measure the distance between the outer boundary point and central one. SD-SFs is one of the outline shape feature types, and they improve the robustness to affine transformations. It should be noted that the extraction of shape features must be based on image processing and image segmentation, and the accuracy of the features must be affected by the segmentation effect.

C. Texture-based Methods

Texture usually has three characteristics: repeated local sequences, nonrandom permutations and roughly uniform texture areas. The texture feature characterizes the repeated local patterns and their arrangement rules in the image. Some commonly used methods are introduced as follows.

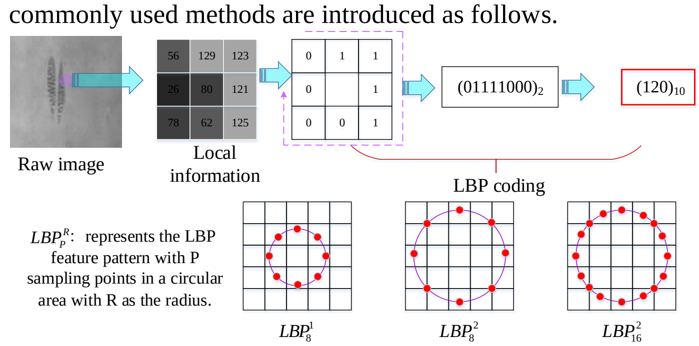

Fig.4. The encoding mode and sampling rules of traditional LBP.

1) Local Binary Pattern (LBP)

LBP is one of the most successful local texture feature operators, which creates an intensity- and rotation-invariant binary descriptor and estimates the local contrast of an image based on the differences between adjacent pixels and central pixel, whose encoding mode and sampling rules are briefly given in Fig. 4, and it has been widely used to extract features of steel surfaces [11, 81-87]. In addition, some variants based on the original LBP have been proposed to overcome the limitations of LBP, such as noise sensitivity. In 2013, Song *et al.* [1] proposed adjacent evaluation completed local binary patterns (AECLBPs) to recognize hot-rolled steel strip surface defects by modifying the threshold scheme of the completed local binary pattern. In 2015, Chu *et al.* [88] presented a smoothed local binary pattern (SLBP), which applied weight on the gray difference between the local neighborhood. These two methods are both robust to noise to a large extent. LBP was introduced for gray-level images, making it ineffective for coloured images, so Shervan *et al.* [89] used a new noise-resistant and multiresolution version of the LBP to extract color and texture features of texture surface jointly. Furthermore, to obtain better visual discrimination, Wang *et al.* [18] designed an LBP-inspired feature descriptor by describing each pixel of the test images with four values corresponding to the four directions so as to characterize each pixel based on pixels at various distances from the different directions. Different from the improvement of the LBP variants mentioned above, Luo *et al.* innovatively extracted the forgotten useful information hidden in nonuniform patterns in [10, 90], which not only improves the accuracy and calculation time simultaneously but also has better robustness to noise.

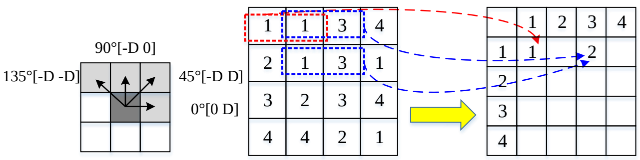

Fig.5. The calculation template of GLCM. (a) is the offset of GLCM to adjust the orientation between two adjacent pixels. (b) is a image block or sub-region. (c) is the GLCM of (b).

2) *Gray-level Co-occurrence Matrix (GLCM)*

The GLCM is another preeminent statistical texture descriptor that calculates the frequency of a special pixel at a special distance and angle, which is able to commendably convert gray value into texture information, such as homogeneity, contrast and correlation [53, 91]. The calculation mode of GLCM when selecting 0° direction is given in Fig. 5. However, it is sensitive to rotation, which could bring about information redundancy. To solve this problem, the gradient magnitude and gradient orientation co-occurrence matrix (GMGOCM) and the gray level and gradient orientation co-occurrence matrix (GLGOCM) are proposed based on the statistical characteristics of the gradient vector information and GLCM. Both GMGOCM and GLGOCM features fully take into account the scale and rotation invariance when extracting the steel defect feature [34]. However, since GLCM and its variants are merely describe spatial features, they cannot reflect the high- or low-frequency components of the multidirectional defects on a surface, while steel strip surface defects vary widely (various types, shapes and orientations). To overcome the above challenge, the discrete Shearlet transform gray-level co-occurrence matrix (DST-GLCM) was designed in [92], which achieves outstanding classification rates on defects with high interclass similarity and high intraclass appearance variations.

3) *Histogram of Oriented Gradients (HOG)*

The HOG [93] first divides the window into several blocks, then divides each block into several cells, and then counts the histogram of the gradient direction inside each cell as the cell's feature vector, then the feature vector of a block is obtained, and finally the HOG description feature for the window is obtained, which has good characterization abilities of local texture and shape. As an expansion of the HOG descriptor, the pyramid of HOG (PHOG) descriptor takes into account the spatial locality of the descriptor's constituents in [94]; the PHOG has an excellent feature description ability and was applied to describe steel texture features.

4) *Others*

There is a problem of optimal scale in texture analysis. For some structural textures, only the texture features at the optimal scale can be used to reflect the intrinsic content of the texture. A method for extracting the fractal dimension of a PELEG blanket coverage image is proposed, which can be used in the automatic identification of surface defects of hot-rolled strip steel [95] and provides a new idea for texture analysis. In contrast, LBP, GLCM and HOG are the three reliable methods most widely used in steel due to their adaptability and robustness. Further explorations of these conventional methods and other effective approaches should be given more attention. In Table I, the advantages and disadvantages of several texture-based feature extraction methods are compared.

D. *Transform-based methods*

Transform coefficient methods that transform images from the spatial domain to the frequency domain are also influential in extracting hidden information from the data. Many works suggest that the features in the spatial-frequency domain show stronger robust to noise and intensity variation than in the spatial domain, and transform features have been reported to be useful in improving the representation of spectral data and increasing the classification accuracy [16]. The methods are mainly based on an image filtering transform and the spectrum information is also used to describe the geometric and texture features. In Table II, the advantages and disadvantages of several transform-based feature extraction methods are compared.

1) *Fourier Transform (FT)*

The traditional spatial domain feature set is very complex, very laborious to extract and difficult to guarantee the real-time recognition of flat steel surface defects. FT can reflect the local outstanding feature information, which is widely used in the extraction of features of steel surface images [96, 97]. Inspired by that, the Fourier amplitude spectrum is translational invariant and is often used to assess the directional information of carbide distribution images [68]. The Fast Fourier Transform (FFT) not only represents the images' gray features and geometrical features but also realizes fast convolution and object recognition simultaneously. Wu *et al.* [98] first obtained an original feature set by the FFT, and then , two extended features (Sum of Valid Pixels (SVP) and Repletion Ration of Center Region (RRCR)) were introduced to reflect the global and local statistic feature information, respectively, which excavated more deep information from the spectrum images.

2) *Gabor Filter (GF)*

The FT only depicts the spatial-frequency distribution without regard to the spatial domain information. However, the GF has optimal joint localization in both the spatial and spatial-frequency domains [62]. The GF can be obtained by

TABLE I
COMPARISON OF SEVERAL TEXTURE-BASED FEATURE EXTRACTION METHODS

Taxonomy	Methods	Refs	Strengths	Weaknesses
Texture-based	Local binary pattern	[1, 10, 11, 18, 81-90]	Be of rotation and gray invariance, fast calculation speed.	Sensitive to scale variation and noise interference.
	Gray-level Co-occurrence Matrix	[34, 53, 91, 92]	Can reflect the comprehensive distribution characteristic of the image gray level, such as direction, adjacent interval, change range, etc.	The selection range of parameters is wide and the calculation is large.
	Histogram of Oriented Gradients	[93, 94]	Invariant to geometric and optical deformations.	High feature dimension and large amount of calculation.

superimposing a trigonometric function and a Gaussian function; which is an effective texture detection tool to extract the features of a specific of specific scale and orientation. The 2D Gabor function contains real and imaginary parts. The former can be utilized to detect blob, and the latter can be used to detect edge. Furthermore, Choi *et al.* [63] combined two Gabor filters to detect seam cracks on steel plates, which offers high detection performance and the effective reduction of noise components.

3) Wavelet Transform (WT)

To support near-real-time operation, the feature extraction need to be competitive in feature dimensions and algorithm properties. A WT may be an ideal candidate because it presents powerful judgment on the spatial-frequency characteristics both horizontally and vertically. Classical WTs can realize time-frequency localization and 1D data sparse representation. The surfaces of steel defect images are transformed using Daubechies wavelets of the fourth order, Haar wavelets, Daubechies wavelets, Bior wavelets and multiwavelet wavelets by decomposing the surface images into different resolution levels [4, 99]. Since the wavelet basis function can only represent 1D directions, it is challenging for wavelet based methods to sparsely express high-dimensional data due to their line singularity and surface singularity. The multi-scale and multidirection localization method (MGA) was suggested to represent the high-dimensional data of hot-rolled steels in [100], which has been proved to be less redundancy. The discrete wavelet transform (DWT) results in different wavelet coefficients when transforming the original signal, the undecimated wavelet transform (UWT) was put forward to overcome this issue in [61]. Which can produce more accurate information for frequency localization and is robust to scales, water marks and uneven illumination. In addition, Gabor wavelets have many useful characteristics and have been performed well for defect classification in textured materials, which is naturally a single layer architecture, yet deep multilayer architecture is in a position to extract more influential features [96].

4) Curvelet Transform (CT) and Biorthogonal Wavelet transform (BWT)

The CT is a higher-dimensional extension of the WT and was created to describe images of different scales and angles. Curvelets have very interesting properties, especially, only a few coefficients are needed to approximate the curved singularities, which makes the curvelet coefficients for pixels pertaining to a particular object particular. CT is a nonadaptive image representation method with two essential features: anisotropy scaling law and directionality. It is applicable to characterize and analyze edge features with curved or linear shapes that perform well in continuous casting slabs [97]. The BWT can be constructed using the lifting-scheme, not only has the properties of compactly support, time-frequency localization, high vanishing moments and anisotropy but also provides the specific characteristics of strict sampling and adaptability. In addition to these advantages, BWT is symmetric, preventing image content from shifting between subbands while allowing for extensions at the boundaries. Based on the above advantages, it behaves remarkably for hot-rolled steel [92].

5) Shearlet Transform (ST)

Gabor wavelets cannot effectively depict the directional properties because of their isotropic support and limited directivity. The ST provides efficient multiscale directional representation, which is a relatively new MGA method. Compared to other methods, it sets up disparate direction amounts at diverse decomposition scales and is preeminent when approximating 2D smooth functions with discontinuities along the C2-curves; the ST is fit to analyze images with complicated backgrounds and has been successfully applied to defecting steel defects in [101, 102].

6) Scattering Transform (SCT)

Gabor and wavelet-based methods cannot tolerate local deformation well. By contrast, the SCT improves the tolerance ability of local deformations for current feature extraction and builds nonlinear invariant representations for the defects on hot-rolled steel strips by cascading wavelet transforms and modulus pooling operators [6], providing a new idea for defect classification.

7) Discrete Cosine Transform (DCT)

The DCT requires a complicated number operation. Despite the FFT can faster the operation speed, it is not very competitive in image coding, especially in real-time processing. Based on the discrete Fourier transform, the DCT is constructed as a real domain transform, which has the characteristic that most of the discriminative information about the steel surface is concentrated in a few coefficients of the DCT [99]. It is also widely used because of this characteristic.

TABLE II

STRENGTHS AND WEAKNESSES OF TRANSFORM-BASED FEATURE EXTRACTION METHODS

Taxonomy	Methods	Refs	Strengths	Weaknesses
Transform-based	Fourier Transform	[68, 96-98]	Invariance to translation, expansion and rotation.	Lack of localized signal analysis function.
	Gabor Filters	[62, 63]	Has good characteristics in extracting the local space and frequency domain information of the target.	Difficulty in determining the optimal filter parameters and not robust to rotation invariance.
	Wavelet Transform	[4, 61, 96, 99, 100]	Capable of multi-resolution analysis and represent local signal features.	Difficulty in choosing wavelet basis.
	Curvelet Transform and Biorthogonal Wavelet transform	[92, 97]	Anisotropic scaling law and directionality.	The process is complicated and not easy to realize.
	Shearlet Transform	[101, 102]	Good sparsity.	Cannot effectively retain the detail information of the original images.
	Scattering Transform	[6]	Local translation invariance and elastic deformation stability.	High computational complexity
	Discrete Cosine Transform	[99]	Great description and anti-noise ability.	Lack of good direction selectivity and multi-resolution analytical ability.

E. Deep-learning-based methods

The features described above use the extraction methods of traditional artificial guidance. Due to the reliance on manual design, these features tend to be simpler and mainly depend on some prior information, and it is difficult to use the advantage of big data. By contrast, the deep-learning-based feature extraction method can learn automatically from the massive data characteristics of multilayers. In addition, deep learning can quickly discover the deep-layer and discriminative feature representations from the training data [103]. Deep-learning-based methods are also widely applied in the feature extraction of flat steel surface images, such as convolutional neural networks (CNNs), convolutional autoencoders (CAE) and generative adversarial networks (GANs). The related methods are described in detail below.

1) Convolutional Neural Network (CNN)

Variants of CNNs have been proven to have record-breaking performance. They are the most basic network framework for deep learning, they can learn deep level features that cannot be extracted by traditional manual feature extraction methods under supervised learning manner, which show stronger discrimination[104]. Standard CNNs lack multiple resolution pooling and are restricted to a constant size of input images, A multiscale pyramidal pooling network (MSPPN) was presented to solve the above problems [105]. Taking the errors of localization result and background into consideration, multigroup CNN (MG-CNN) was created, which can build more effective and explainable feature map groups and can be used for feature extraction of hot-rolled steel images [106]. However, the performance of CNN-based methods mainly depend on plentiful training samples, which stunts the utilization of CNNs in industrial scenes with small datasets. At present, transfer learning makes full use of the previously labelled data and guarantees the precision of the model on new tasks with limited training samples [107], which broadens the application prospect of the CNN. CNNs are the core of deep learning methods, and many more features and applications are worth exploring and should be given more attention.

2) Convolutional Autoencoder (CAE)

As an unsupervised learning method, Autoencoder (AE) can automatically learn from a large amount of unlabelled data to obtain the effective features. CAE combines the convolution and pooling operations of the convolutional neural network to extract more robust and discriminative representations. Xu *et al.* [108] trained CAE to depict fine-grained features and fed them into a softmax classification layer to form a classification network. A group of AutoEncoders were also trained to reduce the dimension of the extracted multiscale features in [109], which improved the performance under inadequate training samples. A novel method such as transfer learning is often been considered for classification tasks due to the most samples of steel are unlabelled. However, the image information of the steel surface is actually distinctive from most pretrained models, which breach the utilization conditions of transfer learning and makes the applications of transfer learning to steel defect detection not as good as the applications in other fields. To solve this problem, the CAE mentioned above is innovatively aimed at unlabelled steel datasets, which is of great referential significance.

3) Manifold Learning (ML)

Supposing the data are a low-dimensional manifold uniformly sampled in a high-dimensional Euclidean space, manifold learning recovers the low-dimensional manifold structure from the high-dimensional sampled data. Correlatively, manifold regularization adds items related to the manifolds to the regularization items to play the role of semisupervision by using the geometric structures in the data. The earlier local descriptors, such as the LBP and HOG, subject to the hand-crafted definition and the limitations of the applications. In contrast, Zhao *et al.* [87] proposed the discriminant manifold regularized local descriptor (DMRLD) based on the new viewpoint learning mechanism, which applies the manifold structure to regularize the local descriptor for describing the features of the image. Its core idea is to employ the learning strategy to establish the local information, while maintaining the original, discriminant, and intrinsic structure of the steel defect image. DMRLD is purposefully designed for depicting the useful and completed local feature for steel surface defect classification without a high defect image quality requirement.

4) *Brief Summary*

Deep learning can make full use of the advantages of big data to automatically learn the multilayer depiction of features, which can involve thousands of features, and the expression ability of these learned features is stronger than that of manually designed features. Deep-learning-based methods can quickly learn modern and powerful feature representations from training data for strange applications. However, most of the existing steel samples are not marked because of the randomness and limitations of the production line, so only a small amount of data with safety labels can be used for learning, resulting in the instability of the final classification results. To speed up the promotion and application of deep learning features, academia and industry have carried out much research on structure optimization. The research methods used to design the network automatically is helpful to the design space exploration of deep learning networks and plays an essential role in accelerating the process of network design and promoting the application of deep learning in engineering.

TABLE III
STRENGTHS AND WEAKNESSES OF DEEP-LEARNING-BASED FEATURE EXTRACTION METHODS

Taxonomy	Methods	Refs	Strengths	Weaknesses
Deep-learning-based	Convolutional neural network	[104-107]	Compare with fully connected network, it reduces many parameters and simplifies the calculation by adopting local connection, weight sharing and down sampling operations.	Because all local parts share weights, it does not take into account the difference of contribution to the whole between each local part.
	Convolution autoencoder	[108, 109]	Compared with the traditional autoencoder, it can well retain the spatial information of 2D signals and can be used in unsupervised learning.	Because all local parts share weights, it does not take into account the difference of contribution to the whole between each local part.
	Manifold learning	[87]	Be able to find the essence of from the observed phenomena, and find the internal law of data generation.	High computational burden and poor classification ability.

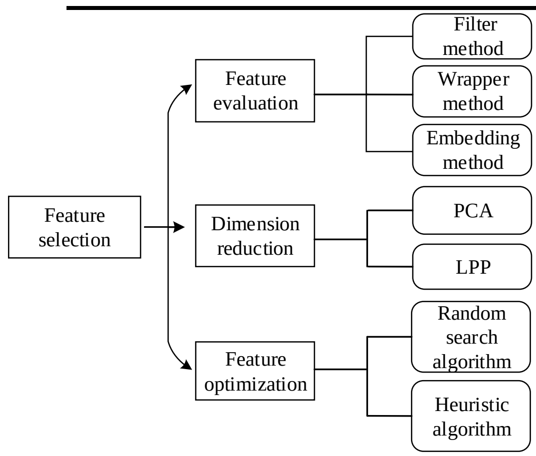

Fig.6. The overall framework of feature selection.

VI. FEATURE SELECTION

Feature selection attempts to eliminate redundant information among the extracted high-dimensional features. One reason feature selection is needed is to avoid the so-called curse of dimensionality, and another is to enhance the generalization ability of the designed classifier. A large number of features may increase the complexity of the classifier, slow down the training process and seriously affect the final classification accuracy and efficiency. Therefore, the appropriate feature optimization methods are applied to remove the features with less information. The feature optimization of the surface defects selectively recombines the features of the defects to refine a set of optimized feature parameters for achieving accurate and efficient defect classification. Fig. 6 shows the framework of feature selection, feature evaluation, dimension reduction and feature optimization are three important parts of feature selection and will be discussed in detail below.

A. *Feature Evaluation*

Feature evaluation is mainly used to estimate the quality of the selected subset of features, and the features that have an outstanding ability to distinguish among the different categories are selected. Subsets are generated from the original feature sets, and the effectiveness of the features is evaluated by different feature evaluation methods to find the best ones. The adequacy of evaluation approaches existing in the literature can be categorized into three groups, namely, *filter method*, *wrapper method* and *embedding method*. Two main approaches were used in [110], where the filter approach assigned the weights before induction, the wrapper approach ran an induction algorithm on the training set and used the accuracy of the resulting description to evaluate the mill scale defect feature set. There are generally two types of reserved features after flat steel feature evaluation. The first is based on the saliency and robustness of the *features* themselves. For example, statistical features such as entropy and variance that dramatically distinguish the edge are picked in [59], and graphs whose dimension and scale are invariant with translation, scale and light conditions are selected in [95]. The second is based on the classifiers that select feature parameters according to some rules, such as the shape parameters and the intensity parameters of the objects, which are computed to better perform the classification phase [111].

B. *Dimension Reduction*

After feature evaluation, the dimension of the feature subsets may be too large, and there exists much redundancy, which will reduce the robustness and generalization speed of the classifier, so the process of dimension reduction is necessary. Numerous algorithms are proposed to handle dimension reduction. Graph embedding is a universal scheme for the methods of dimensionality reduction, including principal component analysis (PCA), isometric mapping (ISOMAP), locally linear embedding (LLE), Laplacian eigenmap (LE) and locality preserving projection (LPP), which are all based on the assumption that the data set is on a low-dimensional manifold embedded in the raw high-dimensional feature space. The calculation of weight matrices and the selection of constraint matrices are the main differences in these methods [100]. Of these methods, the most popular algorithms applied to flat steel surface defect classification are *PCA* and *LPP* [112, 113]. A variety of improved methods based on concrete scenes have emerged, such as the incorporation of the PCA with bootstrap aggregating, which reduces not only the dimensions but also the variance in the decision trees [82]. Because LPP is a linear method and often cannot perform well when images are susceptible to complicated nonlinear changes resulting from noise or lighting variations, Xu *et al.* designed a kernel LPP (KLPP) by implementing the LPP in a kernel space, which was reported to solve nonlinear problems well when applied on the surface inspection for con-casting slabs [97]. Throughout the literature we consulted, we found that the PCA is the most frequently used method to reduce the dimensions in the problem of strip steel surface defect classification because of its reliable performance. However, other methods with better performance and wider application scenarios are still to be explored.

C. *Feature Optimization*

Feature optimization is the selectable regrouping of all the features of the defects to obtain some optimized character parameters that can depict the defects more precisely. After the processing of the two steps mentioned above, the subsets acquired may not be optimal for the classifiers; thus, feature optimization is essential in improving the overall performance. There are two traditional optimization algorithms based on searching strategies: *random search algorithms* and *heuristic algorithms*. The genetic algorithm (GA) is a typical random search algorithm [98]. To enhance the visual feature selection, the adaptive genetic algorithm (AGA) [91] and the hybrid chromosome genetic algorithm (HCGA) [67] were proposed. A representative heuristic algorithm, Relief, is mainly based on sample learning. This method is straightforward and efficient but is restricted to binary classification. For this reason, Chu *et al.* developed the Relief-F to solve the multiclass classification problem in feature optimization for strip steel surface defect recognition [39]. Other effective algorithms are also applied, such as suboptimal feature selection algorithms, which have better results than simple sequential methods [68], recursive feature elimination (RFE), which ranks all features in descending order, and an appropriate number of top features are selected [114]. Both are less commonly used methods, which are briefly presented here for reference. According to the review, we can find that studies have a preference for GA when considering steel feature optimization, which is mainly because there are few superior methods for query. We believe and encourage that various methods should be studied and applied.

D. *Brief Summary*

Feature selection plays a critical role in enhancing the performance of the classifier and indirectly influences the process of steel defect recognition. Feature evaluation, dimension reduction and feature optimization are three steps of great significance. The features that have great robustness or are relevant to classifiers are usually picked after three feature evaluation methods. After evaluation, the PCA is mostly used to reduce dimensions, and almost all studies choose the GA for feature optimization; both are traditional and reliable methods. In general, the algorithms used in the feature selection are generally identical and a little bit unitary in the topic of steel surface defect recognition. Moreover, the feature selection process is discounted. Therefore, more advanced or appropriate feature selection methods are highly encouraged to be applied to AVI instruments in the flat steel industry.

VII. DEFECT CLASSIFIER

Surface defect classification is dedicated to accurately assigning a detected defect to one class or category by learning a classification function or constructing a classification model (known as classifier). Reliable classification performance can be used to improve manufacturing process in a timely manner, effectively ensure the quality of flat steel and grade the end products quantificationally. According to whether the training sample has a label or not, the current classifiers can be classified into supervised, unsupervised and semi-supervised learning-based classifiers. Some classical classifiers of these three categories are introduced below, the contrast of the advantages and disadvantages of the three taxonomies and potential further research directions of the flat steel surface defect classification methods are also discussed.

A. Supervised Learning

The classification methods based on supervised learning utilize massive labelled training data to adjust the classifier parameters for fitting the new defect feature set. The performance of supervised classification methods mainly relies on two factors: the quality of the aforementioned features and the capability of the classifier. In terms of features, a detailed review has been expressed in Section V and Section VI. Next, the development of classification methods for the surface

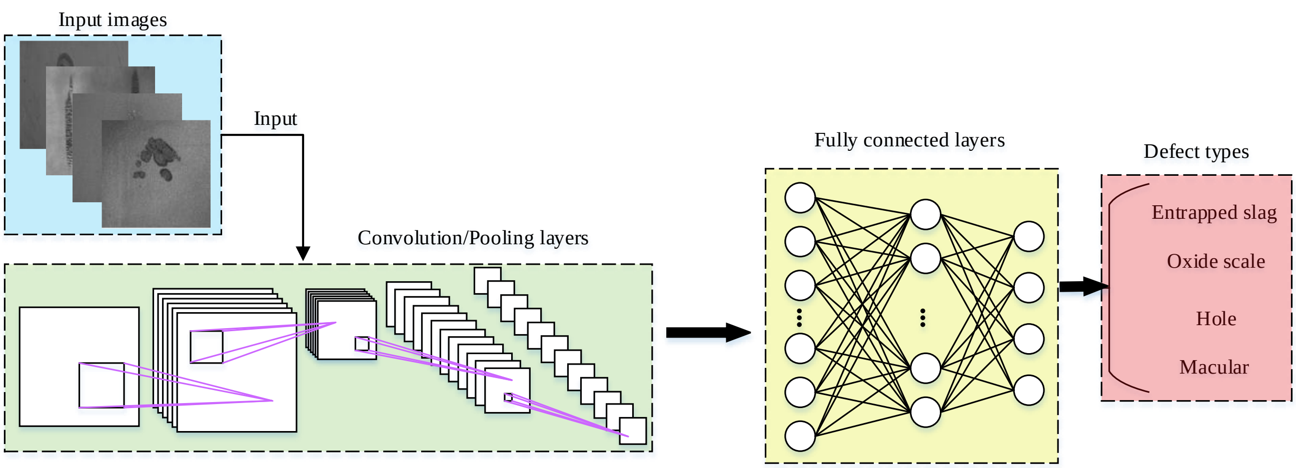

Fig.7. Schematic diagram of defect classification by CNN.

defects of flat steel is introduced from the perspective of classifier design. The most commonly used classifiers in supervised learning are neural networks (NN), support vector machines (SVM), distance functions, dictionary learning, sparse representation and multi-classifier fusion.

1) *Classifiers based on NN*

An artificial neural network is an operational model containing massive nodes connected to each other, which takes the test images as the inputs and then extracts the features to identify the types of defects automatically. This method has achieved satisfactory classification accuracy in the surface defect classification of flat steel [62, 115]. However, the expensive training step limits the generalization of nascent neural networks. Currently, convolutional neural networks are increasingly being developed. In [104] and [105], a CNN was adopted as a classifier for the defect classification of flat steel surfaces, and the experimental results indicate that the CNN is powerful and robust for the classification task. Generally, a dense layer is placed at the end of the network which executes the final classification or regression based on the extracted features, and the schematic diagram of defect classification by CNN is shown in Fig. 7. However, a large number of application scenarios cannot provide the necessary resources. Therefore, compressing and accelerating the model under the premise of ensuring the accuracy of the network has become a hot spot of discussion in the field of network structure optimization. With the gradual deepening of the research on the structure optimization of convolutional neural networks, a large number of achievements continue to emerge. To achieve high classification accuracy with a small training sample set, Fu *et al.* [116] presented a compact yet powerful CNN model by training the low-level features and incorporating multiple receptive fields. This method was reported to realize high classification accuracy of steel surface defects based on limited defect-specific training samples. That is, the problem of the lack of sufficient data is solved to some extent. Moreover, He *et al.* [109] designed a hierarchical learning scheme by combining the CNN and the AutoEncoder, which has greatly improved the performance of the model with insufficient training samples. Neuhauser *et al.* [117] altered the GoogLeNet architecture and enabled transform learning to expedite the training process and to improve performance of the network by compensating for the limited training set. In general, networks with multiple convolutional layers can do better in regression and classification tasks than shallow networks. At present, there exists network architectures containing more than 100 convolutional layers.

2) *Classifiers based on SVM*

SVM is a generalized linear classifier for binary classification, which has been widely used for the defect classification of flat steel surfaces [67, 100-102, 118]. For the multiclass classification problem, Zhang *et al.* [59] succeeded in identifying seven classes of steel surface defects effectively based on a multiclass SVM by simultaneously optimizing the kernel function selection and parameter settings of the traditional SVM method. Inspired by [59], Agarwal *et al.* [119] proposed a classification scheme of the process-knowledge-based multiclass SVM (called PK-MSVM) by combining the feature extraction task of the automated defect inspection with the process knowledge; the PK-MSVM performed better than the traditional multiclass SVM. Notably, Chu *et al.* made great contributions to surface defect classification based on a multiclass SVM, by improving the historic problems of imbalanced training samples [120] and noise robustness [45]. To solve the conflict between efficiency and accuracy in defect classification, Chu's team kept improving the algorithm and came up with a series of SVM variants, such as the enhanced least squares twin SVM [34], multiple support vector hypersphere with feature and sample weights [39], machine learning with quantile hyperspheres [121] and multiple hyperspheres vector machine with additional information [54]. Different from the above improvements, Xiao *et al.* [81] constructed a multiple classifier system for classifying steel surface defects, which contains multiple SVM classifiers and a Bayes kernel classifier. The Bayes kernel fuses the results from the multiple classifiers and adjusts the hybrid parameters with only a small sample set.

3) *Classifiers based on the Distance Function*

Distance is an important measure to describe the relationship between pixels. The distance function is one of the simplest tools for defect classification. The nearest neighbour classifier (NNC) is the commonly used distance classifier for surface defect classification, where the chi-square distance is a simple but effective criterion for measuring the similarity between the training images and the test images. In [74], the authors recommended the K nearest neighbour (KNN) as a classifier to realize defect classification for cold-rolled steel with a co-occurrence matrix. Luo *et al.* [10, 90] selected the NNC as the dissimilarity metric between two multi-region histograms to identify LBP-like histograms. Moreover, Zhao *et al.* [87] simultaneously considered the variation and exemplar distances of the NNC to measure the similarity between the local models. The accuracy of this kind of conventional classifier primarily relies on the precision of the extracted features. Further increasing the classification accuracy requires exploring high-dimensional features, in return, sacrificing the classification speed.

4) Classifiers based on Sparse Representation

To simplify the learning process and reduce the complication of the inspection model, appropriate dictionaries are found for the samples with common dense expressions, and the samples are transformed into appropriate sparse expressions to express most or all original signals with fewer linear combinations of the basic signals. For example, Masci *et al.* [105] emulated a standard dictionary-based encoding strategy as an encoding layer to improve the recognition rate for generic steel defects. Furthermore, Zhou *et al.* [114] utilized the high-quality dictionary to extract the compact, reconstructive and discriminative features of the test images. Testing results prove that this scheme has improved the classification performance efficiently due to the discriminative information obtained from the reconstructive error or the sparse vector. Different from the conventional classification process that treats feature extraction and classifier training as two separate steps, classification methods based on dictionary learning and sparse representation do not have an explicit stage of feature extraction, which might be more effective in surface defect classification for flat steel.

5) Classifiers based on Multi-Classifier Fusion

AVI systems relying on multi-classifiers can achieve better classification performance and robustness than those based on individual classifiers. Consequently, multi-classifier fusion technology is attracting increasing attention from the iron and steel industry. Fernando *et al.* [62] aggressively combined artificial neural networks, the KNN algorithm and a naive Bayesian classifier for the surface defect classification of flat steel, which avoided the limitation of each simple classifier that yields errors on a different region of the input pattern space. Yan *et al.* [122] put forward a classification method with a combination of the LVQ, RBF neural networks and SVM, and a weighted voting algorithm was applied to integrate these basic classifiers. An advantageous complementary defect recognition system was finally established for steel strips. Similarly, Yan *et al.* [123] also designed a kind of classification method by using the cascade structure to improve weak classifier adaptively for the surface defect inspection of strip steel, which successfully addressed the contradiction between algorithm complication and classification accuracy. Beyond that, AdaBoost is an iterative algorithm whose intention is to engender a stronger classifier by assembling several weak classifiers. On the basis of the existing boosting algorithms, Hu *et al.* [124] proposed a new backward AdaBoost (AdaBoost. BK) algorithm for the noncommon defect recognition of steel plate surfaces. This algorithm selected the most applicable weak classifier through a filtering mechanism, which was proven to have satisfactory recognition accuracy on all involved kinds of defects. However, the performance of multi-classifier fusion mainly depends on the selection of weak classifiers. The iteration scale expands with the increase of the number in weak classifiers, and correspondingly, more training time will be spent.

6) Other Classifiers and brief summary

In addition to the above classifiers, some other classifiers have also achieved good effects under supervised learning for the task of flat steel surface defect classification, such as decision trees, random forests, and relevance vector machines (RVMs). Lechwer *et al.* [110] constructed a hybrid classification system based on a decision tree model to classify various kinds of scale defects in hot rolling mills. Zhang *et al.* [125] and Wang *et al.* [51] improved the random forest algorithm to execute defect classification on steel surfaces. Hou *et al.* [126] proposed a second-order cone programming (SOCP) optimized multiple kernel RVM to recognize strip steel surface defects, which showed better performance than both the traditional RVM and the original SVM. The classification methods based on supervised learning can excute sufficient training and learning on the images to obtain the most effective representation. This kind of mind-set has strong adaptability to the data, especially in the case of sufficient labelled data to obtain better results. However, the imbalance of defect samples in actual flat steel production lines has prompted researchers to use limited samples to achieve similar results.

B. Unsupervised Learning

Unsupervised methods separate or cluster the pixels or images belonging to related types through a certain measure of similarity evaluation without sufficient prior knowledge. That is, in unsupervised learning, the classification model needs to determine the relationships between various inputs without being pretrained with given labels. In real-world flat steel industrial production lines, it is extremely labour intensive and time consuming to collect a large number of flat steel surface defect data, and label them manually; this challenge is compounded by the harsh manufacturing environment (e.g., high temperature, poor lighting conditions, mechanical vibrations, and dense dust). Thus, studying unsupervised classification methods greatly benefits surface defect recognition for flat steel.

As an unsupervised learning method, a self-organizing map (SOM) is trained to emerge a low-dimensional representation of the input space of the training sample. After receiving external input, the SOM divides the corresponding regions into different response characteristics automatically. Distinct from the CNN, the SOM establishes lateral connections between neurons in the same layer and excites the neuron response successfully while suppressing the failed neurons by adjusting the weights. With this specialty, SOMs are enjoying their popularity in clustering analysis, damage detection of composite materials and steel surface defect classification. In [127], the SOM was improved by the neural network with error back-propagation (NN-BP) and then applied to classify the defects on cold-rolled strips. Martins *et al.* [50] combined the

PCA and SOM to classify three rolled steel surface defects with complex textures. These application cases show that the SOM and its variants are promising in surface defect classification in the steel manufacturing industry.

However, the quality of the input image and the original parameters of the classification model are the keys to determining the classification performance of the unsupervised learning model. The current unsupervised learning results show that there is still some disparity from our ultimate goal.

C. Semisupervised Learning

Different from the above two manners, the semisupervised learning method chooses a more eclectic way based on both limited labelled samples and ample unlabelled samples. Interestingly, Bratanic *et al.* [128] used a self-training semisupervised approach to train a spatially local representation of each object from a set of unlabelled training images, and then the local depiction in a feature space was obtained by calculating the HOG over a spatially local region. Gao *et al.* [129] proposed a semisupervised annotation approach by learning an optimal graph (OGL) from multicues (i.e., partial tags and multiple features), which can embed the relationships among the data points more accurately. The steel strip surface classification method proposed in [130], namely, the particle swarm optimization second order cone programming multi kernel relevance vector machine (PSO-SOCP-MKRVM), was mainly supported by the compact features refined by the semisupervised PCA and locality preserving projection manifold learning.

The generative adversarial network (GAN) [131], consisting of a generator and a discriminator network, is a typical semisupervised learning method. The latter helps the former to make continuous progress, so that the new image generated by the former cannot be distinguished from the real image. GANs are often utilized to generate labelled defective images based on the existing limited labelled samples and sufficient unlabelled samples from industrial sites. Lian *et al.* [132] and Niu *et al.* [133] also utilized GAN to expand the limited defect samples. Odena [134] extended the traditional GAN to the semisupervised context by employing the discriminator network to output class labels, creating a more data-efficient classifier. On this basis, Song *et al.* [135] utilized the multi-training of the deep convolutional GAN (DCGAN) and residual network to obtain higher-confidence samples, which are added in the training set to improve the robustness. Inspired by this idea, Di *et al.* [108] designed an improved GAN, namely, SGAN, by combining the original CAE and GAN to handle the task of steel surface defect recognition. This classifier was trained by images collected from both actual production lines and randomly created by the GAN, which cleverly solved the engineering problem of sample limitation and improved the generalization ability of the classifiers effectively. In addition to GAN, Yun *et al.* [136] also proposed a modern Convolutional Variational Autoencoder (CVAE) and deep CNN-based defect classification algorithm to address the insufficient of imbalanced data. The experimental results demonstrates the excellent performance of image generation and defect inspection of the presented methods.

In specific industrial practice, the quantity of the original samples might be limited (lack of representativeness and with contingencies), and the distribution can be uneven. If these situations happen, the semisupervised learning methods may become unreliable, creating difficulties for its development. In order to obtain the best semi-supervised learning algorithm with better adaptability, Berthelot *et al.* [137] consolidated the currently prevalent semisupervised learning methods and formed a brand-new algorithm, MixMatch, that guesses low-entropy labels for data-augmented unlabelled examples and mixes labelled and unlabelled data using MixUp. MixMatch has realized ultramodern results across many datasets.

D. Brief Summary

The above methods implemented the classification of flat steel surface defects according to features that were designed manually or learned automatically from the data by the deep neural network in a supervised, unsupervised or semisupervised learning manner. Generally, supervised learning methods need labelled samples for model training, which makes full use of the prior information in the data categories. Unsupervised learning methods mainly separate samples of the same type through the different characteristics of the data, and therefore, they do not need the label information from the data. It is challenging for unsupervised learning methods to realize the high accuracy of supervised classification. Semisupervised learning methods joint the previous two manners, which utilizes the labelled samples and massive unlabelled samples to train classifiers. The results reached with limited sample set can also match the results obtained with massive sample set. We noticed that, the number of labels to get comparable results to fully supervised learning is decreasing. Future research could lower the number of required labels even further. We identified that some common ideas are not often combined and that the combination of broad range and unusual methods is beneficial. We believe that the combination of different field ideas is a promising future research field because many reasonable combinations are yet not explored. Compared with machine learning-based methods for defect detection, defect classification methods focus on extracting the features of different kinds of defects and classifying the defects with similar features into one category. While acting as a binary classifier, the former is dedicated to distinguishing defective and defect-free pixels by analyzing the features of abnormal regions and backgrounds, to achieve isolation of the defects.

VIII. Summary and Discussion

The end customers in planar material processing industries have high expectations for the quality of the steel product, which is usually threatened by the untimely detection of surface defects. By means of online defect detection and recognition, an in situ AVI instrument is gradually developing as a standard configuration to improve the steel quality for flat steel

TABLE IV
STATISTICAL LIST OF TYPICAL METHODS OF DEFECT CLASSIFICATION

Ref.	Year	Feature learning methods	Classifier	Application	Difficulty	Performance
[59]	2011	Fourier spectral measure approach	Multiclass SVM	Metal surface	Strong reflection	Accuracy: 85.00% T: NA
[53]	2011	GLCM	Multikernel learning	Steel surface	Strict timeliness	Accuracy: 97% T: 40 ms per image
[119]	2011	Transformation of variables	Process knowledge based SVM	Hot-rolled strips	Variation of defect size	Accuracy: 90.80% T: NA
[100]	2013	Multiscale feature extraction	SVM	Hot-rolled strips	Limitation to specific defects	Accuracy: 97.33% T: NA
[1]	2013	Adjacent evaluation completed LBP	SVM	Hot-rolled strips	Similar appearance to be easily confused	Accuracy: 98.93% T: NA
[47]	2014	Gabor filter	SVM	Steel slab	Small size and occurring location	Accuracy: 97.26% T: NA
[77]	2014	Multifeature fusion	Multiclass SVM	Steel strips	Similar appearance to be easily confused	Accuracy: 91.28% T: 7.92 ms per image
[34]	2014	Multifeature fusion	Enhanced least squares twin SVM	Steel strips	Variance of scale and rotation	Accuracy: 96.00% T: 2.97 ms per image
[67]	2016	Multifeature fusion	SVM with hybrid chromosome genetic algorithm	Steel strips	Large image size	Accuracy: 95.04% T: 1.56 ms per image
[39]	2016	Feature weight calculated with Relief-F algorithm	Multiple support vector hypersphere with feature and sample weights	Steel strips	Weakly relevant features and abnormal samples	Accuracy: 98.12% T: 1.17 ms per image
[96]	2016	Multifeature fusion	Second-Order Cone Programming-Relevanc e Vector Machine Algorithm	Steel strips	Similar appearance to be easily confused	Accuracy: 99.1% T: 2.77 ms per image
[11]	2017	LBP operator with sign and magnitude	Enhanced twin SVM	Steel surface	Variance of scale and rotation	Accuracy: 95.26% T: 1.93 ms per image
[121]	2017	Multifeature fusion	Multiple quantile hyperspheres classifier	Steel surface	Finite defect dataset and random noise	Accuracy: 94.84% T: 3.49 ms per image
[54]	2018	Multifeature fusion	Multiple hyperspheres SVM with additional information	Steel plate	Corrupted defect	Accuracy: 96.06% T: 1.15 ms per image
[120]	2018	Multifeature fusion	A novel SVM with adjustable hypersphere	Steel strips	Similar appearance to be easily confused	Accuracy: 95.01% T: 4.77 ms per image
[92]	2019	Discrete Shearlet transform and the GLCM	SVM	Hot-rolled strips	Similar appearance to be easily confused	Accuracy: 96.00% T: NA
[69]	2008	Local entropy and morphology	Feedforward neural network	Cold-rolled strips	Strict timeliness	Accuracy: 97.19% T: NA
[64]	2009	Multifractal dimension	Feedforward neural network	Steel surface	Irregular shapes of defect	Accuracy: 97.90% T: NA
[98]	2007	Multifeature fusion	Learning vector quantization	Hot-rolled strips	High speed and strong noise	Accuracy: 83.98% T: NA
[55]	2013	Multifeature fusion	Classification tree	Stainless strip	Finite defect samples	Accuracy: 81.30% T: NA
[6]	2014	Scattering transform	Scattering convolution network	Hot-rolled strips	Similar appearance to be easily confused	Accuracy: 98.60% T: NA
[81]	2017	Multifeature fusion	Evolutionary classifier with a Bayes kernel	Steel surface	Variation of physical condition	Accuracy: 96.31% T: NA
[86]	2018	LBP	Extreme learning machine	Cold-rolled strips	Noncommon defects	Accuracy: 88.93% T: NA
[51]	2018	Multifeature fusion	Improved random forest algorithm with optimal multifeature-set fusion	Steel surface	Similar appearance to be easily confused	Accuracy: 90.91% T: 19.79 ms per image
[90]	2019	Generalized completed local binary patterns	NNC	Hot-rolled strips	Similar appearance to be easily confused	Accuracy: 99.11% T: 266.74 ms per image
[10]	2019	Selectively dominant local binary patterns	Adaptive region weighting NNC	Hot-rolled strips	Similar appearance to be easily confused	Accuracy: 97.62% T: 100.08 ms per image
[62]	2011	Gabor filter	Combination of ANN, K-NN and Bayesian	Flat steel surface	Complexity of integration and data processing chain	Accuracy: 96.70% T: NA
[123]	2011	Extended Haar rectangle feature	Weak classifier adaptive enhancement classification method	Steel strips	Contradiction between algorithm complexity and classification accuracy	Accuracy: 94.00% T: NA

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[122]	2012	Multifeature fusion	Combined multiple classifier	Steel strips	Over-depend on training samples	Accuracy: 96.67% T: NA
[88]	2015	Multifeature fusion	Combination of twin SVM and binary tree	Steel strips	variance of scale, rotation and translation, uneven illumination and random noise	Accuracy: 90.05% T: 7.46 ms per image
[124]	2018	Synthetic minority oversampling technique	New backward AdaBoost (AdaBoost.BK)	Steel plate	Noncommon defects and unbalance samples	Accuracy: 88.35% T: NA
[94]	2012	Max-Pooling convolutional neural networks		Steel surface	Similar appearance to be easily confused	Accuracy: 93.03% T: 6.2 ms per image
[104]	2017	CNN		Steel sheet	Variation of features	Accuracy: 99.00% T: NA
[107]	2017	Deep CNN with a majority voting mechanism		Hot-rolled strips	Finite defect samples	Accuracy: 99.50% T: NA
[114]	2017	Class-specific and shared dictionary learning		Steel sheet	Similar appearance to be easily confused	Accuracy: 94.25% T: NA
[84]	2018	Deep CNN		Hot-rolled strips	Finite defect samples	Accuracy: 99.21% T: NA
[108]	2019	Convolutional AutoEncoder and semisupervised generative adversarial networks		Hot rolled plates Hot-rolled strips Cold-rolled strips	Rare occurrence and appearance variations of defects	Accuracy: Hot-rolled plates: 97.2% Hot-rolled strips: 98.2% Cold-rolled strips: 96.7% T: NA
[109]	2019	Multiscale receptive field convolutional neural network		Hot-rolled plates Hot-rolled strips	Large intraclass variations and unbalanced training samples	Accuracy: Hot-rolled plates: 97.2% Hot-rolled strips: 97% T: NA
[116]	2019	SqueezeNet-based model		Steel surface	Nonuniform illumination, camera noise and motion blur	Accuracy: 97.5% T: 8.0 ms per image

Notes:
Performance criteria. T: Classification time

TABLE V
STRENGTHS AND WEAKNESSES OF DEFECT CLASSIFICATION METHODS

Taxonomy	Strengths	Weaknesses
Supervised methods	Quite simple, effective and robust.	It is unrealistic to label massive flat steel surface defects.
Unsupervised methods	Require no labelled samples for training.	Greatly affected by initialization value.
Semisupervised methods	Not limited by the small labelled samples.	Requires massive interactions and is of low efficiency.

mills. As the twin of our recently published survey (Part-I) on defect detection [12], this survey (Part-II) moves the concentration on defect recognition to continue the topic of how to accurately identify and reliably label detailed defect types among the massive detected defective and suspected-defective regions of the image frames. The three key parts of image acquisition, image preprocessing, feature extraction, feature selection and defect classification are reviewed successively. Some technology trends and the evolution of applications are excavated from a systematic perspective as follows.

1) In the process of image acquisition, we should take reasonable measures to solve the problem of poor image quality. The physical interference can be removed by refitting the mechanical device, for instance, a blower or an air gun should be configured to clean water drops, dust, fibers, etc. And an adaptive uniform illumination system is ought to be installed to handle with the consequences of uneven light caused by the illumination fluctuations during day and night. In addition, some economical actions of cooling configuration and security protection for imaging equipment are also essential for averting imaging distortion due to the harsh environments.

2) Image preprocessing usually makes the contrast, visual effect and entropy of the image reach a balance on the premise of improving the image contrast. The latest image processing or machine learning methods provide novel way to enhance the image quality of flat steel. For instance, the GAN has realized extreme achievement in image enhancement, providing a better solution to the problems of insufficient samples, feature extraction difficulties and poor image quality. To avoid the issue of meager explainability in a GAN, it can be united with reinforcement learning to employ GAN to reverse reinforcement learning and simulation learning, which increases the adaptability of the reinforcement learning and machines understand.

3) Due to the strong randomness of the features of the flat steel surface image, it is very difficult to use a single mathematical model to extract features. Therefore, the research and application of the fusion method of various feature extraction methods should be a direction of feature extraction research. In addition, making full use of the prior knowledge of human visual perception characteristics and combining it with feature extraction methods could be helpful to describe the image more effectively. At the same time, obtaining a real-time, reliable and stable fusion feature extraction scheme will always be a research hotspot.

4) Feature selection is mainly used to remove irrelevant features and redundant features, and there are some practical problems to be solved. After feature selection, the prediction accuracy of the high-dimensional small sample dataset may

decline. Designing a feature selection method for high-dimensional small sample data without decreasing the prediction accuracy of the feature subset is challenging. The feature selection algorithm is subject to the data distribution. If the training set changes, the feature subset is also very different. Therefore, improving the steadiness of the feature selection algorithm is very essential. In addition, excessive deletion of redundant features leads to the loss of a large amount of information. Removing redundant features accurately and effectively is very important.

5) In terms of defect classification, cleverly utilizing multiple learned features and excavating the taxonomy potentials of the latest machine learning algorithms to construct adaptable defect classification schemes with high accuracy, robustness and generalization should be a research focus. Meanwhile, achieving high-precision classification in the case of only a small number of labelled samples is still a hot issue, so both the existing classification methods and open defect databases should be greatly expanded. The statistical table reflects that most of the current classification methods place emphasis on classification accuracy and noise robustness while rarely involving the time cost evaluation of the designed classifiers. To satisfy the requirement in situ AVI of a high-speed production line, the efficiency of the classification algorithm needs to be considered.

6) Deep learning methods such as CNN, GAN, and AutoEncoder have nurtured many novel ideas that have achieved outstanding performance in both feature learning and defect recognition for flat steel surfaces. It is delightful to see these fashionable methods being widely used in steel, but everything should be on the basis of industrial demand. For instance, some techniques have shown prominent results on the image enhancement (i.e., noise removal) of many texture images with rich datasets in multimedia areas, although they are not necessarily suitable for the enhancement of images gathered from industrial production lines where labelled image sets are extremely limited. Whether deep neural networks well trained from other texture datasets or through transfer learning has adequate generalization ability for the AVI task for flat steel remains to be further studied. Overall, the learning-series approaches are promising, but they must be used carefully to meet the specific industrial demands.

The accuracy of a single-mode algorithm for classification is always limited, and internal prior utilization, multimode fusion and interdisciplinary crossing can give full play to their respective advantages, which is the trend of future development. As many up-to-date references and potential proposals as possible have been included in this review; both the platform and the analysis for future steel research can be enhanced with the help of our efforts. We strongly hope that the surface quality inspection level of AVI instruments will be accelerated thanks to our efforts.

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QIWU LUO (M’17) received the B.S. degree in communication engineering from the National University of Defense Technology, Changsha, China, in 2008; and the M.Sc. degree in electronic science and technology and the Ph.D. degree in electrical engineering from Hunan University, Changsha, in 2011 and 2016, respectively.

He was a Senior Engineer of instrumentation with WASION Group Ltd. Company, Changsha, and the Deputy Technical Director with Hunan RAMON Technology Co., Ltd., Changsha. In 2016, he joined the School of Electrical Engineering and Automation, Hefei University of Technology, Hefei, China, where he also completed his postdoctoral research on automatic optic inspection (AOI). Since 2019, he has been an Associate Professor with the School of Automation, Central South University, Changsha. His current research interests include computer vision, industrial AOI, machine learning, parallel hardware architecture design, and reconfigurable computing.

XIAOXIN FANG received the B.S. degree in electrical engineering and automation from the Jiangsu University of Science and Technology in 2018, He is currently pursuing the M.Sc. degree with the School of Electrical Engineering and Automation, Hefei University of Technology, Hefei, China, under the guidance of Dr. Luo.

His current research interests include texture analysis and image classification.

JIAOJIAO SU will receive her B.S. degree in electronic information science and technology from the Hefei University of Technology in June 2020. She is currently pursuing a M.Sc. degree in advance in control science and engineering with the School of Automation, Central South University, Changsha, China, under the supervision of Dr. Luo.

Her current research interests include defect detection, image classification, and machine learning.

JIAN ZHOU will receive her B.S. degree in communication engineering from Sichuan Normal University in June 2020. She is currently pursuing a M.Sc. degree in advance in control science and engineering with the School of Automation, Central South University, Changsha, China, under the supervision of Dr. Luo.

Her current research interests include rain removal and ACF conducting particle detection. Honors include receiving a First Prize in the China National Undergraduate Computer Design Contest (Artificial Intelligence Competition) in 2019.

BINGXING ZHOU will receive her B.S. degree in automation from the Hefei University of Technology in June 2020. She is currently pursuing a M.Sc. degree in advance in control science and engineering with the School of Automation, Central South University, Changsha, China, under the supervision of Dr. Luo.

Her current research interests include texture analysis and image classification.

CHUNHUA YANG (M'09) received the M.S. degree in automatic control engineering and the Ph.D. degree in control science and engineering from Central South University, Changsha, China, in 1988 and 2002, respectively.

From 1999 to 2001, she was a Visiting Professor with the University of Leuven, Leuven, Belgium. Since 1999, she has been a Full Professor with the School of Information Science and Engineering, Central South University, Changsha, China. From 2009 to 2010, she was a Senior Visiting Scholar with the University of Western Ontario, London, ON, Canada. She is currently the HoD of the School of Automation, Central South University. Her current research interests include modeling and optimal control of complex industrial processes, and intelligent control systems.

LI LIU (M'08-SM'19) received the BSc degree in communication engineering, the MSc degree in photogrammetry and remote sensing and the Ph.D. degree in information and communication engineering from the National University of Defense Technology (NUDT), China, in 2003, 2005 and 2012, respectively. She joined the faculty at NUDT in 2012, where she is currently an Associate Professor with the College of System Engineering. During her PhD study, she spent more than two years as a Visiting Student at the University of Waterloo, Canada, from 2008 to 2010. From 2015 to 2016, she spent ten months visiting the Multimedia Laboratory at the Chinese University of Hong Kong. From 2016.12 to 2018.11, she worked as a senior researcher at the Machine Vision Group at the University of Oulu, Finland. She was a cochair of nine International Workshops at CVPR, ICCV, and ECCV. She was a guest editor of special issues for IEEE TPAMI and IJCV. Her current research interests include computer vision, pattern recognition and machine learning. Her papers have currently over 2400+ citations in Google Scholar. She currently serves as Associate Editor of the Visual Computer Journal and Pattern Recognition Letter. She serves as Area Chair of ICME 2020 and ACCV 2020.

WEIHUA GUI (M'09) received the B.Eng. degree in electrical engineering from Central South University, Changsha, China, in 1976, respectively.

From 1986 to 1988, he was a visiting scholar with the University of Duisburg-Essen, Duisburg, Germany. Since 1991, he has been a Professor with the School of Automation, Central South University. Since 2013, he has been an Academician with the Chinese Academy of Engineering, Beijing, China. His research interests include modeling and optimal control of complex industrial processes, distributed robust control, and fault diagnosis.

LU TIAN received the B.S. degree in physics of metals from Wuhan University, Wuhan, China, in 1983, the M.Sc. degree in physics from the Institute of Metal Research, Chinese Academy of Sciences, Liaoning, Shenyang, China, in 1988, and the Ph. D. degree in iron and steel metallurgy from University of Science & Technology Beijing, Beijing, China, in 2013.

In 1993, he co-founded RAMON Science & Technology Co. Ltd., where he is currently the President of the company. He is also a Guest Professor with the Powder Metallurgy Research Institute, Central South University, Changsha, China. He was awarded the Invention Entrepreneur Award of China in 2016. His research interests include automatic steel rolling, steel surface quality inspection, and dynamic soft reduction technology. He is a Senior Member of the academic committee of continuous casting theory and new technology, Chinese Society of Metals.