

Method and Apparatus for Training Defect Detection Model, and Electronic Device

This application claims priority to Chinese Patent Application No. 202310184844.5, filed to the China National Intellectual Property Administration on February 17, 2023 and entitled "Method and Apparatus for Training Defect Detection Model, and Electronic Device", the disclosure of which is hereby incorporated by reference in its entirety.

Technical Field

The present disclosure relates to the field of image recognition, and in particular, to a method and apparatus for training a defect detection model, and an electronic device.

Background

In the related art, when performing defect recognition and classification on a die image to be detected using a defect-free die image, a template image is usually not used to assist in recognition. The commonly used method is to directly fuse the die image to be detected with the defect-free die image, and then determine a defect category and a defect position in the image to be detected according to the fused image. Although this method uses the defect-free image to achieve defect recognition and classification of the image to be detected, the amount of calculation is large and the precision is low when fusing the images and recognizing the fused image.

For the above problems, no effective solution has yet been proposed.

Summary

Embodiments of the present disclosure provide a method and apparatus for training a defect detection model, and an electronic device, so as to at least solve the technical problems in the related art of large amount of calculation and low precision caused by directly fusing a defect-free image with an image to be detected when performing defect recognition and classification on a die image.

According to one aspect of the embodiments of the present disclosure, a method for training a defect detection model is provided, including: acquiring a training sample set and first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes a defect image and a template image corresponding to the defect image, and the first defect label information includes first category information and first position information of each defect in the defect image; determining a target loss function, where the target loss function includes a defect category loss function and a defect position loss function; and by means of using Stochastic Gradient Descent (SGD), training a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, where the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second label information of the defect image according to the first image feature and the second image feature, where the second label information includes second category information and second position information of each defect in the defect image determined by the model to be

trained.

Alternatively, the operation of, by means of using the SGD, training the model to be trained with the training sample set, the defect label information, and the target loss function to obtain the target defect detection model includes: S1, respectively inputting the defect image and the template image into the model to be trained, and acquiring the second label information output by the model to be trained; S2, inputting the first category information and the second category information into the defect category loss function to obtain a first loss function value, inputting the first position information and the second position information into the defect position loss function to obtain a second loss function value, and storing the first loss function value and the second loss function value; S3, by means of using the SGD, adjusting model parameters of the model to be trained through the first loss function value and the second loss function value; and S4, acquiring all the stored first loss function values and the second loss function values, and in a case where the first loss function values and the second loss function values meet a preset condition, determining that the adjusted model to be trained is the target defect detection model, otherwise jumping to S1, where the preset condition includes that a sum of a consecutive preset number of first loss function values and second loss function values is within a target value range.

Alternatively, the step of respectively inputting the defect image and the template image into the model to be trained, and acquiring the second label information output by the model to be trained includes: inputting the defect image and the template image into a backbone network of the model to be trained, where the backbone network is configured to extract image features in the defect image and the template image, thereby obtaining a defect feature image and a template feature image; and acquiring the second label information output by the model to be trained according to the defect feature image and the template feature image.

Alternatively, the model to be trained further includes a feature fusion layer and a feature pyramid layer. The feature fusion layer is configured to obtain a first target feature image according to the defect feature image and the template feature image, and input the first target feature image into the feature pyramid layer. The feature pyramid layer is configured to output the second label information according to the first target feature image.

Alternatively, the feature fusion layer includes a first feature fusion layer. The first feature fusion layer is configured to perform a differential operation on the defect feature image and the template feature image to obtain a differential feature image, where a pixel value of any pixel in the differential feature image is equal to an absolute value of a difference between a defect pixel and a template pixel corresponding to the any pixel, the defect pixel is a pixel corresponding to the any pixel in the defect feature image, and the template pixel is a pixel corresponding to the any pixel in the template feature image; perform channel stitching processing on the differential feature image and the defect feature image to obtain a second target feature image; and perform convolution processing on the second target feature image through a target convolution kernel to obtain the first target feature image.

Alternatively, the feature fusion layer includes a second feature fusion layer. The second feature fusion layer is configured to perform convolution processing on the defect feature image and the template feature image respectively through a target convolution kernel, and generate the first target feature image according to the defect feature image and the template feature image after the convolution processing, where a pixel value of any pixel in the first target feature image is equal to a sum of pixel values of a defect pixel and a template pixel corresponding to the any pixel.

Alternatively, the step of determining that the adjusted model to be trained is the target defect detection model includes: acquiring a verification sample set and third defect label information corresponding to each group of samples in the verification sample set, where each group of samples in the verification sample set includes a defect image and a template image corresponding to the defect image, and the third defect label information includes third category information and third position information of each defect in the defect image; in a case where the number of adjusted models to be trained is multiple, determining mean Average Precision (mAP) of each of the multiple adjusted models to be trained through the verification sample set and the third defect label information; and determining that the adjusted model to be trained with the largest mAP is the target defect detection model.

Alternatively, the step of acquiring the training sample set includes: acquiring a first defect image and a first template image corresponding to the first defect image; and performing geometric transformation processing on the first defect image and the first template image in the same processing manner, taking the first defect image subjected to the geometric transformation processing as the defect image sample, and taking the first template image subjected to the geometric transformation processing as the template image sample, where the processing manner includes at least one of the following: random cropping, image flipping, and image stitching.

Alternatively, the category information includes a defect category number of the defect, and the position information includes position information of a defect box corresponding to the defect.

According to another aspect of the embodiments of the present disclosure, a defect image classification method is further provided, including: determining a defect image to be detected and a template image corresponding to the defect image to be detected; inputting the defect image to be detected and the template image into a target defect detection model, and acquiring defect position information and defect category information output by the target defect detection model, where the target defect detection model is configured to extract a third image feature of the defect image to be detected and a fourth image feature of the template image, and output the defect position information and the defect category information according to the third image feature and the fourth image feature; determining a preset number of target defects in the defect image to be detected closest to a center point of the defect image to be detected according to the defect position information; and determining a category confidence of each target defect among the preset number of target defects, and determining that a defect category of the target defect with the largest category confidence is a defect category of the defect image to be detected.

According to another aspect of the embodiments of the present disclosure, an apparatus for training a defect detection model is further provided, including: an input component, configured to acquire a training sample set and first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes a defect image and a template image corresponding to the defect image, and the first defect label information includes first category information and first position information of each defect in the defect image; a first processing component, configured to determine a target loss function, where the target loss function includes a defect category loss function and a defect position loss function; and a second processing component, configured to, by means of using SGD, train a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, where the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected.

According to another aspect of the embodiments of the present disclosure, a nonvolatile storage medium is further provided. A program is stored in the nonvolatile storage medium. The program, when running,

controls a device where the nonvolatile storage medium is located to perform the method for training the defect detection model, or the defect image classification method.

According to another aspect of the embodiments of the present disclosure, an electronic device is further provided. The electronic device includes a memory and a processor. The processor is configured to run a program stored in the memory. The program, when running, performs the method for training the defect detection model, or the defect image classification method.

In the embodiments of the present disclosures, by acquiring the training sample set and the first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes the defect image and the template image corresponding to the defect image, and the first defect label information includes the first category information and the first position information of each defect in the defect image; determining the target loss function, where the target loss function includes the defect category loss function and the defect position loss function; and by means of using the SGD, training the model to be trained with the training sample set, the defect label information, and the target loss function to obtain the target defect detection model, where the target defect detection model is configured to determine the defect position information and the defect category information in the defect image to be detected, the model to be trained is configured to extract the first image feature of the defect image and the second image feature of the template image, and output the second label information of the defect image according to the first image feature and the second image feature, where the second label information includes the second category information and the second position information of each defect in the defect image determined by the model to be trained, the defect detection model is trained with the training sample set including the defect images and the template images and the defect label information, so that the purpose of acquiring the defect detection model capable of using the template image in the defect recognition process is achieved, thereby achieving the technical effect of using the template image to assist in classification and recognition in the process of performing defect recognition and classification on the die image, and then solving the technical problem in the related art of poor recognition and classification results caused by not using the template image when performing defect recognition and classification on the die image.

Brief Description of the Drawings

The drawings described herein are used to provide a further understanding of the present disclosure, and constitute a part of the present disclosure, and the exemplary embodiments of the present disclosure and the description thereof are used to explain the present disclosure, but do not constitute improper limitations to the present disclosure. In the drawings:

Fig. 1 is a schematic structural diagram of a computer terminal according to some embodiments of the present disclosure.

Fig. 2 is a flowchart of a method for training a defect detection model according to some embodiments of the present disclosure.

Fig. 3a is a schematic diagram of a golden die image according to some embodiments of the present disclosure.

Fig. 3b is a schematic diagram of a defect image and a template image according to some embodiments of the present disclosure.

Fig. 4 is a flowchart of a training sample set acquisition method according to some embodiments of the present disclosure.

Fig. 5 is a flowchart of a method for training a defect detection model based on a training sample set and defect label information according to some embodiments of the present disclosure.

Fig. 6 is a flowchart of a method for acquiring second label information according to some embodiments of the present disclosure.

Fig. 7 is a schematic diagram of a model structure of a defect detection model according to some embodiments of the present disclosure.

Fig. 8 is a schematic diagram of a model structure of another defect detection model according to some embodiments of the present disclosure.

Fig. 9 is a flowchart of a method for screening a defect detection model according to some embodiments of the present disclosure.

Fig. 10 is a flowchart of a defect image classification method according to some embodiments of the present disclosure.

Fig. 11 is a flowchart of a model training and classification process according to some embodiments of the present disclosure.

Fig. 12 is a schematic structural diagram of an apparatus for training a defect model according to some embodiments of the present disclosure.

Detailed Description of the Embodiments

In order to enable those skilled in the art to better understand the solutions of the present disclosure, the technical solutions in the embodiments of the present disclosure will be clearly and completely described below in combination with the drawings in the embodiments of the present disclosure. It is apparent that the described embodiments are only part of the embodiments of the present disclosure, not all the embodiments. All other embodiments obtained by those of ordinary skill in the art on the basis of the embodiments in the present disclosure without creative work shall fall within the scope of protection of the present disclosure.

It is to be noted that the terms "first", "second" and the like in the specification, claims and the above drawings of the present disclosure are used for distinguishing similar objects rather than describing a specific sequence or a precedence order. It should be understood that the data used in such a way may be exchanged where appropriate, in order that the embodiments of the present disclosure described here can be implemented in an order other than those illustrated or described herein. In addition, the terms "include" and "have" and any variations thereof are intended to cover non-exclusive inclusions. For example, it is not limited for processes, methods, systems, products or devices containing a series of steps or units to clearly list those steps or units, and other steps or units which are not clearly listed or are inherent to these processes, methods, products or devices may be included instead.

With the development of semiconductor device technology, there are more and more processes for manufacturing semiconductor devices, the main purpose of which is to manufacture circuits and electronic components in a die, such as transistors, capacitors, and logic switches, for example, by performing oxidation and chemical vapor deposition on a die surface, followed by coating, exposure, development, etching, ion

implantation, metal sputtering, and other steps, and finally completing processing and manufacturing of multiple layers of circuits and components on the die. However, due to a certain complexity of each process in the manufacturing process, the processing of the die in each process may produce some unexpected structures at different layers, and these structures may cause the circuit on a chip to fail to work normally, which are usually called die defects.

In order to eliminate the die defects, a die defect detection step may be arranged after many key processes in the chip manufacturing process to monitor the key processes and ensure their correctness. However, due to the extremely complex process of chip manufacturing and various types of die defects, there is no unified classification manner at present. At present, Automated Optical Inspection (AOI) usually uses conventional vision, i.e., image difference (target die and golden die) or threshold segmentation detection algorithms to perform positioning detection on the defects on the die. However, due to the complex die background, various processes, and different die patterns, although the use of conventional visual algorithms can achieve defect positioning, it is almost impossible to manually extract defect features for classification. Often, after formulating a series of rules (defect patterns and defect shape and size thereof, grayscale values of defect position areas, defect signal strength, etc.), the classification results obtained by screening are not accurate, and there are many over-detection and false detection phenomena. Therefore, most of the time, die defect classification depends heavily on the original manual re-inspection method, and manual classification operations have the disadvantages of slow speed and poor consistency/reliability, and are easily affected by external factors, which enables die defect classification to have certain technical bottlenecks.

In addition, in recent years, with the rapid research and development of deep learning algorithms and hardware devices, especially the iterative optimization of neural networks in the fields of target classification, target detection, and target segmentation, automated defect detection/classification in the field of semiconductors has been increasingly applied to deep learning algorithm technology to achieve increasingly higher detection/classification precision.

However, the related art depends on feature extraction technology when performing defect recognition and classification, and the defects on the dies with complex background are only recognized by a few manually selected features, and the resulting model classification performance is limited. Convolutional neural networks can automatically learn and extract features suitable for classification, thereby improving the detection and classification performance. However, in actual production, the die background is complex, the texture is numerous, the defect features are not obvious, and the features of different types of defects are similar and difficult to distinguish. How to ignore the useless background and accurately extract the features of defect areas of interest is the key and difficult point of the die defect detection and classification. Therefore, there is a problem of being unable to efficiently and accurately determine the fault type in the die image and classify the fault. In order to solve this problem, a relevant solution is provided in the embodiments of the present disclosure, which is described in detail below.

According to the embodiments of the present disclosure, a method embodiment of a method for training a defect detection model is provided. It is to be noted that the steps shown in the flowchart of the drawings may be executed in a computer system, such as a set of computer-executable instructions, and although a logical sequence is shown in the flowchart, in some cases, the steps shown or described may be executed in a different order than here.

The method embodiment provided in the embodiments of the present disclosure may be implemented in a mobile terminal, a computer terminal or a similar computing apparatus. Fig. 1 shows a block diagram of a hardware structure of a computer terminal (or a mobile device) configured to implement a method for training

a defect detection model. As shown in Fig. 1, a computer terminal 10 (or a mobile device 10) may include one or more (shown as 102a, 102b, ..., 102n in the figure) processors 102 (the processors 102 may include, but are not limited to, a Micro Controller Unit (MCU) or a Field Programmable Gate Array (FPGA), and other processing apparatuses), a memory 104 configured to store data, and a transmission apparatus 106 for communication functions. In addition, the above computer terminal may further include: a display, an Input/Output interface (I/O interface), a Universal Serial Bus (USB) port (which may be included as one of ports of a BUS bus), a network interface, a power supply, and/or a camera. Those of ordinary skill in the art may understand that the structure shown in Fig. 1 is merely illustrative, and does not limit the structure of the above electronic apparatus. For example, the computer terminal 10 may further include more or fewer components than shown in Fig. 1, or has a different configuration from that shown in Fig. 1.

It is to be noted that one or more processors 102 and/or other data processing circuits may be generally referred to herein as "data processing circuits". The data processing circuit may be embodied in whole or in part as software, hardware, firmware, or any other combination. Further, the data processing circuit may be a single and stand-alone processing module, or combined in whole or in part into any of other elements of the computer terminal 10 (or the mobile device). As referred to in the embodiments of the present disclosure, the data processing circuit acts as a processor control (such as selection of a variable resistance terminal path connected to the interface).

The memory 104 may be configured to store a software program and a module of application software, such as a program instruction/data storage apparatus corresponding to the method for training the defect detection model in the embodiments of the present disclosure, and the processor 102 performs various functional applications and data processing by running the computer program and the module stored in the memory 104, that is, implements the above method for training the defect detection model method for the application program. The memory 104 may include a high speed Random Access Memory (RAM) and may further include a nonvolatile memory such as one or more magnetic storage apparatuses, a flash memory, or other nonvolatile solid state memories. In some examples, the memory 104 may further include memories remotely set relative to the processor 102, which may be connected to the computer terminal 10 through a network. Examples of the above network include, but are not limited to, the Internet, the Intranet, a local area network, a mobile communication network, and a combination thereof.

The transmission apparatus 106 is configured to receive or transmit data through a network. A specific example of the above network may include a wireless network provided by a communication provider of the computer terminal 10. In one example, the transmission apparatus 106 includes a Network Interface Controller (NIC), which may be connected with other network devices through a base station, thereby communicating with the Internet. In one example, the transmission apparatus 106 may be a Radio Frequency (RF) module, which is configured to communicate with the Internet in a wireless manner.

The display may be, for example, a touch screen type Liquid Crystal Display (LCD) that enables a user to interact with a user interface of the computer terminal 10 (or the mobile device).

In the above operating environment, the embodiments of the present disclosure provide a method for training a defect detection model, as shown in Fig. 2, the method includes the following steps.

At S202, a training sample set and first defect label information corresponding to each group of samples in the training sample set are acquired, where each group of samples in the training sample set includes a defect image and a template image corresponding to the defect image, and the first defect label information includes first category information and first position information of each defect in the defect image.

In the technical solution provided in S202, the defect image and the template image in the sample image are as shown in Fig. 3b. As can be seen from Fig. 3b, the template image and the defect image correspond to the same position in a die image, and the only difference is that there are no defects or flaws in the template image.

As one alternative implementation, after determining the position information of the defect image in the die image, the corresponding template image may be acquired from a golden die image as shown in Fig. 3a according to the position information, where the golden die image refers to an image without any defects or flaws. The golden die image is usually stored in an AOI.

In addition, the first category information in S202 includes a category number of the defect. Alternatively, defect categories to be recognized and the corresponding category numbers in the die image may be determined in advance, for example, assuming that the defect categories to be recognized include eight categories such as opening dirt, line dirt, opening damage, line etching, adhesive surface damage, poor development, line bridging, and edge pressing, the corresponding category numbers may be {0, 1, 2, 3, 4, 5, 6, 7} in sequence.

The first position information in S202 includes coordinate information of a defect box corresponding to the defect in the image. Alternatively, tools such as labelling may be used to perform defect box labeling on all the defects in the defect image, and in the process of labeling, images that cannot be analyzed and labeled can be filtered out.

Alternatively, the above first defect label information may be stored in the form of a label file. Each row in the label file may record the relevant information of one defect in the defect image in the format: [x0, y0, x1, y1, category label], where x0 represents a horizontal coordinate of an upper left corner of the defect box, y0 represents a vertical coordinate of the upper left corner of the defect box, x1 represents a horizontal coordinate of a lower right corner of the defect box, and y1 represents a vertical coordinate of the lower right corner of the defect box. Since sides of the defect box are parallel to one side of the defect image, only the two coordinates of the upper left corner and the lower right corner of the defect box are needed to determine the position of the defect box, and then the position of the defect is determined. It is to be noted that the coordinates of the upper left corner and the lower right corner of the defect box are coordinates of these two points in a defect plane rectangular coordinate system, and the defect plane rectangular coordinate system is a plane rectangular coordinate system established in the defect image.

As one alternative implementation, in order to efficiently train the defect detection model with limited die defect data, the training sample set may also be processed using a training sample set acquisition method as shown in Fig. 4. As shown in Fig. 4, the method includes the following steps.

At S402, a first defect image and a first template image corresponding to the first defect image are acquired.

At S404, geometric transformation processing is performed on the first defect image and the first template image in the same processing manner, the first defect image subjected to the geometric transformation processing is taken as the defect image sample, and the first template image subjected to the geometric transformation processing is taken as the template image sample, where the processing manner includes at least one of the following: random cropping, image flipping, and image stitching.

Alternatively, the cropping scale range of the random cropping is user-definable, for example, set to 70% to 130% of the original image size, and a pixel value of a blank part of the cropped image may be set to zero.

When flipping, multiple rows or columns of pixels in the image may be flipped horizontally or vertically according to a preset probability. For image stitching, the image may be processed using R-Stitch stitching and other manners.

After sorting out the sample data in this manner, the training batches in the training process are indirectly increased, the problem of unbalanced category distribution is solved, the diversity of samples is increased, the occurrence of over-fitting in the training process is effectively prevented, and the robustness of the model to the size of an image to be detected is improved.

At S204, a target loss function is determined, where the target loss function includes a defect category loss function and a defect position loss function.

In the technical solution provided in S204, the defect category loss function may be a cross-entropy loss function, and the defect position loss function may be a smooth L1 loss function.

At S206, by means of using SGD, a model to be trained is trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, where the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second label information of the defect image according to the first image feature and the second image feature, where the second label information includes second category information and second position information of each defect in the defect image determined by the model to be trained.

In the technical solution provided in S206, a specific process of training the target defect detection model is shown in Fig. 5, and includes the following steps.

At S502, the defect image and the template image are respectively input into the model to be trained, and the second label information output by the model to be trained is acquired, where the second label information includes the second category information and the second position information of each defect in the defect image determined by the model to be trained.

At S504, the first category information and the second category information are input into the defect category loss function to obtain a first loss function value, the first position information and the second position information are input into the defect position loss function to obtain a second loss function value, and the first loss function value and the second loss function value are stored.

At S506, by means of using the SGD, model parameters of the model to be trained are adjusted through the first loss function value and the second loss function value.

It is to be noted that official pre-training weights may be loaded as initial model parameters of the model to be trained. Since the officially provided pre-training weights are trained on an open source data set ImageNet containing a large number of sample images, the use of pre-training weights may enable the model to be trained to better learn the features of a target bottom layer, thereby greatly alleviating the problem of over-fitting caused by too few samples in the training sample set, and speeding up the convergence of the model.

At S508, all the stored first loss function values and the second loss function values are acquired, and in a case where the first loss function values and the second loss function values meet a preset condition, it is determined that the adjusted model to be trained is the target defect detection model, otherwise S502 is

jumped.

The above preset condition may be that neither the first loss function value nor the second loss function value fluctuates. For example, a difference between any two first loss function values among a consecutive preset number of first loss function values is less than a first preset difference, and a difference between any two second loss function values among a consecutive preset number of second loss function values is less than a second preset difference.

Alternatively, the common cross-entropy loss is taken as a loss calculation function of the category, a smooth L1 loss is taken as a loss calculation function of a real coordinate box, and classical SGD is taken as an optimizer for back propagation of the network. The training set is fed into the above model to be trained in batches, and an output (second label information) is calculated by the forward propagation process of the neural network, the loss function value is calculated by comparing the output with a real value (first label information), and then the model parameters are updated by the back propagation process (SGD). The training is repeated until the loss function value remains stable and no longer changes significantly.

In the technical solution provided in S502, the specific method of acquiring the second label information is as shown in Fig. 6, and includes the following steps.

At S602, the defect image and the template image are input into a backbone network of the model to be trained, where the backbone network is configured to extract image features in the defect image and the template image, thereby obtaining a defect feature image and a template feature image.

At S604, the second label information output by the model to be trained is acquired according to the defect feature image and the template feature image.

Alternatively, compared with the model in the related art, the model to be trained provided in the embodiments of the present disclosure needs to input the defect image and the template image at the same time, so that two backbone networks of the same structure extract the image features of the defect image and the template image at the same time. The structure of the backbone network may select the appropriate parameter amount and network type according to the existing hardware memory conditions, such as VGG series, ResNet series, RegNet series, Efficient series, and MobileNet series.

The model to be trained provided in the embodiments of the present disclosure further includes a feature fusion layer and a feature pyramid layer. The feature fusion layer is configured to obtain a first target feature image according to the defect feature image and the template feature image, and input the first target feature image into the feature pyramid layer. The feature pyramid layer is configured to output the second label information according to the first target feature image.

Alternatively, as one alternative implementation, as shown in Fig. 7, the above feature fusion layer includes a first feature fusion layer. The first feature fusion layer is configured to perform a differential operation on the defect feature image and the template feature image to obtain a differential feature image, where a pixel value of any pixel in the differential feature image is equal to an absolute value of a difference between a defect pixel and a template pixel corresponding to the any pixel, the defect pixel is a pixel corresponding to the any pixel in the defect feature image, and the template pixel is a pixel corresponding to the any pixel in the template feature image; perform channel stitching processing on the differential feature image and the defect feature image to obtain a second target feature image; and perform convolution processing on the second target feature image through a target convolution kernel to obtain the first target feature image.

In some embodiments, the structure of the model to be trained may also be as shown in Fig. 8. As can be seen from Fig. 8, the above feature fusion layer includes a second feature fusion layer. The second feature fusion layer is configured to perform convolution processing on the defect feature image and the template feature image respectively through a target convolution kernel, and generate the first target feature image according to the defect feature image and the template feature image after the convolution processing, where a pixel value of any pixel in the first target feature image is equal to a sum of pixel values of a defect pixel and a template pixel corresponding to the any pixel.

The models to be trained shown in Fig. 7 and Fig. 8 may both efficiently use the information of the template image to position defects or flaws in the defect image. The difference is that in the model shown in Fig. 7, a difference image between the defect image and the template image is first obtained, and then the difference image and the defect image are subjected to channel splicing (i.e., the addition on an image channel, which is equivalent to expanding to twice the number of original channels of the feature image) and then are sent to the subsequent feature pyramid layer after channel reduction processing through a 1×1 convolution kernel. The solution used in Fig. 8 is to directly superimpose the defect image and the template image, and then send them to the subsequent feature pyramid layer.

In order to ensure the training effect, multiple models to be trained may also be trained at the same time, and after the training is completed, a verification set is input into each model, mAP is calculated, and the model with the highest mAP is selected as the final target model. The specific process is as shown in Fig. 9, and includes the following steps.

At S902, a verification sample set and third defect label information corresponding to each group of samples in the verification sample set are acquired, where each group of samples in the verification sample set includes a defect image and a template image corresponding to the defect image, and the third defect label information includes third category information and third position information of each defect in the defect image.

It is to be noted that the verification sample set may perform geometric transformation processing on the images in the verification sample set using the same processing method as the training sample set.

At S904, in a case where the number of adjusted models to be trained is multiple, mAP of each of the multiple adjusted models to be trained is determined through the verification sample set and the third defect label information.

At S906, it is determined that the adjusted model to be trained with the largest mAP is the target defect detection model.

By acquiring the training sample set and the first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes the defect image and the template image corresponding to the defect image, and the first defect label information includes the first category information and the first position information of each defect in the defect image; determining the target loss function, where the target loss function includes the defect category loss function and the defect position loss function; and by means of using the SGD, training the model to be trained with the training sample set, the defect label information, and the target loss function to obtain the target defect detection model, where the target defect detection model is configured to determine the defect position information and the defect category information in the defect image to be detected, the die defect detection and classification based on template image feature matching are achieved, die background information

obtained in the previous detection process is fully utilized, the template image intercepted from the defect-free golden die and the defect image are taken as an input end of a network model, and the feature images after feature extraction are matched and fused. This method efficiently uses the information of the template image, avoids the interference of circuit boards with the complex background, and due to the translation invariance of the neural network, effectively reduces the impact caused by slight misalignment of the template image and the defect image, and reduces the dependence on data preprocessing. Compared with the conventional visual inspection algorithm and the neural network model of a single input network, the problem that the conventional visual inspection algorithm depends too much on manual feature extraction when classifying the die defects with the complex background is solved, and the problem that the single input network ignores the unique golden die information in the AOI and cannot reasonably use the existing die background information for defect feature extraction is also solved.

In addition, although the model to be detected provided in the embodiments of the present disclosure may input the defect image and the template image at the same time, since the backbone networks used by the two images are the same, the parameter amount of the model is hardly increased, thereby ensuring the reasoning speed of the model.

Moreover, in the embodiments of the present disclosure, by means of using a data enhancement method such as pre-training weight fine-tuning and on-line random geometric transformation and splicing, the problem of unbalanced category distribution is solved without additional data amount (data storage space), the diversity of samples is increased, the occurrence of over-fitting phenomenon in the network training process is effectively prevented, and the robustness of the model to the size of the image to be detected is improved.

Moreover, the feature matching fusion model structure in the present disclosure is applicable to the transformation of any neural network, including classification, detection, segmentation, etc., is not limited to the field of die defect detection, and is applicable to the field of defect detection in all complex background scenarios, and has strong universality.

The embodiments of the present disclosure provide a defect image classification method. Fig. 10 is a flowchart of a defect image classification method. As shown in Fig. 10, the method includes the following steps.

At S1002, a defect image to be detected and a template image corresponding to the defect image to be detected are determined.

At S1004, the defect image to be detected and the template image are input into a target defect detection model, and defect position information and defect category information output by the target defect detection model are acquired, where the target defect detection model is configured to extract a third image feature of the defect image to be detected and a fourth image feature of the template image, and output the defect position information and the defect category information according to the third image feature and the fourth image feature.

At S1006, a preset number of target defects in the defect image to be detected closest to a center point of the defect image to be detected are determined according to the defect position information.

At S1008, a category confidence of each target defect among the preset number of target defects is determined, and it is determined that a defect category of the target defect with the largest category confidence is a defect category of the defect image to be detected.

Alternatively, when the positions and category labels of all defects in the defect image are obtained, the category with the largest category confidence in topk (k may take any value, such as 3) detection boxes closest to the center point of the image is selected as the final defect category of the current image.

Because there may be multiple defects of different types and different positions in the defect image obtained in actual production, a simple classification network often cannot obtain an accurate category of an area of interest (a single classification model may not converge, and a multi-classification model cannot determine a category position). In the embodiments of the present disclosure, a target detection model is designed to perform defect positioning and classification detection on the defect image first, and then the final category is determined by a distance from the area of interest and the category confidence, thereby ensuring the normal convergence of the model while obtaining an accurate category label.

The embodiments of the present disclosure further provide an actual application process of model training and image classification. Fig. 11 is a flowchart of a model training and classification process. As shown in Fig. 11, first, in the model training process, after acquiring the defect image, the AOI may intercept the corresponding template image in the golden die image according to the defect image, and generate the label file of the defect image. Then, the defect image and the template image may be subjected to the processing such as geometric transformation and R-stitch stitching. After the processing is completed, the processed images are divided into the training set and the verification set according to a certain proportion. The training set is configured to train the model to be trained. In the training process, the loss function may be constructed to determine whether the training process is completed, and the model parameters may be updated by the back propagation method. Alternatively, the training completion may be determined when the function value of the loss function remains stable. When the trained model is verified using the verification set, the verification set may be input into the trained model, the mAP corresponding to each model is calculated, and it is determined that the model with the highest mAP is the finally obtained best model.

When applying the best model to a task of image classification, first, the AOI intercepts the corresponding template image from the golden die image according to the image to be detected, and inputs the template image and the image to be detected into the best model. The best model may determine the positions and types of all the defects in the image to be detected, and determines the category of the image to be detected according to the categories of several defects boxes closest to the center of the image to be detected. Alternatively, the defect category corresponding to the defect box with the highest confidence among these defect boxes may be taken as the category of the image to be detected.

The embodiments of the present disclosure provide an apparatus for training a defect detection model. Fig. 12 is a schematic structural diagram of the apparatus. As shown in Fig. 12, the apparatus includes: an input component 120, configured to acquire a training sample set and first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes a defect image and a template image corresponding to the defect image, and the first defect label information includes first category information and first position information of each defect in the defect image; a first processing component 122, configured to determine a target loss function, where the target loss function includes a defect category loss function and a defect position loss function; and a second processing component 124, configured to, by means of using SGD, train a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, where the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second

label information of the defect image according to the first image feature and the second image feature, where the second label information includes second category information and second position information of each defect in the defect image determined by the model to be trained.

In some embodiments of the present disclosure, the step that the second processing component 124 trains the model to be trained by means of using the SGD with the training sample set, the defect label information, and the target loss function to obtain the target defect detection model includes that: S1, respectively inputting the defect image and the template image into the model to be trained, and acquiring the second label information output by the model to be trained, where the second label information includes the second category information and the second position information of each defect in the defect image determined by the model to be trained; S2, inputting the first category information and the second category information into the defect category loss function to obtain a first loss function value, inputting the first position information and the second position information into the defect position loss function to obtain a second loss function value, and storing the first loss function value and the second loss function value; S3, by means of using the SGD, adjusting model parameters of the model to be trained through the first loss function value and the second loss function value; and S4, acquiring all the stored first loss function values and the second loss function values, and in a case where a difference between any two first loss function values among a consecutive preset number of first loss function values is less than a first preset difference, and a difference between any two second loss function values among a consecutive preset number of second loss function values is less than a second preset difference, determining that the adjusted model to be trained is the target defect detection model, otherwise jumping to S1.

In some embodiments of the present disclosure, the step that the second processing component 124 respectively inputs the defect image and the template image into the model to be trained, and acquires the second label information output by the model to be trained includes: inputting the defect image and the template image into a backbone network of the model to be trained, where the backbone network is configured to extract image features in the defect image and the template image, thereby obtaining a defect feature image and a template feature image; and acquiring the second label information output by the model to be trained according to the defect feature image and the template feature image.

In some embodiments of the present disclosure, the model to be trained further includes a feature fusion layer and a feature pyramid layer. The feature fusion layer is configured to obtain a first target feature image according to the defect feature image and the template feature image, and input the first target feature image into the feature pyramid layer. The feature pyramid layer is configured to output the second label information according to the first target feature image.

In some embodiments of the present disclosure, the feature fusion layer includes a first feature fusion layer. The first feature fusion layer is configured to perform a differential operation on the defect feature image and the template feature image to obtain a differential feature image, where a pixel value of any pixel in the differential feature image is equal to an absolute value of a difference between a defect pixel and a template pixel corresponding to the any pixel, the defect pixel is a pixel corresponding to the any pixel in the defect feature image, and the template pixel is a pixel corresponding to the any pixel in the template feature image; perform channel stitching processing on the differential feature image and the defect feature image to obtain a second target feature image; and perform convolution processing on the second target feature image through a target convolution kernel to obtain the first target feature image.

In some embodiments of the present disclosure, the feature fusion layer includes a second feature fusion layer. The second feature fusion layer is configured to perform convolution processing on the defect feature

image and the template feature image respectively through a target convolution kernel, and generate the first target feature image according to the defect feature image and the template feature image after the convolution processing, where a pixel value of any pixel in the first target feature image is equal to a sum of pixel values of a defect pixel and a template pixel corresponding to the any pixel.

In some embodiments of the present disclosure, the step that the second processing component 124 determines that the adjusted model to be trained is the target defect detection model includes: acquiring a verification sample set and third defect label information corresponding to each group of samples in the verification sample set, where each group of samples in the verification sample set includes a defect image and a template image corresponding to the defect image, and the third defect label information includes third category information and third position information of each defect in the defect image; in a case where the number of adjusted models to be trained is multiple, determining mAP of each of the multiple adjusted models to be trained through the verification sample set and the third defect label information; and determining that the adjusted model to be trained with the largest mAP is the target defect detection model.

In some embodiments of the present disclosure, the step that the input component 120 acquires the training sample set includes: acquiring a first defect image and a first template image corresponding to the first defect image; and performing geometric transformation processing on the first defect image and the first template image in the same processing manner, taking the first defect image subjected to the geometric transformation processing as the defect image sample, and taking the first template image subjected to the geometric transformation processing as the template image sample, where the processing manner includes at least one of the following: random cropping, image flipping, and image stitching.

In some embodiments of the present disclosure, the category information includes a defect category number of the defect, and the position information includes position information of a defect box corresponding to the defect.

It is to be noted that, each module in the above apparatus for training the defect detection model may be a program module (for example, a program instruction set implementing a certain specific function) or may be a hardware module. For the latter, it may be implemented in the following manners, but is not limited to the follow: each module is expressed as a processor, or, the function of each module is implemented through the processor.

The embodiments of the present disclosure further provide a nonvolatile storage medium. A program is stored in the nonvolatile storage medium. The program, when running, controls a device where the nonvolatile storage medium is located to perform the following method for training the defect detection model, including: acquiring a training sample set and first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes a defect image and a template image corresponding to the defect image, and the first defect label information includes first category information and first position information of each defect in the defect image; determining a target loss function, where the target loss function includes a defect category loss function and a defect position loss function; and by means of using SGD, training a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, where the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second label information of the defect image according to the first image feature and the second image feature, where the second label information includes second category information and second position information of each defect in the defect

image determined by the model to be trained.

In some embodiments of the present disclosure, the program, when running, may also control the device where the nonvolatile storage medium is located to perform the following defect image classification method, including: determining a defect image to be detected and a template image corresponding to the defect image to be detected; inputting the defect image to be detected and the template image into a target defect detection model, and acquiring defect position information and defect category information output by the target defect detection model, where the target defect detection model is configured to extract a third image feature of the defect image to be detected and a fourth image feature of the template image, and output the defect position information and the defect category information according to the third image feature and the fourth image feature; determining a preset number of target defects in the defect image to be detected closest to a center point of the defect image to be detected according to the defect position information; and determining a category confidence of each target defect among the preset number of target defects, and determining that a defect category of the target defect with the largest category confidence is a defect category of the defect image to be detected.

The embodiments of the present disclosure further provide an electronic device. The electronic device includes a memory and a processor. The processor is configured to run a program stored in the memory. The program, when running, controls a device where the nonvolatile storage medium is located to perform the following method for training the defect detection model, including: acquiring a training sample set and first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes a defect image and a template image corresponding to the defect image, and the first defect label information includes first category information and first position information of each defect in the defect image; determining a target loss function, where the target loss function includes a defect category loss function and a defect position loss function; and by means of using SGD, training a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, where the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second label information of the defect image according to the first image feature and the second image feature, where the second label information includes second category information and second position information of each defect in the defect image determined by the model to be trained.

In some embodiments of the present disclosure, the program, when running, may also perform the following defect image classification method, including: determining a defect image to be detected and a template image corresponding to the defect image to be detected; inputting the defect image to be detected and the template image into a target defect detection model, and acquiring defect position information and defect category information output by the target defect detection model, where the target defect detection model is configured to extract a third image feature of the defect image to be detected and a fourth image feature of the template image, and output the defect position information and the defect category information according to the third image feature and the fourth image feature; determining a preset number of target defects in the defect image to be detected closest to a center point of the defect image to be detected according to the defect position information; and determining a category confidence of each target defect among the preset number of target defects, and determining that a defect category of the target defect with the largest category confidence is a defect category of the defect image to be detected.

In the above embodiments of the present disclosure, the description of the embodiments has its own focus. For parts that are not described in detail in a certain embodiment, reference may be made to related descriptions of other embodiments.

In the several embodiments provided in the present disclosure, it should be understood that, the disclosed technical content may be implemented in other ways. The apparatus embodiments described above are merely illustrative. For example, the division of the units may be a logical function division, and there may be other divisions in actual implementation. For example, a plurality of units or components may be combined or integrated into another system, or some features may be ignored, or not implemented. In addition, the displayed or discussed mutual coupling or direct coupling or communication connection may be indirect coupling or communication connection through some interfaces, units or modules, and may be in electrical or other forms. The units described as separate components may or may not be physically separated.

The units described as separate components may or may not be physically separated. The components displayed as units may or may not be physical units, that is, the components may be located in one place, or may be distributed on the plurality of units. Part or all of the units may be selected according to actual requirements to achieve the purposes of the solutions of this embodiment.

In addition, functional units in the embodiments of the present disclosure may be integrated into one processing unit, or each of the units may exist alone physically, or two or more units are integrated into one unit. The above integrated unit may be implemented in the form of hardware, or may be implemented in the form of a software functional unit.

When being implemented in form of software functional unit and sold or used as an independent product, the integrated unit may be stored in a computer-readable storage medium. Based on this understanding, the technical solutions of the present disclosure essentially or the parts that contribute to the related art, or all or part of the technical solutions may be embodied in the form of a software product. The computer software product is stored in a storage medium, including a plurality of instructions for causing a computer device (which may be a personal computer, a server, or a network device, and the like) to execute all or part of the steps of the method described in the various embodiments of the present disclosure. The foregoing storage medium includes a USB flash disk, a Read-Only Memory (ROM), an RAM, and various media that may store program codes, such as a mobile hard disk, a magnetic disk, or an optical disk.

The above are only preferred implementations of the present disclosure, and it is to be noted that those of ordinary skill in the art may also make several improvements and refinements without departing from the principle of the present disclosure, and it should be considered that these improvements and refinements shall all fall within the scope of protection of the present disclosure.

Industrial Applicability

Embodiments of the present disclosure provide a method and apparatus for training a defect detection model, and an electronic device, which are applied to the field of image recognition. In the embodiments of the present disclosures, by acquiring a training sample set and first defect label information corresponding to each group of samples in the training sample set, where each group of samples in the training sample set includes a defect image and a template image corresponding to the defect image, and the first defect label information includes first category information and first position information of each defect in the defect image; determining a target loss function, where the target loss function includes a defect category loss function and

a defect position loss function; and by means of using SGD, training a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, where the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second label information of the defect image according to the first image feature and the second image feature, where the second label information includes second category information and second position information of each defect in the defect image determined by the model to be trained, the defect detection model is trained with the training sample set including the defect images and the template images and the defect label information, so that the purpose of acquiring the defect detection model capable of using the template image in the defect recognition process is achieved, thereby achieving the technical effect of using the template image to assist in classification and recognition in the process of performing defect recognition and classification on a die image, and then solving the technical problem in the related art of poor recognition and classification results caused by not using the template image when performing defect recognition and classification on the die image.

Claims

1. A method for training a defect detection model, comprising:

acquiring a training sample set and first defect label information corresponding to each group of samples in the training sample set, wherein each group of samples in the training sample set comprises a defect image and a template image corresponding to the defect image, and the first defect label information comprises first category information and first position information of each defect in the defect image;

determining a target loss function, wherein the target loss function comprises a defect category loss function and a defect position loss function; and

by means of using Stochastic Gradient Descent (SGD), training a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, wherein the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second label information of the defect image according to the first image feature and the second image feature, wherein the second label information comprises second category information and second position information of each defect in the defect image determined by the model to be trained.

2. The method for training the defect detection model as claimed in claim 1, wherein the step of, by means of using SGD, training the model to be trained with the training sample set, the defect label information, and the target loss function to obtain the target defect detection model comprises:

S1, respectively inputting the defect image and the template image into the model to be trained, and acquiring the second label information output by the model to be trained;

S2, inputting the first category information and the second category information into the defect category loss function to obtain a first loss function value, inputting the first position information and the second position information into the defect position loss function to obtain a second loss function value, and storing the first loss function value and the second loss function value;

S3, by means of using the SGD, adjusting model parameters of the model to be trained through the first loss function value and the second loss function value; and

S4, acquiring all the stored first loss function values and the second loss function values, and in a case where the first loss function values and the second loss function values meet a preset condition, determining that the adjusted model to be trained is the target defect detection model, otherwise jumping to S1, wherein the preset condition comprises that a sum of a consecutive preset number of first loss function values and second loss function values is within a target value range.

3. The method for training the defect detection model as claimed in claim 2, wherein the step of respectively inputting the defect image and the template image into the model to be trained, and acquiring the second label information output by the model to be trained comprises:

inputting the defect image and the template image into a backbone network of the model to be trained, wherein the backbone network is configured to extract image features in the defect image and the template image, thereby obtaining a defect feature image and a template feature image; and

acquiring the second label information output by the model to be trained according to the defect feature image and the template feature image.

4. The method for training the defect detection model as claimed in claim 3, wherein the model to be trained further comprises a feature fusion layer and a feature pyramid layer;

the feature fusion layer is configured to obtain a first target feature image according to the defect feature image and the template feature image, and input the first target feature image into the feature pyramid layer; and

the feature pyramid layer is configured to output the second label information according to the first target feature image.

5. The method for training the defect detection model as claimed in claim 4, wherein the feature fusion layer comprises a first feature fusion layer;

the first feature fusion layer is configured to perform a differential operation on the defect feature image and the template feature image to obtain a differential feature image, wherein a pixel value of any pixel in the differential feature image is equal to an absolute value of a difference between a defect pixel and a template pixel corresponding to the any pixel, the defect pixel is a pixel corresponding to the any pixel in the defect feature image, and the template pixel is a pixel corresponding to the any pixel in the template feature image; perform channel stitching processing on the differential feature image and the defect feature image to obtain a second target feature image; and perform convolution processing on the second target feature image through a target convolution kernel to obtain the first target feature image.

6. The method for training the defect detection model as claimed in claim 4, wherein the feature fusion layer comprises a second feature fusion layer;

the second feature fusion layer is configured to perform convolution processing on the defect feature image and the template feature image respectively through a target convolution kernel, and generate the first target feature image according to the defect feature image and the template feature image after the convolution processing, wherein a pixel value of any pixel in the first target feature image is equal to a

sum of pixel values of a defect pixel and a template pixel corresponding to the any pixel.

7. The method for training the defect detection model as claimed in claim 2, wherein the step of determining that the adjusted model to be trained is the target defect detection model comprises:

acquiring a verification sample set and third defect label information corresponding to each group of samples in the verification sample set, wherein each group of samples in the verification sample set comprises a defect image and a template image corresponding to the defect image, and the third defect label information comprises third category information and third position information of each defect in the defect image;

in a case where the number of adjusted models to be trained is multiple, determining mean Average Precision (mAP) of each of the multiple adjusted models to be trained through the verification sample set and the third defect label information; and

determining that the adjusted model to be trained with the largest mAP is the target defect detection model.

8. The method for training the defect detection model as claimed in claim 1, wherein the step of acquiring a training sample set comprises:

acquiring a first defect image and a first template image corresponding to the first defect image; and

performing geometric transformation processing on the first defect image and the first template image in the same processing manner, taking the first defect image subjected to the geometric transformation processing as the defect image sample, and taking the first template image subjected to the geometric transformation processing as the template image sample, wherein the processing manner comprises at least one of the following: random cropping, image flipping, and image stitching.

9. The method for training the defect detection model as claimed in claim 1, wherein the category information comprises a defect category number of the defect, and the position information comprises position information of a defect box corresponding to the defect.

10. A defect image classification method, comprising:

determining a defect image to be detected and a template image corresponding to the defect image to be detected;

inputting the defect image to be detected and the template image into a target defect detection model, and acquiring defect position information and defect category information output by the target defect detection model, wherein the target defect detection model is configured to extract a third image feature of the defect image to be detected and a fourth image feature of the template image, and output the

defect position information and the defect category information according to the third image feature and the fourth image feature;

determining a preset number of target defects in the defect image to be detected closest to a center point of the defect image to be detected according to the defect position information; and

determining a category confidence of each target defect among the preset number of target defects, and determining that a defect category of the target defect with the largest category confidence is a defect category of the defect image to be detected.

11. An apparatus for training a defect detection model, comprising:

an input component, configured to acquire a training sample set and first defect label information corresponding to each group of samples in the training sample set, wherein each group of samples in the training sample set comprises a defect image and a template image corresponding to the defect image, and the first defect label information comprises first category information and first position information of each defect in the defect image;

a first processing component, configured to determine a target loss function, wherein the target loss function comprises a defect category loss function and a defect position loss function; and

a second processing component, configured to, by means of using Stochastic Gradient Descent (SGD), train a model to be trained with the training sample set, the defect label information, and the target loss function to obtain a target defect detection model, wherein the target defect detection model is configured to determine defect position information and defect category information in a defect image to be detected, the model to be trained is configured to extract a first image feature of the defect image and a second image feature of the template image, and output second label information of the defect image according to the first image feature and the second image feature, wherein the second label information comprises second category information and second position information of each defect in the defect image determined by the model to be trained.

12. A nonvolatile storage medium, in which a program is stored, wherein the program, when running, controls a device where the nonvolatile storage medium is located to perform the method for training the defect detection model as claimed in any one of claims 1 to 9, or the defect image classification method as claimed in claim 10.

13. An electronic device, comprising: a memory and a processor, the processor being configured to run a program stored in the memory, wherein the program, when running, performs the method for training the defect detection model as claimed in any one of claims 1 to 9, or the defect image classification method as claimed in claim 10.