

IMAGE PROCESSING METHOD AND APPARATUS, IMAGE SAMPLE CLASSIFICATION METHOD AND APPARATUS, AND STORAGE MEDIUM

[0001] This application claims the priority to Chinese Patent Application No. 202410010706.X, titled "IMAGE PROCESSING METHOD AND APPARATUS, IMAGE
5 SAMPLE CLASSIFICATION METHOD AND APPARATUS, AND STORAGE MEDIUM",
filed on January 4, 2024 with the China National Intellectual Property Administration, which
is incorporated herein by reference in its entirety.

FIELD

10 [0002] The present disclosure relates to the technical field of image processing, and in
particular to an image processing method, an image sample classification method, an image
processing apparatus, an image sample classification apparatus, an electronic device, and a
storage medium.

BACKGROUND

15 [0003] With the development of machine vision technology, images are used in many
application scenarios to achieve various production purposes.

[0004] For example, in the industrial field, particularly in high-precision and advanced
sub-fields such as wafer fabrication, the yield requirements for products are extremely high.

20 Therefore, it is desirable to detect the product defect by using product images. However, when
production output is insufficient or when mass production has not yet started, the number of
defective products is limited. Consequently, the number of defective product images is also
limited, making it extremely difficult to acquire a sample set of defective product images. Due
to the limited number of images in the image sample set, it is often difficult to perfectly
25 represent the features of the defective products, which leads to extremely low detection
accuracy in automated defect detection.

[0005] In view of this, there is an urgent need for an image processing method to process
limited images so as to ideally represent the features of target objects in the images.

SUMMARY

[0006] To at least partially address the issues existing in the prior art, an image processing method is provided according to a first aspect of the present disclosure, including:

performing feature extraction on a plurality of first images by using a feature extraction
5 network to obtain a plurality of first feature vectors, respectively;

performing clustering processing on the plurality of first feature vectors to obtain a first preset number of first vector groups representing the plurality of first images and first representative feature vectors respectively representing the first vector groups;

for each of the first vector groups, calculating distribution data of the first vector group,
10 where the distribution data includes a weight of the first vector group and/or a distribution variance of first feature vectors in the first vector group;

correcting the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images, where the reference vector groups correspond one-to-one to the first vector groups; and

15 determining, after the correction, first representative feature vectors of at least part of the first vector groups and corrected distribution data of the at least part of the first vector groups as feature representation data of the plurality of first images.

[0007] In a possible implementation, the feature extraction network includes two cascaded feature extraction networks.

20 **[0008]** In a possible implementation, for each of the first vector groups, calculating distribution data of the first vector group, the distribution data being a weight, includes:

calculating a distance between each of all the first feature vectors in the first vector group and the first representative feature vector of the first vector group; and

calculating a ratio of a first number to a total number of the plurality of first feature
25 vectors as the weight of the first vector group, where the first number is a number of first feature vectors where the distance between each of the first number of the first feature vectors and the first representative feature vector of the first vector group is less than a distance threshold.

[0009] In a possible implementation, the distribution data includes the weight, and the

correcting the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images includes:

selecting, from weights of the first preset number of the first vector groups, a second preset number of the weights, where the selected weights are greater than unselected weights;
5 and

replacing the selected weights with weights of first reference vector groups correspondingly.

[0010] In a possible implementation, the image processing method further includes:

calculating a statistical value of the plurality of first feature vectors;

10 performing feature extraction on a plurality of groups of reference images by using the feature extraction network to obtain a plurality of reference feature vectors, where different groups of reference images belong to different types;

for each group of the plurality of groups of reference images, performing clustering processing on the reference feature vectors of the group of reference images to obtain the first
15 preset number of second vector groups representing the group of reference images and second representative feature vectors respectively representing the second vector groups;

for each of the second vector groups, calculating distribution data of the second vector group;

for each group of the plurality of groups of reference images, calculating a statistical
20 value of the reference feature vectors of the group of reference images;

calculating a distance between the plurality of first images and each group of the plurality of groups of reference images based on the statistical value of the plurality of first feature vectors and the statistical value of the reference feature vectors of the group of reference images; and

25 selecting one group of reference images from the plurality of groups of reference images based on the respective distances between the plurality of first images and the plurality of groups of reference images, and determining the second vector groups representing the selected group of reference images as the reference vector groups.

[0011] According to another aspect of the present disclosure, an image sample classification

method is further provided, including:

performing feature extraction on an image sample by using a feature extraction network to obtain a sample feature vector; and

5 determining a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images, where the feature representation data of the plurality of groups of first images is obtained by using the image processing method described above, and different groups of first images belong to different types.

[0012] In a possible implementation, the determining a type to which the image sample
10 belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images includes:

calculating a first distance between each group of the plurality of groups of first images and the image sample based on the sample feature vector and the feature representation data of the group of first images, to obtain a plurality of first distances; and

15 determining a type to which a group of first images corresponding to a minimum first distance among the plurality of first distances belongs as the type to which the image sample belongs.

[0013] In a possible implementation, the first images are images of products, and types of the first images are determined based on defect types of the products.

20 **[0014]** According to another aspect of the present disclosure, an image processing apparatus is further provided, including:

a first feature extraction module, configured to perform feature extraction on a plurality of first images by using a feature extraction network to obtain a plurality of first feature vectors, respectively;

25 a clustering module, configured to perform clustering processing on the plurality of first feature vectors to obtain a first preset number of first vector groups representing the plurality of first images and first representative feature vectors respectively representing the first vector groups;

a first calculation module, configured to, for each of the first vector groups, calculate

distribution data of the first vector group, where the distribution data includes a weight of the first vector group and/or a distribution variance of first feature vectors in the first vector group;

a correction module, configured to correct the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images, where the reference vector groups correspond one-to-one to the first vector groups; and

a second calculation module, configured to determine, after the correction, first representative feature vectors of at least part of the first vector groups and corrected distribution data of the at least part of the first vector groups as feature representation data of the plurality of first images.

[0015] According to another aspect of the present disclosure, an image sample classification apparatus is further provided, including:

a second feature extraction module, configured to perform feature extraction on an image sample by using a feature extraction network to obtain a sample feature vector; and

a classification module, configured to determine a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images, where the feature representation data of the plurality of groups of first images is obtained by using the image processing method, and different groups of first images belong to different types.

[0016] According to another aspect of the present disclosure, an electronic device is further provided, including a processor and a memory. The memory stores computer program instructions, and the computer program instructions, when executed by the processor, are configured to perform the image processing method described above and/or the image sample classification method described above.

[0017] According to another aspect of the present disclosure, a storage medium is further provided. The storage medium stores program instructions, where the program instructions, when executed, are configured to perform the image processing method described above and/or the image sample classification method described above.

[0018] According to the above technical solutions, the distribution data of the first vector

groups of the first images is corrected based on the respective distribution data of the plurality of reference vector groups of reference images, and the corrected distribution data and the first representative feature vectors of the first vector groups are determined as the feature representation data of the plurality of first images. The corrected distribution data and the first representative feature vectors of the first vector groups may accurately represent the features of the target object in the plurality of first images, and therefore automatic classification for images of the same type is achieved quickly and accurately by using the feature representation data. Moreover, the above solutions are still applicable in scenarios where the number of first images is limited, making the application scope of the solutions broader.

[0019] A series of simplified concepts are introduced in the Summary, which will be further described in detail in the Detailed Description. The Summary is not intended to limit the key features and essential technical features of the claimed technical solution, nor is it intended to determine the protection scope of the claimed technical solution.

[0020] The advantages and features of the present disclosure will be described in detail below with reference to the drawings.

BRIEF DESCRIPTION OF THE DRAWINGS

[0021] The following drawings of the present disclosure are incorporated herein as part of the present disclosure for understanding the present disclosure. The drawings illustrate implementations of the present disclosure and description thereof, and are used to explain the principles of the present disclosure.

[0022] FIG. 1 shows a schematic flowchart of an image processing method according to an embodiment of the present disclosure;

[0023] FIG. 2 shows a schematic block diagram of a feature extraction network according to an embodiment of the present disclosure;

[0024] FIG. 3 shows a schematic flowchart of an image sample classification method according to an embodiment of the present disclosure;

[0025] FIG. 4 shows a flowchart of an image sample classification method according to another embodiment of the present disclosure;

[0026] FIG. 5 shows a schematic block diagram of an image processing apparatus according to an embodiment of the present disclosure;

[0027] FIG. 6 shows a schematic block diagram of an image sample classification apparatus according to an embodiment of the present disclosure; and

5 [0028] FIG. 7 shows a schematic block diagram of an electronic device according to an embodiment of the present disclosure.

DETAILED DESCRIPTION

[0029] In the following description, numerous details are set forth to provide a thorough
10 understanding of the present disclosure. However, those skilled in the art can understand that the following description is merely exemplary of preferred embodiments of the present disclosure, and the present disclosure may be practiced without one or more of these details. Furthermore, to avoid confusion with the present disclosure, some technical features well-known in the art are not described in detail.

15 [0030] To at least partially address the above technical issues, according to one aspect of the present disclosure, an image processing method is provided. FIG. 1 shows a schematic flowchart of an image processing method 100 according to an embodiment of the present disclosure. As shown in FIG. 1, the method 100 includes steps S120, S130, S140, S150, and S160.

20 [0031] In step S110, feature extraction is performed on multiple first images by using a feature extraction network to obtain multiple first feature vectors, respectively.

[0032] The first images may be images of any suitable objects, which are not limited in the present disclosure. For example, the first images are images of a product, and a type of the first images is determined based on a defect type of the product. By applying the method in
25 the present disclosure to product detection, precise classification of product defects can be achieved even when defect samples for a new product are difficult to be acquired, and labor costs are significantly reduced, production efficiency is improved, and detection accuracy is further enhanced. In embodiments not shown, an image sample classification method in the present disclosure may be applied to other scenarios, such as facial recognition. Therefore, the
30 first images may also be other suitable images, and the type of the first images may also be

suitable classification types for various objects, such as persons or landscapes. For ease of description, the following continues with the example where the first images are the images of a product and the type of the first images is the defect type of the product.

[0033] Taking the object being a wafer as an example, the multiple first images are images of defect samples of a new wafer product. The first images may be defect images manually labeled with the defect type. The number of the first images may be arbitrary, and the present disclosure is not limited thereto. It can be understood that the defect samples of the new wafer product may be few. The multiple first images may be images labeled as one defect type. For example, if 50 samples are selected for each defect type, the number of the first images is 50. Steps S110 to S150 may be performed for the 50 first images of each defect type.

[0034] The first images may be grayscale images or color images, each of which may be an image with any suitable size and resolution, or may be an image meeting a preset requirement. The first images may be acquired by using any existing or future image acquisition manner. The first images may be original images directly acquired from an image acquisition device, or images obtained after performing preprocessing operations on the original images. The preprocessing operations include all operations to improve the visual effect of the images, enhance the clarity of the images, or highlight certain features in the images to facilitate feature extraction. For example, the preprocessing operations include denoising operations such as filtering, and image adjustment operations that do not affect feature extraction, such as adjusting the overall grayscale, contrast, and brightness of the images.

[0035] The feature extraction network according to the embodiments of the present disclosure may be any suitable image feature extraction network, including but not limited to a convolutional neural network, a residual network, a densely connected network, and the like, which is not limited in the present disclosure. Exemplarily and without limitation, the feature extraction network includes two cascaded feature extraction networks. For example, the feature extraction network includes two cascaded convolutional neural networks or two cascaded recurrent neural networks.

[0036] FIG. 2 shows a schematic block diagram of a feature extraction network according to an embodiment of the present disclosure. As shown in FIG. 2, the feature extraction network is a part of a trained feature extraction and classification network. The feature extraction network includes two cascaded resnet18 feature extraction networks. The feature

extraction and classification network is composed of the two cascaded resnet18 feature extraction networks and a classification network. A case that the above object is a wafer and the first images are images of small-batch defect samples of a new wafer product is taken as an example. The feature extraction and classification network may be trained by using defect samples of a large batch of wafer products that are highly similar to the new wafer product, such as those produced previously or currently in production. Defect data of the large batch of wafer products may be manually classified and labeled with type labels, serving as training samples for the feature extraction and classification network. The overall feature extraction and classification network is trained by using these large-batch training samples. It can be understood that while training the overall feature extraction and classification network by using the training samples, the feature extraction network is also trained. As a result, the feature extraction network has an excellent capability for extracting defect features of images of the new wafer product. For example, a resnet18_1 network is pre-trained separately by using an image dataset of the ImageNet, and then the overall feature extraction and classification network is trained by using the above large-batch training samples, thereby improving training efficiency and training effectiveness.

[0037] It can be understood that the above two trained cascaded feature extraction networks are used to perform feature extraction on the multiple first images, thereby improving the expressiveness and discriminability of features, and improving the accuracy of feature extraction.

[0038] In an embodiment, the size of each of the first images is, for example, 512×512 , and each of the first feature vectors is a feature vector of 512×1 . A case of selecting 50 samples for each defect type is taken as an example. Feature extraction is performed on 50 first images for each defect type, and 50 feature vectors are obtained and determined as the multiple first feature vectors representing the current defect type. Assuming there are 10 defect types in the overall defect samples, 10 first feature vector sets may be obtained. Each first feature vector set corresponds to a defect type. Each first feature vector set includes multiple first feature vectors of 512×1 .

[0039] In step S120, clustering processing is performed on the multiple first feature vectors to obtain a first preset number of first vector groups representing the multiple first images and first representative feature vectors respectively representing the first vector groups.

[0040] It can be understood that this step is performed on the multiple first feature vectors in each first feature vector set. The clustering processing is a representative unsupervised classification method, which may be used to classify the first feature vectors in each first feature vector set. Any suitable clustering algorithm may be used to implement this step, including but not limited to K-means clustering, hierarchical clustering, and the like.

[0041] In an embodiment, taking the K-means clustering as an example, suitable cluster centers (representative data points) are first selected as initial cluster centers. Then, distances between the first feature vectors are calculated, where a distance or similarity between each first feature vector and each of other first feature vectors is calculated based on a selected distance metric (such as a Euclidean distance or a cosine similarity). Subsequently, each first feature vector is assigned to the category corresponding to the cluster center closest to the first feature vector based on the calculated distances or similarities. Next, for each category, the center or representative point of first feature vectors in this category is recalculated, which may be a mean value, a median, or the like of these first feature vectors. Iterative optimization is performed so that the cluster center better represents the first feature vectors of the category they belong to. The process of assigning the first feature vectors and updating the cluster centers is repeated until termination conditions are met, such as a fixed number of iterations being reached or the change in each cluster center being less than a certain threshold, thereby obtaining the final clustering result, that is, the category each first feature vector belongs to. Thus, first feature vectors in the same category are determined as one first vector group. Differences between the first vector groups are significant, while differences within a first vector group are small.

[0042] The first preset number may be any suitable value, which may be arbitrarily set based on the total sample size and sample distribution. In an embodiment, the first preset number may be 5, 4, 3, etc. Taking the first preset number being 5 as an example, it is assumed that each first feature vector set includes 50 first feature vectors. In step S120, the K-means clustering is used to classify the 50 first feature vectors in each first feature vector set into 5 groups, to obtain 5 first vector groups. After the clustering processing is completed, the cluster center in each first vector group may be directly determined as the first representative feature vector of the first vector group, or a mean vector of the first feature vectors included in each first vector group may be calculated as the first representative feature vector of the first vector group. Thus, for each first feature vector set, 5 first vector groups are

obtained, and 5 first representative feature vectors corresponding one-to-one to the 5 first vector groups are obtained.

[0043] In step S130, for each of the first vector groups, distribution data of the first vector group is calculated, where the distribution data includes a weight of the first vector group and/or a distribution variance of first feature vectors in the first vector group.

[0044] In an embodiment, the distribution data includes a weight. In the above example, for the first feature vector set of 50 first images corresponding to each defect type, 5 first vector groups are obtained through clustering. Then, multiple suitable manners may be used to calculate the weight of each first vector group.

[0045] In an example, a ratio of the number of the first feature vectors in each first vector group to the total number of all the first feature vectors is directly determined as the weight of the first vector group. For example, for the first feature vector set of 50 first images corresponding to each defect type, if the numbers of first feature vectors in the 5 clustered first vector groups are 15, 10, 10, 8, and 7, respectively, the weights of these 5 first vector groups are determined as 0.3, 0.2, 0.2, 0.16, and 0.14, respectively. In another example, calculating the distribution data of each first vector group includes: calculating distances between all the first feature vectors in the first vector group and the first representative feature vector of the first vector group; and calculating a ratio of a first number to a total number of the multiple first feature vectors as the weight of the first vector group, where the first number is a number of first feature vectors, each of which has a distance to the first representative feature vector of the first vector group being less than a distance threshold. For example, for a first vector group including 20 first feature vectors, the weight of the first vector group is determined as 0.4.

[0046] In other words, the distance threshold is set to determine the weight of each first vector group. The calculated distances between all the first feature vectors in the first vector group and the first representative feature vector of the first vector group are compared with the distance threshold to obtain the number of first feature vectors, each of which has a distance less than the distance threshold, that is, the first number. Further, the ratio of the first number to the total number of all the first feature vectors is obtained. The distance threshold may be arbitrarily set based on the actual sample situation.

[0047] In an embodiment, the distribution data includes a distribution variance, that is, the

variance of the first feature vectors in each first vector group. It can be understood that the variance reflects the degree of dispersion of the first feature vectors in each first vector group. In step S130, the weight and variance of each first vector group may be separately calculated as the distribution data.

5 **[0048]** In step S140, the distribution data of the first vector groups is corrected based on respective distribution data of the first preset number of reference vector groups of reference images. The reference vector groups correspond one-to-one to the first vector groups.

10 **[0049]** The respective distribution data of the first preset number of reference vector groups may be obtained in advance by using any suitable manner, and the present disclosure is not limited thereto.

15 **[0050]** The reference images and the first images may be images of products of the same type. In an embodiment, taking the aforementioned 50 first images being defect images of one defect type (such as defect A) of the new wafer product as an example, the reference images in this step may be defect images of a large batch of wafer products produced previously or currently in production, having a high similarity in defect features to the new wafer product. In other words, the defect type of the reference images is similar to the defect type of the first images. For example, the defect type of the reference images is defect A'.

20 **[0051]** Taking the first preset number being 5 as an example, the distribution data of the 5 first vector groups may be corrected based on the respective distribution data of the 5 reference vector groups of the reference images. The distribution data of the 5 first vector groups may be obtained through a method similar to steps S110 to S130 described above. For example, the reference images may be images of one defect type selected from defect images of a large batch of wafer products, and the defect images of the large batch of wafer products may be determined as the reference images that are manually labeled with the defect type.

25 The reference images for each defect type may include 1000 images. Feature extraction is performed on the 1000 reference images for each defect type by using the above feature extraction network to obtain 1000 reference feature vectors. Then, for the reference feature vectors of the 1000 reference images for each defect type, a method similar to steps S120 and S130 described above is adopted for performing clustering to obtain 5 second vector groups,

30 and further obtaining respective distribution data and second representative feature vectors for the 5 second vector groups. Thus, the 5 second vector groups for the 1000 reference images of

the defect type (such as defect A') are determined as the 5 reference vector groups of the 1000 reference images by using various suitable methods. The respective distribution data of the 5 first vector groups of the 50 first images obtained in step S130 may then be corrected based on the distribution data of the 5 reference vector groups.

- 5 **[0052]** Any suitable method may be used to correct the distribution data of the 5 first vector groups. In an embodiment, the 5 reference vector groups are matched with the 5 first vector groups, and the distribution data of the reference vector groups is used to correspondingly replace the distribution data of the first vector groups. In step S140, the distribution data of all the first vector groups may be adjusted, or only the distribution data of some of the first vector
10 groups may be adjusted.

[0053] In an embodiment, for the case where the distribution data includes a weight and a variance, the weight and variance of each matched first vector group are corrected separately based on the weight and variance of the reference vector group, or only one of the weight and variance is corrected.

- 15 **[0054]** In step S150, after the correction, first representative feature vectors of at least part of the first vector groups and corrected distribution data of the at least part of the first vector groups are determined as feature representation data of the multiple first images.

[0055] The first representative feature vectors and the corrected distribution data of the at least part of the first vector groups may be stored as the feature representation data of the
20 multiple first images. Taking the first preset number being 5 as an example, the first representative feature vectors and the corrected distribution data of the 5 first vector groups are determined as the feature representation data of the 50 first images. Alternatively, first representative feature vectors and corrected distribution data of 3 or 4 of the 5 first vector groups are determined as the feature representation data of the 50 first images.

- 25 **[0056]** According to the above technical solutions, the distribution data of the first vector groups of the first images is corrected based on the respective distribution data of the multiple reference vector groups of reference images, and the corrected distribution data and the first representative feature vectors of the first vector groups are determined as the feature representation data of the multiple first images. The corrected distribution data and the first
30 representative feature vectors of the first vector groups may accurately represent the features of the target object in the multiple first images, and therefore automatic classification for

images of the same type is achieved quickly and accurately by using the feature representation data. Moreover, the above solutions are still applicable in scenarios where the number of first images is limited, making the application scope of the solutions broader.

[0057] In an embodiment, the distribution data includes a weight. The correcting the distribution data of the multiple first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images includes: selecting, from weights of the first preset number of the first vector groups, a second preset number of the weights, where the selected weights are greater than unselected weights; and replacing the selected weights with weights of first reference vector groups correspondingly.

[0058] As described above, a larger weight corresponds to a defect category with a higher occurrence frequency. For defects with higher occurrence frequencies, adjusting the weights has better reference significance. For example, if the first preset number is 5, for the multiple first images, 5 weights corresponding to the 5 first vector groups may be obtained. The 5 vector groups may be sorted in descending order of the weights, with the larger weights first and the smaller weights last. Similarly, the 5 reference vector groups of the reference images may be sorted by their weights.

[0059] The second preset number is less than or equal to the first preset number. Taking the first preset number being 5 as an example, the second preset number may be any number less than or equal to 5. For example, the second preset number is 3. In this example, the first 3 first vector groups sorted in the descending order are selected from the 5 first vector groups, and the weights of these 3 first vector groups are determined as the weights to be corrected. Similarly, the first 3 reference vector groups sorted in the descending order are selected from the 5 reference vector groups, and the weights of these 3 reference vector groups are determined as target weights. Then, the 3 to-be-corrected weights are correspondingly replaced with the 3 target weights one by one. For example, if the weights of the 5 reference vector groups are 0.3, 0.2, 0.2, 0.15, and 0.15, respectively, and the weights of the 5 first vector groups are 0.5, 0.2, 0.15, 0.1, and 0.05, respectively, the corrected weights of the 5 first vector groups are 0.3, 0.2, 0.2, 0.1, and 0.05, respectively. In embodiments not shown, the largest 2 or 4 weights may be replaced depending on the situation. In this way, the feature representation data of small-sample defect categories with relatively concentrated distributions is corrected, improving the accuracy of the final classification results.

[0060] In other examples, the distribution data includes a distribution variance and a weight. The correcting the distribution data of the multiple first vector groups based on respective distribution data of the first preset number of the reference vector groups of the reference images may further include: correspondingly replacing the distribution variances of the second preset number of the first vector groups with the distribution variances of the second preset number of the reference vector groups based on the respective weights of the multiple first vector groups. For example, the variances of the 3 reference vector groups with larger weights may be used to correspondingly replace the variances of the 3 first vector groups with larger weights.

[0061] In an embodiment, the determining, after the correction, first representative feature vectors of at least part of the first vector groups and corrected distribution data of the at least part of the first vector groups as feature representation data of the multiple first images in step S150 includes: determining the weights and the first representative feature vectors of the first vector groups whose weights are replaced as the feature representation data of the multiple first images. For example, the weights and the first representative feature vectors of the first 3 first vector groups sorted in the descending order are determined as the feature representation data of the 50 first images.

[0062] In an embodiment, the method 100 further includes steps S161, S162, S163, S164, S165, S166, and S167.

[0063] In step S161, a statistical value of the multiple first feature vectors is calculated. Taking the first images being defect images of a new wafer product as an example, a mean vector of the first feature vectors of the 50 first images for the current defect type is calculated, representing general features of the defect, such as grayscale variation. A variance vector of the first feature vectors of the 50 first images for the current defect type is calculated, representing frequency features of the defect, such as changes in high and low frequencies. A covariance of the first feature vectors of the 50 first images for the current defect type is calculated, representing other attributes of the defect, such as changes in texture and color.

[0064] In step S162, feature extraction is performed on multiple groups of reference images by using the feature extraction network to obtain multiple reference feature vectors, where different groups of reference images belong to different types.

[0065] As previously described, a large amount of defect data is acquired, and accordingly

classified and labeled. For example, the defect data may be defect data from a large batch of products produced previously, or defect data from a large batch of products currently in production. The acquired large amount of defect data may be manually classified and labeled with type labels. The defect samples labeled with defect types may be determined as the reference images with different types. For example, if 10 types of defect samples are acquired and labeled in advance, each type containing 1000 images, the 1000 images of each type of defect sample may be determined as a group of reference images. The two trained cascaded resnet18 feature extraction networks shown in FIG. 2 may be used to perform feature extraction on these 10 groups of reference images, to obtain 10000 reference feature vectors corresponding one-to-one to the 10000 reference images.

[0066] As mentioned above, some defects with obvious differences, such as a missing corner and a stain, may be easily distinguished. Therefore, the reference images of different types may be grouped, and feature extraction may be performed on each reference image in each group, thereby generating multiple groups of reference feature vectors.

[0067] In step S163, for each group of reference images, clustering processing is performed on the reference feature vectors of the group of reference images to obtain the first preset number of second vector groups representing the group of reference images and second representative feature vectors respectively representing the second vector groups.

[0068] A method similar to step S120 described above is used to perform clustering processing on the 1000 reference feature vectors in each group of reference images to obtain 5 second vector groups and the second representative feature vector of the 5 second vector groups.

[0069] In step S164, for each second vector group, distribution data of the second vector group is calculated. The implementation of this step is similar to the implementation of step S140 described above, and is not repeated herein.

[0070] In step S165, for each group of reference images, a statistical value of the reference feature vectors of the group of reference images is calculated. For example, a mean vector, a variance vector, and a covariance of the 1000 reference feature vectors of each group of reference images are calculated.

[0071] In step S166, based on the statistical value of the multiple first feature vectors and

the statistical value of the reference feature vectors of each group of reference images, a distance between the multiple first images and each group of reference images is calculated.

[0072] In step S167, based on the respective distances between the multiple first images and the multiple groups of reference images, one group of reference images is selected from the multiple groups of reference images, and the second vector groups representing the selected group of reference images are determined as the reference vector groups.

[0073] In an embodiment, a correlation coefficient is calculated by using a Euclidean distance based on the statistical value of the multiple first feature vectors, such as the mean, variance, and covariance of features, and the statistical value of the reference feature vectors for each group of reference images, as follows:

$$Y = a(\text{distance}(\text{mean})) + b(\text{distance}(\text{variance})) + c(\text{distance}(\text{covariance}))$$

where a, b, and c represent weighting coefficients, which may be arbitrarily set according to actual needs. For example, a, b, and c may be 0.5, 0.3, and 0.2, respectively. Exemplarily, the above equation may be used to calculate the distance between a first defect type represented by the multiple first images and a second defect type represented by each group of reference images. A group of reference images corresponding to the second defect type with a minimum distance may be determined as the reference images for the correction, and the first preset number of second vector groups representing the reference images for the correction may be determined as the corresponding reference vector groups. In other words, the defect type similar to the defect type of the 50 first images of the new wafer product may be determined from the large batch of wafer products.

[0074] In this way, the correspondence between the type of the multiple first images and the type of each group of reference images may be determined based on the statistical data. If there are multiple groups of first images, a group of reference images matching (having a similar type to) each group of first images may be determined. That is, by matching the second vector groups with the first vector groups, the reference vector groups having a similar type to the first vector groups may be determined, and then the distribution data of the first vector groups may be corrected by using the distribution data of the reference vector groups.

[0075] According to another aspect of the present disclosure, an image sample classification method is further provided. FIG. 3 shows a schematic flowchart of an image sample

classification method 300 according to an embodiment of the present disclosure. The image sample classification method 300 includes steps S310 and S320.

[0076] In step S310, feature extraction is performed on an image sample by using a feature extraction network to obtain a sample feature vector. In an embodiment, the image sample may be defect image data of a new product image to be classified for defects. The above two trained cascaded resnet18 feature extraction networks may be used to extract features of the image sample to obtain the sample feature vector.

[0077] In step S320, a type to which the image sample belongs is determined based on the sample feature vector and respective feature representation data of multiple groups of first images, where the feature representation data of the multiple groups of first images is obtained by using the above image processing method. Different groups of first images belong to different types. The sample feature vector may be matched with the feature representation data of each group of first images, and the type to which the image sample belongs may be determined based on the matching result.

[0078] In the field of industrial production, machine learning is widely used for operations such as product positioning and defect detection. Machine learning algorithms may be divided into supervised learning and unsupervised learning. For example, the supervised learning may detect a defect of a product, such as a stain, by comparing inference results with manually labeled results to output results according to user requirements. The unsupervised learning may allow the user to simply determine the number of types, and allow the machine to determine the defect type, thereby grouping defects with a similar type into one group, and determining multiple groups of different types of defects. Defects differ greatly between different groups, but defects within the same group have small differences. Thus, when detecting defects, the machine may automatically group the defects and adjust a center of each group based on newly added samples in the group, making the defect grouping more accurate. In other words, as the sample size increases, the distribution of samples becomes closer to a normal distribution, the data is less susceptible to abnormal sample data, and reliability is higher. However, for a small sample size, the above unsupervised learning may cause the classification accuracy of defects to be seriously affected since the values of individual samples deviate significantly from the mean value. According to the above image sample classification method in the embodiments of the present disclosure, feature extraction and

training may be performed for a product that has accumulated a large amount of data to obtain the distribution of each defect type, and the obtained feature distribution is used for correction in a new similar or related product, effectively solving the problem of poor classification performance for a small sample size in the prior art, and improving the classification accuracy.

[0079] In an embodiment, the determining a type to which the image sample belongs based on the sample feature vector and respective feature representation data of multiple groups of first images includes:

calculating a first distance between each group of the multiple groups of first images and the image sample based on the sample feature vector and the feature representation data of the group of first images, to obtain multiple first distances; and

determining a type to which a group of first images corresponding to a minimum first distance among the multiple first distances belongs as the type to which the image sample belongs.

[0080] As described above, for example, the first representative feature vectors of the 5 first vector groups for a group of first images are A, B, C, D, and E, respectively, and the corresponding corrected weights are 0.3, 0.2, 0.2, 0.1, and 0.05, respectively. The feature representation data may include the weights of some of the 5 first vector groups and the first representative feature vectors of these first vector groups. For example, the feature representation data for the group of first images includes first representative feature vectors A, B, and C, and corresponding weights 0.3, 0.2, and 0.2. In this embodiment, a weighted average method is used to calculate the first distance between each group of first images and the image sample. For example, if the sample feature vector of the image sample is x, the first distance between the image sample and this group of first images is equal to $0.3 \times (x-A) + 0.2 \times (x-B) + 0.2 \times (x-C)$. Alternatively, a similar method may be used to calculate the first distance between each group of first images and the image sample. The defect type to which the group of first images corresponding to a minimum first distance belongs is determined as the defect type to which the current image sample belongs. By calculating and comparing the first distances, the type to which the image sample belongs is quickly determined. This solution has a simple execution logic and a small amount of calculation, resulting in high classification efficiency and accurate classification results for the image

sample classification method.

[0081] FIG. 4 shows a flowchart of an image sample classification method according to another embodiment of the present disclosure. As shown in FIG. 4, in the first stage, defect data of old products is acquired and analyzed. First, a large amount of defect data is acquired, and classified and labeled accordingly. Defect data from a large batch of products produced previously, or defect data from a large batch of products currently in production, may be used. A large amount of defect dataset A is acquired, and defects are manually classified and labeled with type labels (the defect types may be referred to as old defect types). Then, a feature extraction and classification network is trained. The feature extraction and classification network is composed of three sub-networks, including two resnet18 feature extraction networks and a classification network. A resnet18_1 network may use weights obtained by pre-training ImageNet data. The feature extraction and classification network is trained by using the defect dataset A manually classified and labeled in S1. After training is completed, an optimal feature extraction and classification network is obtained. Subsequently, statistical distribution is performed on features of defect images for each defect type in the defect dataset A. The defect dataset A includes, for example, 3 groups of reference images corresponding to 3 defect types. Specifically, for multiple reference images of each defect type, feature extraction is performed by using the two trained resnet18 feature extraction networks to obtain multiple reference feature vectors. A mean vector, a variance vector, and a covariance of the multiple reference feature vectors are calculated. Next, clustering processing is performed on the multiple reference feature vectors to obtain 5 second vector groups, and second representative feature vectors, weights, and variances for the 5 second vector groups. Subsequently, all old defect types and the above statistical information of the 5 reference vector groups for each old defect type are stored in a recipe of a current product.

[0082] In the second stage, defect data of a new product is acquired and analyzed. For example, 30-50 images are acquired for each defect type of the new product, which can meet the requirement on defect data for small-sample classification in this solution. A defect dataset B of the new product includes, for example, 3 defect types (the defect types may be referred to as new defect types) manually labeled. According to the above method, the above trained feature extraction network is used to perform feature extraction on multiple first images for each new defect type to obtain multiple first feature vectors. A mean vector, a variance vector, and a covariance of the multiple first feature vectors are calculated. Then, clustering

processing is performed on the multiple first feature vectors to obtain 5 first vector groups. A first representative feature vector, a weight, and a variance of each first vector group are calculated. Since the number of samples for the new product is small, the obtained feature distribution is referred to as a sparse feature distribution.

5 **[0083]** In the third stage, the feature distribution of the new product is corrected by using the feature distribution of the old products. First, a distance between each new defect type and each old defect type is calculated. Specifically, the distance between the new defect type and the old defect type is calculated based on the mean vector, variance vector, and covariance of the multiple first feature vectors of the new defect type and the mean vector, variance vector, and covariance of the multiple reference feature vectors of the old defect type. The old defect type with a minimum distance to the new defect type is determined as a similar defect type, and 5 second vector groups of the similar defect type are determined as the reference vector groups for images of the new defect type. For each new defect type, weights or variances of the 5 first vector groups of the new defect type are corrected by using weights or variances of the corresponding 5 reference vector groups. For example, the weights of the 3 reference vector groups with the largest weights are directly used to correspondingly replace the weights of the 3 first vector groups with the largest weights, respectively. Moreover, feature representation data for each of 3 new defect types is obtained.

20 **[0084]** In the fourth stage, defect images to be classified are inferred and classified. When a defect is detected in the new product, a defect image is inputted, and feature extraction is performed by using the feature extraction network to obtain a sample feature vector. Then, based on the respective feature representation data of the 3 new defect types and the sample feature vector, a distance between the current defect image and each new defect type is calculated. The new defect type with a minimum distance is determined as the defect type of the current defect image.

25 **[0085]** According to another aspect of the present disclosure, an image processing apparatus is further provided. FIG. 5 shows a schematic block diagram of an image processing apparatus 500 according to an embodiment of the present disclosure. As shown in FIG. 5, the image processing apparatus 500 includes:

30 a first feature extraction module 510, configured to perform feature extraction on multiple first images by using a feature extraction network to obtain multiple first feature

vectors, respectively;

a clustering module 520, configured to perform clustering processing on the multiple first feature vectors to obtain a first preset number of first vector groups representing the multiple first images and first representative feature vectors respectively representing the first vector groups;

a first calculation module 530, configured to, for each of the first vector groups, calculate distribution data of the first vector group, where the distribution data includes a weight of the first vector group and/or a distribution variance of first feature vectors in the first vector group;

a correction module 540, configured to correct the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images, where the reference vector groups correspond one-to-one to the first vector groups; and

a second calculation module 550, configured to determine, after the correction, first representative feature vectors of at least part of the first vector groups and corrected distribution data of the at least part of the first vector groups as feature representation data of the multiple first images.

[0086] According to another aspect of the present disclosure, an image sample classification apparatus is further provided. FIG. 6 shows a schematic block diagram of an image sample classification apparatus 600 according to an embodiment of the present disclosure. As shown in FIG. 6, the image sample classification apparatus 600 includes:

a second feature extraction module 610, configured to perform feature extraction on an image sample by using a feature extraction network to obtain a sample feature vector; and

a classification module 620, configured to determine a type to which the image sample belongs based on the sample feature vector and respective feature representation data of multiple groups of first images, where the feature representation data of the multiple groups of first images is obtained by using the image processing method described above, and different groups of first images belong to different types.

[0087] According to another aspect of the present disclosure, an electronic device is further provided. FIG. 7 shows a schematic block diagram of an electronic device 700 according to

an embodiment of the present disclosure. As shown in FIG. 7, the electronic device 700 includes a processor 710 and a memory 720. The memory 720 stores computer program instructions, and the computer program instructions, when executed by the processor 710, are configured to perform the above image processing method 100.

5 [0088] According to another aspect of the present disclosure, a storage medium is further provided. The storage medium stores program instructions, and the program instructions, when executed, are configured to perform the above image processing method 100. The storage medium may include, for example, an erasable programmable read-only memory (EPROM), a compact disc read-only memory (CD-ROM), a USB memory, or any
10 combination of the above storage media. The storage medium may be any combination of one or more computer-readable storage media.

[0089] Those of ordinary skill in the art can understand the specific implementation solutions and beneficial effects of the above image processing apparatus 500, image sample classification apparatus 600, electronic device 700, and storage medium by reading the above
15 related descriptions of the image processing method 100 and the image sample classification method 300, which are not repeated herein for brevity.

[0090] Embodiments:

[0091] Embodiment 1: An image processing method, comprising:

performing feature extraction on a plurality of first images by using a feature extraction
20 network to obtain a plurality of first feature vectors, respectively;

performing clustering processing on the plurality of first feature vectors to obtain a first preset number of first vector groups representing the plurality of first images and first representative feature vectors respectively representing the first vector groups;

for each of the first vector groups, calculating distribution data of the first vector group,
25 wherein the distribution data comprises a weight of the first vector group and/or a distribution variance of first feature vectors in the first vector group;

correcting the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images, wherein the reference vector groups correspond one-to-one to the first vector groups; and

30 determining, after the correction, first representative feature vectors of at least part of the

first vector groups and corrected distribution data of the at least part of the first vector groups as feature representation data of the plurality of first images.

[0092] Embodiment 2: The method according to Embodiment 1, wherein the feature extraction network comprises two cascaded feature extraction networks.

- 5 **[0093]** Embodiment 3: The method according to Embodiment 1 or 2, wherein for each of the first vector groups, calculating distribution data of the first vector group, the distribution data being a weight, comprises:

calculating a distance between each of all the first feature vectors in the first vector group and the first representative feature vector of the first vector group; and

- 10 calculating a ratio of a first number to a total number of the plurality of first feature vectors as the weight of the first vector group, wherein the first number is a number of first feature vectors where the distance between each of the first number of the first feature vectors and the first representative feature vector of the first vector group is less than a distance threshold.

- 15 **[0094]** Embodiment 4: The method according to any one of Embodiments 1 to 3, wherein the distribution data comprises the weight, and the correcting the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images comprises:

- 20 selecting, from weights of the first preset number of the first vector groups, a second preset number of the weights, wherein the selected weights are greater than unselected weights; and

replacing the selected weights with weights of first reference vector groups correspondingly.

- 25 **[0095]** Embodiment 5: The method according to any one of Embodiments 1 to 4, further comprising:

calculating a statistical value of the plurality of first feature vectors;

performing feature extraction on a plurality of groups of reference images by using the feature extraction network to obtain a plurality of reference feature vectors, wherein different groups of reference images belong to different types;

for each group of the plurality of groups of reference images, performing clustering processing on the reference feature vectors of the group of reference images to obtain the first preset number of second vector groups representing the group of reference images and second representative feature vectors respectively representing the second vector groups;

5 for each of the second vector groups, calculating distribution data of the second vector group;

for each group of the plurality of groups of reference images, calculating a statistical value of the reference feature vectors of the group of reference images;

10 calculating a distance between the plurality of first images and each group of the plurality of groups of reference images based on the statistical value of the plurality of first feature vectors and the statistical value of the reference feature vectors of the group of reference images; and

15 selecting one group of reference images from the plurality of groups of reference images based on the respective distances between the plurality of first images and the plurality of groups of reference images, and determining the second vector groups representing the selected group of reference images as the reference vector groups.

[0096] Embodiment 6: An image sample classification method, comprising:

performing feature extraction on an image sample by using a feature extraction network to obtain a sample feature vector; and

20 determining a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images, wherein the feature representation data of the plurality of groups of first images is obtained by using the image processing method according to any one of Embodiments 1 to 5, and different groups of first images belong to different types.

25 **[0097]** Embodiment 7: The method according to Embodiment 6, wherein the determining a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images comprises:

30 calculating a first distance between each group of the plurality of groups of first images and the image sample based on the sample feature vector and the feature representation data of the group of first images, to obtain a plurality of first distances; and

determining a type to which a group of first images corresponding to a minimum first distance among the plurality of first distances belongs as the type to which the image sample belongs.

[0098] Embodiment 8: The method according to Embodiment 6 or 7, wherein the first images are images of products, and types of the first images are determined based on defect types of the products.

[0099] Embodiment 9: An image processing apparatus, comprising:

a first feature extraction module, configured to perform feature extraction on a plurality of first images by using a feature extraction network to obtain a plurality of first feature vectors, respectively;

a clustering module, configured to perform clustering processing on the plurality of first feature vectors to obtain a first preset number of first vector groups representing the plurality of first images and first representative feature vectors respectively representing the first vector groups;

a first calculation module, configured to, for each of the first vector groups, calculate distribution data of the first vector group, wherein the distribution data comprises a weight of the first vector group and/or a distribution variance of first feature vectors in the first vector group;

a correction module, configured to correct the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images, wherein the reference vector groups correspond one-to-one to the first vector groups; and

a second calculation module, configured to determine, after the correction, first representative feature vectors of at least part of the first vector groups and corrected distribution data of the at least part of the first vector groups as feature representation data of the plurality of first images.

[0100] Embodiment 10: An image sample classification apparatus, comprising:

a second feature extraction module, configured to perform feature extraction on an image sample by using a feature extraction network to obtain a sample feature vector; and

a classification module, configured to determine a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images, wherein the feature representation data of the plurality of groups of first images is obtained by using the image processing method according to any one of Embodiments 1 to 5, and different groups of first images belong to different types.

[0101] Embodiment 11: An electronic device, comprising a processor and a memory, wherein the memory stores computer program instructions, and the computer program instructions, when executed by the processor, are configured to perform the image processing method according to any one of Embodiments 1 to 5 and/or the image sample classification method according to any one of Embodiments 6 to 8.

[0102] Embodiment 12: A storage medium, storing program instructions, wherein the program instructions, when executed, are configured to perform the image processing method according to any one of Embodiments 1 to 5 and/or the image sample classification method according to any one of Embodiments 6 to 8.

[0103] Although example embodiments have been described herein with reference to the drawings, it should be understood that the above example embodiments are merely illustrative and are not intended to limit the scope of the present disclosure. Those of ordinary skill in the art can make various changes and modifications therein without departing from the scope and spirit of the present disclosure. All such changes and modifications are intended to be included within the scope of the present disclosure as required by the appended claims.

[0104] Those of ordinary skill in the art can realize that the units and algorithm steps of the examples described in conjunction with the embodiments disclosed herein may be implemented in electronic hardware, or a combination of computer software and electronic hardware. Whether these functions are executed in hardware or software depends on the specific application and design constraints of the technical solution. Professional technicians can use different methods for each specific application to implement the described functions, but such implementation should not be considered beyond the scope of the present disclosure.

[0105] In the several embodiments provided in the present disclosure, it should be understood that the disclosed device and method may be implemented in other ways. For example, the device embodiments described above are merely illustrative. For example, the division of the units is only a logical functional division, and there may be other division

methods in actual implementation, such as multiple units or components may be combined or integrated into another device, or some features may be ignored or not executed.

[0106] In the description provided herein, numerous specific details are set forth. However, it can be understood that embodiments of the present disclosure may be practiced without these specific details. In some instances, well-known methods, structures, and techniques are not shown in detail so as not to obscure the understanding of this description.

[0107] Similarly, it should be understood that, in order to streamline the present disclosure and help understand one or more of the various inventive aspects, various features of the present disclosure are sometimes grouped together in a single embodiment, figure, or description thereof in the description of exemplary embodiments of the present disclosure. However, the method of the present disclosure should not be interpreted as reflecting an intention that the claimed present disclosure requires more features than those expressly recited in each claim. Rather, as the corresponding claims reflect, the inventive point lies in being able to solve the corresponding technical problem with fewer than all features of a single disclosed embodiment. Therefore, the claims following the Detailed Description are hereby expressly incorporated into this Detailed Description, with each claim standing on its own as a separate embodiment of the present disclosure.

[0108] Those skilled in the art can understand that, except for mutually exclusive features, any combination of all features disclosed in this specification (including the accompanying claims, abstract, and drawings) and all processes or units of any method or device so disclosed can be used. Unless expressly stated otherwise, each feature disclosed in this specification (including the accompanying claims, abstract, and drawings) may be replaced by an alternative feature serving the same, equivalent, or similar purpose.

[0109] Furthermore, those skilled in the art can understand that, although some embodiments described herein include certain features included in other embodiments but not others, combinations of features of different embodiments are meant to be within the scope of the present disclosure and form different embodiments. For example, in the claims, any one of the claimed embodiments can be used in any combination.

[0110] The various component embodiments of the present disclosure may be implemented in hardware, or in software modules running on one or more processors, or in a combination thereof. Those skilled in the art should understand that a microprocessor or a Digital signal

processor (DSP) may be used in practice to implement some or all of the functions of some modules in the image processing apparatus 500 and the image sample classification apparatus 600 according to the embodiments of the present disclosure. The present disclosure may also be implemented as apparatus programs (such as computer programs and computer program products) for executing part or all of the methods described herein. Such programs implementing the present disclosure may be stored on computer-readable media, or may be in the form of one or more signals. Such signals may be downloaded from internet websites, provided on carrier signals, or provided in any other form.

[0111] It should be noted that the above embodiments are intended to illustrate the present disclosure and not to limit it, and those skilled in the art can design alternative embodiments without departing from the scope of the appended claims. In the claims, any reference signs placed between parentheses shall not be construed as limiting the claim. The word "comprising" does not exclude the presence of elements or steps not listed in a claim. The word "a" or "an" preceding an element does not exclude the presence of a plurality of such elements. The present disclosure may be implemented by means of hardware comprising several different elements and by means of a suitably programmed computer. In the unit claims enumerating several apparatuses, several of these apparatuses may be embodied by one and the same item of hardware. The use of the words "first", "second", "third", etc. does not indicate any order. These words may be interpreted as names.

[0112] The above is only the specific implementation of the present disclosure or the description of the specific implementation. The protection scope of the present disclosure is not limited thereto. Any person skilled in the art can easily think of changes or substitutions within the technical scope disclosed in the present disclosure, which should be covered within the protection scope of the present disclosure. The protection scope of the present disclosure should be based on the protection scope of the claims.

CLAIMS

1. An image processing method, comprising:

performing feature extraction on a plurality of first images by using a feature extraction
5 network to obtain a plurality of first feature vectors, respectively;

performing clustering processing on the plurality of first feature vectors to obtain a first
preset number of first vector groups representing the plurality of first images and first
representative feature vectors respectively representing the first vector groups;

for each of the first vector groups, calculating distribution data of the first vector group,
10 wherein the distribution data comprises a weight of the first vector group and/or a distribution
variance of first feature vectors in the first vector group;

correcting the distribution data of the first vector groups based on respective distribution
data of the first preset number of reference vector groups of reference images, wherein the
reference vector groups correspond one-to-one to the first vector groups; and

15 determining, after the correction, first representative feature vectors of at least part of the
first vector groups and corrected distribution data of the at least part of the first vector groups
as feature representation data of the plurality of first images.

2. The image processing method according to claim 1, wherein the feature extraction
20 network comprises two cascaded feature extraction networks.

3. The image processing method according to claim 1, wherein for each of the first
vector groups, calculating distribution data of the first vector group, the distribution data
being a weight, comprises:

25 calculating a distance between each of all the first feature vectors in the first vector group
and the first representative feature vector of the first vector group; and

calculating a ratio of a first number to a total number of the plurality of first feature
vectors as the weight of the first vector group, wherein the first number is a number of first
feature vectors where the distance between each of the first number of the first feature vectors

and the first representative feature vector of the first vector group is less than a distance threshold.

4. The image processing method according to claim 1, wherein the distribution data comprises the weight, and the correcting the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images comprises:

selecting, from weights of the first preset number of the first vector groups, a second preset number of the weights, wherein the selected weights are greater than unselected weights; and

replacing the selected weights with weights of first reference vector groups correspondingly.

5. The image processing method according to any one of claims 1 to 4, further comprising:

calculating a statistical value of the plurality of first feature vectors;

performing feature extraction on a plurality of groups of reference images by using the feature extraction network to obtain a plurality of reference feature vectors, wherein different groups of reference images belong to different types;

for each group of the plurality of groups of reference images, performing clustering processing on the reference feature vectors of the group of reference images to obtain the first preset number of second vector groups representing the group of reference images and second representative feature vectors respectively representing the second vector groups;

for each of the second vector groups, calculating distribution data of the second vector group;

for each group of the plurality of groups of reference images, calculating a statistical value of the reference feature vectors of the group of reference images;

calculating a distance between the plurality of first images and each group of the plurality of groups of reference images based on the statistical value of the plurality of first

feature vectors and the statistical value of the reference feature vectors of the group of reference images; and

selecting one group of reference images from the plurality of groups of reference images based on the respective distances between the plurality of first images and the plurality of groups of reference images, and determining the second vector groups representing the selected group of reference images as the reference vector groups.

6. An image sample classification method, comprising:

performing feature extraction on an image sample by using a feature extraction network to obtain a sample feature vector; and

determining a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images, wherein the feature representation data of the plurality of groups of first images is obtained by using the image processing method according to any one of claims 1 to 5, and different groups of first images belong to different types.

7. The image sample classification method according to claim 6, wherein the determining a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images comprises:

calculating a first distance between each group of the plurality of groups of first images and the image sample based on the sample feature vector and the feature representation data of the group of first images, to obtain a plurality of first distances; and

determining a type to which a group of first images corresponding to a minimum first distance among the plurality of first distances belongs as the type to which the image sample belongs.

8. The image sample classification method according to claim 6 or 7, wherein the first images are images of products, and types of the first images are determined based on defect types of the products.

9. An image processing apparatus, comprising:

a first feature extraction module, configured to perform feature extraction on a plurality of first images by using a feature extraction network to obtain a plurality of first feature vectors, respectively;

a clustering module, configured to perform clustering processing on the plurality of first feature vectors to obtain a first preset number of first vector groups representing the plurality of first images and first representative feature vectors respectively representing the first vector groups;

a first calculation module, configured to, for each of the first vector groups, calculate distribution data of the first vector group, wherein the distribution data comprises a weight of the first vector group and/or a distribution variance of first feature vectors in the first vector group;

a correction module, configured to correct the distribution data of the first vector groups based on respective distribution data of the first preset number of reference vector groups of reference images, wherein the reference vector groups correspond one-to-one to the first vector groups; and

a second calculation module, configured to determine, after the correction, first representative feature vectors of at least part of the first vector groups and corrected distribution data of the at least part of the first vector groups as feature representation data of the plurality of first images.

10. An image sample classification apparatus, comprising:

a second feature extraction module, configured to perform feature extraction on an image sample by using a feature extraction network to obtain a sample feature vector; and

a classification module, configured to determine a type to which the image sample belongs based on the sample feature vector and respective feature representation data of a plurality of groups of first images, wherein the feature representation data of the plurality of groups of first images is obtained by using the image processing method according to any one

of claims 1 to 5, and different groups of first images belong to different types.

11. An electronic device, comprising a processor and a memory, wherein the memory stores computer program instructions, and the computer program instructions, when executed
5 by the processor, are configured to perform the image processing method according to any one of claims 1 to 5 and/or the image sample classification method according to any one of claims 6 to 8.

12. A storage medium, storing program instructions, wherein the program instructions,
10 when executed, are configured to perform the image processing method according to any one of claims 1 to 5 and/or the image sample classification method according to any one of claims 6 to 8.