

METHOD AND DEVICE FOR FUNDUS-IMAGE SAMPLE EXPANSION, ELECTRONIC DEVICE, AND NON-TRANSITORY COMPUTER READABLE STORAGE MEDIUM

CROSS-REFERENCE TO RELATED APPLICATION(S)

[1] This application claims priority to Chinese Patent Application No. 201910878147.3, filed on September 17, 2019, and entitled “METHOD AND DEVICE FOR FUNDUS-IMAGE SAMPLE EXPANSION, MEDIUM, AND ELECTRONIC DEVICE”, the entire disclosure of which is hereby incorporated by reference.

TECHNICAL FIELD

[2] This disclosure relates to the field of machine learning application, and particularly to a method and device for fundus-image sample expansion, an electronic device, and a non-transitory computer readable storage medium.

BACKGROUND

[3] At present, artificial intelligence has made significant progress in fundus-image based lesion recognition. Deep convolutional neural network-based machine learning algorithms already assist in diagnosis of diseases such as glaucoma, diabetic retinopathy, and age-related macular degeneration by learning and analyzing fundus images. However, accuracy of a model is strongly dependent on its own training-data set, resulting in poor generalization ability of the model. In actual image collection, fundus images are usually captured by different models of fundus cameras, which leads to difference in image information such as image size, color distribution, and the like.

[4] In the field, model training is generally based on fundus images collected by a single device. For fundus images collected by multiple devices, algorithm performance of the model is, however, greatly reduced. Considering the problem of uneven distribution of data of multiple data sources, training data annotated with multiple data sources is usually adopted to improve the generalization ability of the model. However, the inventor of the disclosure realizes that using

the foregoing method requires a lot of human resources and time cost for training.

[5] It should be noted that, contents disclosed in Background are merely used to facilitate understanding of background of the disclosure, and therefore contents that do not constitute the related art known to those of ordinary skill in the art may be included.

SUMMARY

[6] In view of the above deficiencies, an object of the disclosure is to provide a method and device for fundus-image sample expansion, an electronic device, and a non-transitory computer readable storage medium.

[7] Technical solutions of the disclosure include the following.

[8] In a first aspect, a method for fundus-image sample expansion is provided. A first fundus-image initial sample and a second fundus-image initial sample are obtained, where the first fundus-image initial sample is based on a first fundus-image data source, and the second fundus-image initial sample is based on a second fundus-image data source. Feature extraction is performed on the first fundus-image initial sample to obtain first fundus-image initial feature data having a first data-source feature. Feature extraction is performed on the second fundus-image initial sample to obtain second fundus-image initial feature data having a second data-source feature. The first fundus-image initial feature data is converted into second fundus-image expansion feature data having the second data-source feature. The second fundus-image initial feature data is converted into first fundus-image expansion feature data having the first data-source feature. Image restoration is performed on the first fundus-image expansion feature data to obtain a first fundus-image expansion sample corresponding to the first fundus-image data source. Image restoration is performed on the second fundus-image expansion feature data to obtain a second fundus-image expansion sample corresponding to the second fundus-image data source.

[9] In a second aspect, a device for fundus-image sample expansion is provided. The device includes an initial-sample obtaining module, a feature-extraction module, a feature-data conversion module, and an image-restoration module. The initial-sample obtaining module is configured to obtain a first fundus-image initial sample and a second fundus-image initial sample, where the first fundus-image initial sample is based on a first fundus-image data source, and the second fundus-image initial sample is based on a second fundus-image data source. The feature-

extraction module is configured to perform feature extraction on the first fundus-image initial sample to obtain first fundus-image initial feature data having a first data-source feature, and perform feature extraction on the second fundus-image initial sample to obtain second fundus-image initial feature data having a second data-source feature. The feature-data conversion module is configured to convert the first fundus-image initial feature data into second fundus-image expansion feature data having the second data-source feature, and convert the second fundus-image initial feature data into first fundus-image expansion feature data having the first data-source feature. The image-restoration module is configured to perform image restoration on the first fundus-image expansion feature data to obtain a first fundus-image expansion sample corresponding to the first fundus-image data source, and perform image restoration on the second fundus-image expansion feature data to obtain a second fundus-image expansion sample corresponding to the second fundus-image data source.

[10] In a third aspect, an electronic device is provided. The electronic device includes a processor and a memory. The memory is configured to store fundus-image sample expansion programs which, when executed by the processor, cause the processor to execute the foregoing method for fundus-image sample expansion.

[11] In a fourth aspect, a non-transitory computer readable storage medium is provided. The computer readable storage medium is configured to store fundus-image sample expansion programs which, when executed by a processor, cause the processor to execute the foregoing method for fundus-image sample expansion.

[12] In a fifth aspect, a computer program product is provided. The computer program product includes a non-transitory computer readable storage medium configured to store computer programs. The computer programs are operable with a computer to execute the method described in the first aspect of implementations.

[13] According to the technical solutions of the disclosure, a user feature combination corresponding to an optimization target can be accurately and efficiently predicted through a machine learning model based on distinguishing features of some user feature combinations. As such, while improving practical effect of the model, it is conducive to reduce cost of sample collection and annotation and improve training efficiency of the model.

[14] It should be understood that, the above general description and the following detailed description are merely illustrative and explanatory, which however are not intended to limit the

disclosure.

BRIEF DESCRIPTION OF THE DRAWINGS

[15] Accompanying drawings described below are incorporated into specification and constitute a part of specification. The accompanying drawings applicable to implementations of the disclosure are illustrated, and the principles of the disclosure are interpreted with reference to the accompanying drawings and specification.

[16] FIG. 1 is a schematic flowchart illustrating a method for fundus-image sample expansion according to some implementations.

[17] FIG. 2 is a schematic flowchart of obtaining fundus-image initial samples according to some implementations.

[18] FIG. 3 is a schematic flowchart illustrating feature extraction performed on fundus-image initial samples according to some implementations.

[19] FIG. 4 is a schematic flowchart illustrating data conversion performed on fundus-image initial feature data according to some implementations.

[20] FIG. 5 is a schematic flowchart illustrating image restoration performed on fundus-image expansion feature data according to some implementations.

[21] FIG. 6 is a schematic flowchart of training models involved in sample expansion according to some implementations.

[22] FIG. 7 is a block diagram illustrating a device for fundus-image sample expansion according to some implementations.

[23] FIG. 8 is a block diagram illustrating an electronic device for implementing the method for fundus-image sample expansion according to some implementations.

[24] FIG. 9 is a schematic diagram illustrating a non-transitory computer readable storage medium for implementing the method for fundus-image sample expansion according to some implementations.

[25] While specific implementations of the disclosure have been illustrated with reference to the accompanying drawings, the following will give a detailed description. These accompanying drawings and related descriptions are not intended to limit the scope of the disclosure in any way, but to explain concepts of the disclosure for those skilled in the art by referring to specific implementations.

DETAILED DESCRIPTION

[26] Hereinafter, exemplary implementations will be described in detail, and examples thereof are illustrated in the accompanying drawings. Throughout the accompanying drawings related to implementations described hereinafter, same reference numerals in different figures generally refer to the same or similar elements unless otherwise indicates. Implementation manners described in the following exemplary implementations are not all implementation manners of the disclosure. On the contrary, the implementation manners are merely some examples of the device and method described in respective aspects of the disclosure and the appended claims.

[27] The exemplary implementations will be described below in a comprehensive manner with reference to the accompanying drawings. The exemplary implementations can be implemented in various forms, and the disclosure should not be construed as being limited to the disclosed examples but, on the contrary, is intended to describe the disclosure in a comprehensive and complete manner and fully convey the concepts of the exemplary implementations to those skilled in the art by providing these implementations. The described features, structures, or characteristics may be combined in one or more implementations in any suitable way.

[28] In addition, the accompanying drawings are merely illustrative and not necessarily drawn to scale. The same reference numerals in the figures represent the same or similar parts, and thus their repeated description will be omitted. Some of the block diagrams illustrated in the figures are functional entities and do not necessarily correspond to physically or logically independent entities. These functional entities may be implemented in a form of software, or implemented in one or more hardware modules or integrated circuits, or implemented in different networks and/or processor devices and/or microcontroller devices.

[29] In some implementations of the disclosure, a method for fundus-image sample expansion is provided. The method can be used for data expansion of fundus-image samples of different data sources. As such, distribution uniformity of fundus images can be improved. Fundus-image samples after data expansion is used as training samples to train a machine learning model, in this way, the cost of model training can be reduced and generalization ability of the model can be improved.

[30] As an example, in the related art, a fundus-image segmentation model can be trained based on fundus-image training sample set, and then the trained fundus-image segmentation model is used to segment optic cup and optic disc in a fundus image, to assist doctors in accurate diagnosis and pathological analysis of eye diseases. The fundus-image training sample set for example includes fundus-image samples of two fundus-image data sources. If a first fundus-image data source has a relatively large number of fundus-image samples and a second fundus-image data source has a relatively small number of fundus-image samples, when a fundus-image segmentation model trained based on the fundus-image training sample set performs a task of fundus-image segmentation, a fundus image corresponding to the first fundus-image data source generally obtains a better segmentation effect than a fundus image corresponding to the second fundus-image data source. In short, if the number of training samples corresponding to a certain data source is relatively small, an application effect of the model will be relatively poor. Therefore, distribution of training samples will directly affect the fundus-image segmentation model's ability to segment fundus images of different data sources.

[31] According to the method for fundus-image sample expansion of the implementations, fundus-image samples of different fundus-image data sources in the training sample set are expanded, so that fundus-image samples in the training sample set can correspond to a relatively uniform source distribution. In this way, the fundus-image segmentation model can obtain a relatively balanced image-segmentation ability for fundus images of different data sources. Accordingly, the generalization ability of the fundus-image segmentation model can be improved.

[32] Hereinafter, technical solutions of the disclosure will be described in detail with reference to specific exemplary implementations.

[33] FIG. 1 a schematic flowchart illustrating a method for fundus-image sample expansion according to some implementations. In some implementations, as illustrated in FIG. 1, the method for fundus-image sample expansion mainly includes the following.

[34] At block S110, a first fundus-image initial sample and a second fundus-image initial sample are obtained, where the first fundus-image initial sample is based on a first fundus-image data source, and the second fundus-image initial sample is based on a second fundus-image data source.

[35] In this implementation, sample expansion on fundus images from two data sources (i.e., the first fundus-image data source and the second fundus-image data source) can be

performed. As an example, the first fundus-image data source is a sample data set consisting of fundus images captured by a fundus camera (e.g., a Zeiss Visucam 500 fundus camera) and other fundus cameras with a similar shooting effect to the fundus camera; the second fundus-image data source is a sample data set consisting of fundus images captured by another fundus camera (e.g., a Canon CR-2 fundus camera) and other fundus cameras with a similar shooting effect to the fundus camera. As another example, the first fundus-image data source is a sample data set consisting of fundus images captured by a fundus camera in a certain imaging mode; the second fundus-image data source is a sample data set consisting of fundus images captured by the same fundus camera in another imaging mode.

[36] At block S120, perform feature extraction on the first fundus-image initial sample to obtain first fundus-image initial feature data having a first data-source feature, and perform feature extraction on the second fundus-image initial sample to obtain second fundus-image initial feature data having a second data-source feature.

[37] For fundus images of different data sources, image data itself of the fundus image has a feature representing a data source to a certain extent, such as the first data-source feature corresponding to the first fundus-image data source and the second data-source feature corresponding the second fundus-image data source. In appearance, differences in fetures of the two data sources appear to be differences in detailed information (e.g., color distribution of the image, etc.), however in essence, differences in fetures of the two data sources are reflected in deep fetures. In this step, perform feature extraction on the first fundus-image initial sample and the second fundus-image initial sample (obtained at block S110) respectively, to obtain the first fundus-image initial feature data and the second fundus-image initial feature data.

[38] At block S130, the first fundus-image initial feature data is converted into second fundus-image expansion feature data having the second data-source feature, and the second fundus-image initial feature data is converted into first fundus-image expansion feature data having the first data-source feature.

[39] Feature migration on the first fundus-image initial feature data and the second fundus-image initial feature data is performed in this step after obtaining the two initial feature data. As an example, shared features of the two initial feature data can be retained, and a mapping relationship can be established for difference features of the two initial feature data, to realize mutual conversion between the two initial feature data. In the process of mapping deep

difference features of fundus images of the two data sources for feature conversion, some shallow features of an initial fundus image (e.g., the size and shape of a target object in the fundus image) need to be retained, so that deviations between an expanded sample and the initial sample can be reduced to avoid excessive feature shifts.

[40] At block S140, perform image restoration on the first fundus-image expansion feature data to obtain a first fundus-image expansion sample corresponding to the first fundus-image data source, and perform image restoration on the second fundus-image expansion feature data to obtain a second fundus-image expansion sample corresponding to the second fundus-image data source.

[41] The first fundus-image expansion feature data and the second fundus-image expansion feature data can be obtained after feature data conversion. Then through a process opposite to the feature extraction performed at block S120, perform image restoration on the first fundus-image expansion feature data and the second fundus-image expansion feature data respectively. As such, the first fundus-image expansion sample corresponding to the first fundus-image data source and the second fundus-image expansion sample corresponding to the second fundus-image data source can be obtained. After the image restoration in this step, each first fundus-image initial sample obtained at block S110 generates a second fundus-image expansion sample corresponding to the first fundus-image initial sample, and each second fundus-image initial sample generates a first fundus-image expansion sample corresponding to the second fundus-image initial sample.

[42] According to the method for fundus-image sample expansion of the implementations of the disclosure, a relatively small number of fundus-image samples obtained from a different data source can be expanded, to obtain fundus-image samples with an increased number and evenly distributed data sources. Then related machine learning models are trained based on the expanded fundus-image samples. In this way, generalization ability of the model in terms of data sources can be improved. In addition, while improving practical effect of the model, it is conducive to reduce cost of sample collection and annotation and improve training efficiency of model.

[43] FIG. 2 is a schematic flowchart of obtaining fundus-image initial samples according to some implementations. As illustrated in FIG. 2, similar to the foregoing implementations, the operation of obtaining the first fundus-image initial sample and the second fundus-image initial

sample (where the first fundus-image initial sample is based on the first fundus-image data source and the second fundus-image initial sample is based on the second fundus-image data source) at block S110 includes the following.

[44] At block S210, fundus images are collected, and data source information of the fundus images is obtained.

[45] In this step, some fundus images are collected, and data source information of each of the fundus images can be obtained. The data source information may include information such as the type, brand, and model of a fundus camera used to capture each of the fundus images, or include information such as a shooting mode, a shooting parameter, and light-source information used when shooting the fundus images.

[46] At block S220, for each of the fundus images, whether data source of the fundus image is the first fundus-image data source, the second fundus-image data source, or a fundus-image data source to-be-determined is determined according to the data source information.

[47] For each of the fundus images, data source of the fundus image can be determined according to data source information of the fundus image. Specifically, the data source of each fundus image can be determined as the first fundus-image data source, the second fundus-image data source, or the fundus-image data source to-be-determined. As an example, the first fundus-image data source is a fundus-image data set captured by using a near-infrared light as a light source. The second fundus-image data source is a fundus-image data set captured by using a red-free light as a light source. The fundus-image data source to-be-determined includes a data source other than the first fundus-image data source and the second fundus-image data source. In addition, for a fundus image missing data source information, data source of the fundus image can also be determined as the fundus-image data source to-be-determined.

[48] At block S230, a fundus image whose data source is the first fundus-image data source is determined as the first fundus-image initial sample, and a fundus image whose data source is the second fundus-image data source is determined as the second fundus-image initial sample.

[49] The fundus images can be classified according to a result of determining data sources of respective fundus images at block S220. The fundus image whose data source is the first fundus-image data source is directly determined as the first fundus-image initial sample. The fundus image whose data source is the second fundus-image data source is directly determined as

the second fundus-image initial sample. The fundus image whose data source is the fundus-image data source to-be-determined will be further judged and classified in the next step.

[50] At block S240, a fundus image whose data source is the fundus-image data source to-be-determined is inputted into a pre-trained fundus-image classification model, and the fundus image is determined, according to an output result of the fundus-image classification model, as the first fundus-image initial sample, the second fundus-image initial sample, or a noise sample.

[51] For a fundus image whose data source is determined as the fundus-image data source to-be-determined, the fundus image can be inputted into the pre-trained fundus-image classification model in this step. The fundus-image classification model can perform feature recognition and matching on the inputted fundus image, and then can classify the inputted fundus image to a corresponding data-source label, and a classification probability of each data-source label can be outputted. If the first fundus-image data source has a relatively high classification probability, a fundus image corresponding to the first fundus-image data source can be determined as the first fundus-image initial sample. If the second fundus-image data source has a relatively high classification probability, a fundus image corresponding to the second fundus-image data source can be determined as the second fundus-image initial sample. If both the first fundus-image data source and the second fundus-image data source have a relatively low classification probability, a fundus image corresponding to the first fundus-image data source or the second fundus-image data source can be determined as a noise sample, and the fundus image is removed from an original sample set.

[52] FIG. 3 is a schematic flowchart illustrating feature extraction performed on fundus-image initial samples according to some implementations. As illustrated in FIG. 3, similar to the foregoing implementations, the operations of performing feature extraction on the first fundus-image initial sample to obtain the first fundus-image initial feature data having the first data-source feature, and performing feature extraction on the second fundus-image initial sample to obtain the second fundus-image initial feature data having the second data-source feature at block S120 include the following.

[53] At block S310, a pre-trained first encoder and a pre-trained second encoder are determined, where the first encoder is based on a convolutional neural network, and the second encoder is based on a convolutional neural network.

[54] At block S320, the first fundus-image initial sample is inputted into the first encoder,

and feature extraction on the first fundus-image initial sample is performed with the first encoder to obtain the first fundus-image initial feature data having the first data-source feature.

[55] At block S330, the second fundus-image initial sample is inputted into the second encoder, and feature extraction on the second fundus-image initial sample is performed with the second encoder to obtain the second fundus-image initial feature data having the second data-source feature.

[56] In this implementation, in order to perform accurate and efficient feature extraction on fundus-image initial samples, the first encoder for performing feature extraction on the first fundus-image initial sample and the second encoder for performing feature extraction on the second fundus-image initial sample can be trained in advance. The first encoder can use a convolutional neural network having a same model structure as the second encoder. After training the convolutional neural network based on different training data, the first encoder and the second encoder with different model parameters can be obtained. In this implementation, a fundus-image initial sample having a size of 256*256 pixels and 3 color channels is used as an input image for example. Convolution kernels of different sizes are moved on the input image and features are extracted to form a feature map. A feature map outputted by a convolutional layer is used as an input of a next convolutional layer for deeper feature extraction. In a convolution process, a non-linear activation layer (e.g., a ReLU layer) or a batch normalization layer (e.g., BN Floor) may be further included. After convolution performed by each convolution layer, a fundus-image initial feature data composed of 256 feature vectors having a size of 64*64 can be finally outputted.

[57] FIG. 4 is a schematic flowchart illustrating data conversion performed on fundus-image initial features data according to some implementations. As illustrated in FIG. 4, similar to the foregoing implementations, the operations of converting the first fundus-image initial feature data into the second fundus-image expansion feature data having the second data-source feature, and converting the second fundus-image initial feature data into the first fundus-image expansion feature data having the first data-source feature at block S130 include the following.

[58] At block S410, a pre-trained first transcoder and a pre-trained second transcoder are determined, where the first transcoder is based on a residual network, and the second transcoder is based on a residual network.

[59] At block S420, the first fundus-image initial feature data is inputted into the first

transcoder, and the first fundus-image initial feature data is converted, with the first transcoder, into the second fundus-image expansion feature data having the second data-source feature.

[60] At block S430, the second fundus-image initial feature data is inputted into the second transcoder, and the second fundus-image initial feature data is converted, with the second transcoder, into the first fundus-image expansion feature data having the first data-source feature.

[61] In this implementation, in order to realize mutual conversion of two types of data-source feature, the first transcoder for converting the first fundus-image initial feature data into the second fundus-image expansion feature data and the second transcoder for converting the second fundus-image initial feature data into the first fundus-image expansion feature data can be trained in advance. The first transcoder can use a convolutional neural network having a same structure as the second transcoder, for example, a residual network (e.g., ResNet) of the convolutional neural network. After training the residual network based on different training data, the first transcoder and the second transcoder with different model parameters can be obtained. After the fundus-image initial feature data is inputted into the residual network, the fundus-image initial feature data is convolved by multiple convolutional layers. A final convolution output result can be superimposed with the initially outputted fundus-image initial feature data, to obtain the fundus-image expansion feature data. Residual connection can preserve part of the original features while performing feature data conversion, thereby avoiding excessive feature deviations.

[62] FIG. 5 is a schematic flowchart illustrating image restoration performed on fundus-image expansion feature data according to some implementations. As illustrated in FIG. 5, similar to the foregoing implementations, the operations of perform image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source, and perform image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source at block S140 include the following.

[63] At block S510, a first decoder and a second decoder are determined, where the first decoder is based on a deconvolutional neural network and corresponds to the second encoder, and the second decoder is based on a deconvolutional neural network and corresponds to the first encoder.

[64] At block S520, the first fundus-image expansion feature data is inputted into the first

decoder, and perform, with the first decoder, image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source.

[65] At block S530, the second fundus-image expansion feature data is inputted into the second decoder, and perform, with the second decoder, image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source.

[66] In this implementation, in order to realize image restoration on the fundus-image expansion feature data, the first decoder for obtaining the first fundus-image expansion sample by restoring the first fundus-image expansion feature data and the second decoder for obtaining the second fundus-image expansion sample by restoring the second fundus-image expansion feature data can be determined in advance. The first decoder can use a deconvolution neural network having a mirror structure and a same model parameter as the second encoder. The second decoder can use a deconvolution neural network having a mirror structure and a same model parameter as the first encoder. Based on above, the first encoder can perform feature extraction on the first fundus-image initial sample through operations such as convolution and pooling to obtain the first fundus-image initial feature data, while the second decoder can perform image restoration on the second fundus-image expansion feature data (which is obtained by transcoding the first fundus-image initial feature data) through operations such as mirrored deconvolution and depooling operations, to obtain the second fundus-image expansion sample. Similarly, the second encoder can perform feature extraction on the second fundus-image initial sample through operations such as convolution and pooling to obtain the second fundus-image initial feature data, while the first decoder can perform image restoration on the first fundus-image expansion feature data (which is obtained by transcoding the second fundus-image initial feature data) through operations such as mirrored deconvolution and depooling operations, to obtain the first fundus-image expansion sample. After performing image restoration by the first decoder and the second decoder, second fundus-image expansion samples having the same number as first fundus-image initial samples can be obtained, and first fundus-image expansion samples having the same number as second fundus-image initial samples can also be obtained.

[67] FIG. 6 is a schematic flowchart of training models involved in sample expansion according to some implementations. As illustrated in FIG. 6, similar to the foregoing

implementations, the first encoder, the second encoder, the first transcoder, the second transcoder, the first decoder, and the second decoder are trained as follows.

[68] At block S610, a first discriminator and a second discriminator are constructed, where the first discriminator is configured to determine whether an input image is from the first fundus-image data source, and the second discriminator is configured to determine whether an input image is from the second fundus-image data source.

[69] After performing encoding, transcoding, and decoding in sequence, second fundus-image expansion samples (having a same number as first fundus-image initial samples) can be obtained by converting according to the first fundus-image initial samples. First fundus-image expansion samples (having a same number as second fundus-image initial samples) can be obtained by converting according to the second fundus-image initial samples. In this step, the first discriminator and second discriminator can be constructed, and a conversion effect of converting the first fundus-image initial sample to the second fundus-image expansion sample and a conversion effect of converting the second fundus-image initial sample to the first fundus-image expansion sample can be evaluated.

[70] At block S620, a first generative adversarial network is formed by sequentially connecting the first encoder, the first transcoder, the second decoder, and the second discriminator, and a second generative adversarial network is formed by sequentially connecting the second encoder, the second transcoder, the first decoder, and the first discriminator.

[71] The first generative adversarial network can be formed based on the second discriminator (constructed at block S610), the first encoder, the first transcoder, and the second decoder. Related models are trained jointly, in this way, while improving discrimination ability of the second discriminator, it is conducive to gradually increase similarity between the converted second fundus-image expansion sample and the original second fundus-image initial sample. Similarly, the second generative adversarial network can be formed based on the first discriminator (constructed at block S610), the second encoder, the second transcoder, and the first decoder. Related models are trained jointly, in this way, while improving discrimination ability of the first discriminator, it is conducive to gradually increase similarity between the converted first fundus-image expansion sample and the original first fundus-image initial sample.

[72] At block S630, the first generative adversarial network and the second generative adversarial network are trained jointly with a same loss function.

[73] A conversion process from the first fundus-image initial sample to the second fundus-image expansion sample and a conversion process from the second fundus-image initial sample to the first fundus-image expansion sample are two opposite conversion processes. In this step, in order to improve conversion consistency of the two conversion processes, the first generative adversarial network and the second generative adversarial network are jointly trained based on a same loss function. The loss function may include three parts, namely, a first-network loss function of the first generative adversarial network, a second-network loss function of the second generative adversarial network, and a conversion loss function. Both the first-network loss function and the second-network loss function include two parts, namely, a reconstruction loss function for generating fundus-image expansion samples and a discriminant loss function for discriminating the fundus-image expansion samples. The reconstruction loss function may be a L1 loss function or L2 loss function. The discriminant loss function may be a binary classification loss function. The conversion loss function mainly includes an expectation value of a second conversion of the first fundus-image expansion sample and an expectation value of a second conversion of the second fundus-image expansion sample.

[74] It should be noted that, although the foregoing implementations describe the operations of the method of the disclosure in a specific order, which does not require or imply that these operations must be performed in the specific order, or that all the operations must be performed so as to achieve a desired result. Additionally or alternatively, some steps/operations may be omitted, multiple steps may be combined into one step for execution, and/or one step may be decomposed into multiple steps for execution, and so on.

[75] In implementations of the disclosure, a device for fundus-image sample expansion is further provided. As illustrated in FIG. 7, a device 700 for fundus-image sample expansion mainly includes an initial-sample obtaining module 710, a feature-extraction module 720, a feature-data conversion module 730, and an image-restoration module 740.

[76] The initial-sample obtaining module 710 is configured to obtain a first fundus-image initial sample and a second fundus-image initial sample, where the first fundus-image initial sample is based on a first fundus-image data source, and the second fundus-image initial sample is based on a second fundus-image data source.

[77] The feature-extraction module 720 is configured to perform feature extraction on the first fundus-image initial sample to obtain first fundus-image initial feature data having a first

data-source feature, and perform feature extraction on the second fundus-image initial sample to obtain second fundus-image initial feature data having a second data-source feature.

[78] The feature-data conversion module 730 is configured to convert the first fundus-image initial feature data into second fundus-image expansion feature data having the second data-source feature, and convert the second fundus-image initial feature data into first fundus-image expansion feature data having the first data-source feature.

[79] The image-restoration module 740 is configured to perform image restoration on the first fundus-image expansion feature data to obtain a first fundus-image expansion sample corresponding to the first fundus-image data source, and perform image restoration on the second fundus-image expansion feature data to obtain a second fundus-image expansion sample corresponding to the second fundus-image data source.

[80] In some implementations, based on the above technical solutions, the initial-sample obtaining module 710 further includes a fundus-image collecting module, a data-source determining module, an initial-sample determining module, and a fundus-image classification module. The fundus-image collecting module is configured to collect fundus images, and obtain data source information of the fundus images. The data-source determining module is configured to determine, for each of the fundus images, according to the data source information, whether data source of the fundus image is the first fundus-image data source, the second fundus-image data source, or a fundus-image data source to-be-determined. The initial-sample determining module is configured to determine a fundus image whose data source is the first fundus-image data source as the first fundus-image initial sample, and determine a fundus image whose data source is the second fundus-image data source as the second fundus-image initial sample. The fundus-image classification module is configured to input a fundus image whose data source is the fundus-image data source to-be-determined into a pre-trained fundus-image classification model, and determine, according to an output result of the fundus-image classification model, the fundus image as the first fundus-image initial sample, the second fundus-image initial sample, or a noise sample.

[81] In some implementations, based on the above technical solutions, the first fundus-image data source is a fundus-image data set captured by using a near-infrared light as a light source, and the second fundus-image data source is a fundus-image data set captured by using a red-free light as a light source.

[82] In some implementations, based on the above technical solutions, the feature-extraction module 720 further includes an encoder determining module, a first encoding module, and a second encoding module. The encoder determining module is configured to determine a pre-trained first encoder and a pre-trained second encoder, where the first encoder is based on a convolutional neural network, and the second encoder is based on a convolutional neural network. The first encoding module is configured to input the first fundus-image initial sample into the first encoder, and perform, with the first encoder, feature extraction on the first fundus-image initial sample to obtain the first fundus-image initial feature data having the first data-source feature. The second encoding module is configured to input the second fundus-image initial sample into the second encoder, and perform, with the second encoder, feature extraction on the second fundus-image initial sample to obtain the second fundus-image initial feature data having the second data-source feature.

[83] In some implementations, based on the above technical solutions, the feature-data conversion module 730 further includes a transcoder determining module, a first transcoding module, and a second transcoding module. The transcoder determining module is configured to determine a pre-trained first transcoder and a pre-trained second transcoder, where the first transcoder is based on a residual network, and the second transcoder is based on a residual network. The first transcoding module is configured to input the first fundus-image initial feature data into the first transcoder, and convert, with the first transcoder, the first fundus-image initial feature data into the second fundus-image expansion feature data having the second data-source feature. The second transcoding module is configured to input the second fundus-image initial feature data into the second transcoder, and convert, with the second transcoder, the second fundus-image initial feature data into the first fundus-image expansion feature data having the first data-source feature.

[84] In some implementations, based on the above technical solutions, the image-restoration module 740 further includes a decoder determining module, a first decoding module, and a second decoding module. The decoder determining module is configured to determine a first decoder and a second decoder, where the first decoder is based on a deconvolutional neural network and corresponds to the second encoder, and the second decoder is based on a deconvolutional neural network and corresponds to the first encoder. The first decoding module is configured to input the first fundus-image expansion feature data into the first decoder, and

perform, with the first decoder, image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source. The second decoding module is configured to input the second fundus-image expansion feature data into the second decoder, and perform, with the second decoder, image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source.

[85] In some implementations, based on the above technical solutions, the first encoder, the second encoder, the first transcoder, the second transcoder, the first decoder, and the second decoder are trained by a model training device. The model training device includes a discriminator constructing module, a network connection module, and a joint training module. The discriminator constructing module is configured to construct a first discriminator and a second discriminator, where the first discriminator is configured to determine whether an input image is from the first fundus-image data source, and the second discriminator is configured to determine whether an input image is from the second fundus-image data source. The network connection module is configured to form a first generative adversarial network by sequentially connecting the first encoder, the first transcoder, the second decoder, and the second discriminator, and form a second generative adversarial network by sequentially connecting the second encoder, the second transcoder, the first decoder, and the first discriminator. The joint training module is configured to jointly train, with a same loss function, the first generative adversarial network and the second generative adversarial network.

[86] For details of the foregoing device for fundus-image sample expansion, reference may be made to the corresponding method for fundus-image sample expansion, which will not be repeated herein.

[87] It should be noted that, although several modules or units of the device for action execution are mentioned in the above detailed description, the division is not mandatory. In fact, according to the implementations of the disclosure, features and functions of two or more modules or units described above may be embodied in a module or unit. On the contrary, features and functions of a module or unit described above may be further divided to be embodied in multiple modules or units.

[88] In implementations of the disclosure, a computer readable storage medium is further provided. The computer readable storage medium stores computer programs which, when

executed by a processor, cause the processor to execute the foregoing method for fundus-image sample expansion of the disclosure. In some implementations, various aspects of the disclosure can also be implemented in a form of a program product. The program product includes program codes. The program product may be stored in a non-transitory storage medium (which may be a CD-ROM, a U Disk, a mobile hard disk, or the like) or on the network. The program codes of the program product which, when running on a computing device (which may be a personal computer, a server, a terminal device, a network device, or the like), cause the computing device to execute the operations of the method of the foregoing implementations of the disclosure.

[89] Referring to FIG. 8, a program product 800 for implementing the foregoing method according to implementations of the disclosure can adopt a portable compact disk read-only memory (CD-ROM) and include program codes, and can be run in a computing device (e.g., a personal computer, a server, a terminal device, a network equipment, or the like). However, the program product of the disclosure is not limited herein. In the implementation, the computer readable storage medium may be any tangible medium that contains or stores programs. The programs may be used by or in combination with an instruction execution system, apparatus, or device.

[90] The program product can use any combination of one or more readable medium. The readable medium may be a readable signal medium or a readable storage medium.

[91] The readable storage medium may be, but not limited to, an electrical, magnetic, optical, electromagnetic, infrared, or semiconductor system, apparatus, or device, or any combination of thereof. For example, the readable storage medium includes (non-exhaustive list): an electrical connection with one or more wires, a portable disk, a hard disk, a random access memory (RAM), a read-only memory (ROM), an erasable programmable read only memory (EPROM, or flash memory), an optical fiber, a portable compact disk read-only memory (CD-ROM), an optical storage device, a magnetic storage device, or any suitable combination of thereof.

[92] The readable signal medium may include a data signal propagated in baseband or as a part of a carrier wave, and readable program codes are carried therein. The propagated data signal may adopt many forms, including but not limited to an electromagnetic signal, an optical signal, or any suitable combination thereof. The readable signal medium may also be any readable medium other than the readable storage medium. The readable medium may send,

propagate, or transmit programs used by or in combination with an instruction execution system, apparatus, or device.

[93] The program codes contained on the readable medium can be transmitted by any suitable medium, including but not limited to wireless, wired, optical cable, RF, or any suitable combination thereof.

[94] The program codes used to perform the operations of the disclosure can be written in any combination of one or more programming languages. The programming languages may include object-oriented programming languages (e.g., Java, C++, etc.) and conventional procedural programming languages (e.g., C language or similar programming languages). The program codes may be executed entirely on a user's computing device, executed partly on the user's computing device, executed as an independent software package, executed partly on the user's computing device and partly on a remote computing device, or entirely on the remote computing device or on a server. In the case of a remote computing device, the remote computing device can be connected to a user computing device through any kind of network (including a local area network (LAN) or a wide area network (WAN), etc.), or can be connected to an external computing device, for example, by means of an Internet service provider for Internet connection.

[95] In implementations of the disclosure, an electronic device is further provided. The electronic device includes at least one processor and at least one memory configured to store executable instructions of the processor. The processor, when executing the executable instructions, is configured to execute the operations of the foregoing method of the implementations of the disclosure.

[96] Hereinafter, an electronic device 900 of the implementations of the disclosure will be described with reference to FIG. 9. The electronic device 900 is merely illustrative, and should not be considered as any limitation to the function and scope of use of the implementations of the disclosure.

[97] Referring to FIG. 9, the electronic device 900 is represented in a form of a general-purpose computing device. Components of the electronic device 900 may include, but not limited to, at least one processing unit 910, at least one storage unit 920, a bus 930 connecting different system components (including the processing unit 910 and the storage unit 920), and a display unit 940.

[98] The storage unit 920 is configured to store program codes. The program codes can be executed by the processing unit 910, so that the processing unit 910 executes the operations of the method of the foregoing implementations of the disclosure.

[99] The storage unit 920 may include a readable medium in a form of a transitory storage unit, such as a random access storage unit 921 (RAM) and/or a cache storage unit 922, and may further include a read-only storage unit 923 (ROM).

[100] The storage unit 920 may also include a program/utility tool 924 having a set of (at least one) program modules 925. Such program modules include, but are not limited to, an operating system, one or more application programs, other program modules and program data. Each of the examples or some combination thereof may include the realization of a network environment.

[101] The bus 930 may represent one or more of several types of bus structures, including a storage unit bus or a storage unit controller, a peripheral bus, a graphics acceleration port, a processing unit, or a local bus that uses any of various bus structures.

[102] The electronic device 900 may also communicate with one or more external devices 1000 (e.g., keyboards, pointing devices, Bluetooth devices, etc.), and may also communicate with one or more devices that allow users to interact with the electronic device 900, and/or communicate with any device (e.g., router, modem, etc.) that enables the electronic device 900 to communicate with one or more other computing devices. The communication can be performed through an input/output (I/O) interface 950. In addition, the electronic device 900 may also communicate with one or more networks (e.g., a local area network (LAN), a wide area network (WAN), and/or a public network, such as Internet) through a network adapter 960. As illustrated in FIG. 9, the network adapter 960 can communicate with other modules of the electronic device 900 through the bus 930. It should be understood that, although not illustrated in the figure, other hardware and/or software modules can be used in conjunction with the electronic device 900, including but not limited to: microcodes, device drivers, redundant processing units, external disk drive arrays, RAID systems, tape drives and data backup storage system, and so on.

[103] Those skilled in the art can understand that, various aspects of the disclosure can be implemented as a system, a method, or a program product. Therefore, various aspects of the disclosure can be specifically implemented in the following forms, that is, a complete hardware implementation, complete software implementation (including firmware, microcode, etc.), or a

combination of hardware and software, which can be collectively referred to herein as “circuit”, “module”, or “system”.

[104] According to implementations of the disclosure, a computer program product is further provided. The computer program product includes a non-transitory computer readable storage medium storing computer programs. The computer programs are operable with a computer to execute the method for fundus-image sample expansion of the foregoing implementations of the disclosure.

[105] After considering the specification and practicing the invention disclosed herein, those skilled in the art will easily think of other implementations of the disclosure. The disclosure is intended to cover any variations, uses, or adaptive changes of the disclosure. These variations, uses, or adaptive changes follow the general principles of the disclosure and include common knowledge or customary technical means in the technical field which are not disclosed in the disclosure. The description and implementations are merely regarded as exemplary, and the scope and spirit of the disclosure are pointed out by the appended claims.

[106] The features, structures, or characteristics described above can be combined in one or more implementations in any suitable manner. If possible, the features discussed in the various implementations are interchangeable. In the foregoing description, many specific details are provided to give a sufficient understanding of the implementations of the disclosure. However, those skilled in the art will realize that the technical solutions of the disclosure can be practiced without one or more of the specific details, or can be practiced by other methods, components, materials, etc. In other cases, well-known structures, materials, or operations are not illustrated or described in detail to avoid obscuring various aspects of the disclosure.

WHAT IS CLAIMED IS:

1. A method for fundus-image sample expansion, comprising:
 - obtaining a first fundus-image initial sample and a second fundus-image initial sample, wherein the first fundus-image initial sample is based on a first fundus-image data source, and the second fundus-image initial sample is based on a second fundus-image data source;
 - performing feature extraction on the first fundus-image initial sample to obtain first fundus-image initial feature data having a first data-source feature, and performing feature extraction on the second fundus-image initial sample to obtain second fundus-image initial feature data having a second data-source feature;
 - converting the first fundus-image initial feature data into second fundus-image expansion feature data having the second data-source feature, and converting the second fundus-image initial feature data into first fundus-image expansion feature data having the first data-source feature; and
 - performing image restoration on the first fundus-image expansion feature data to obtain a first fundus-image expansion sample corresponding to the first fundus-image data source, and performing image restoration on the second fundus-image expansion feature data to obtain a second fundus-image expansion sample corresponding to the second fundus-image data source.
2. The method for fundus-image sample expansion of claim 1, wherein obtaining the first fundus-image initial sample and the second fundus-image initial sample comprises:
 - collecting fundus images, and obtaining data source information of the fundus images;
 - for each of the fundus images, determining, according to the data source information, whether data source of the fundus image is the first fundus-image data source, the second fundus-image data source, or a fundus-image data source to-be-determined;
 - determining a fundus image whose data source is the first fundus-image data source as the first fundus-image initial sample, and determining a fundus image whose data source is the second fundus-image data source as the second fundus-image initial sample; and
 - inputting a fundus image whose data source is the fundus-image data source to-be-determined into a pre-trained fundus-image classification model, and determining, according to an output result of the fundus-image classification model, the fundus image as the first fundus-image initial sample, the second fundus-image initial sample, or a noise sample.

3. The method for fundus-image sample expansion of claim 2, wherein the first fundus-image data source is a fundus-image data set captured by using a near-infrared light as a light source, and the second fundus-image data source is a fundus-image data set captured by using a red-free light as a light source.

4. The method for fundus-image sample expansion of any of claims 1 to 3, wherein performing feature extraction on the first fundus-image initial sample to obtain the first fundus-image initial feature data having the first data-source feature, and performing feature extraction on the second fundus-image initial sample to obtain the second fundus-image initial feature data having the second data-source feature comprise:

determining a pre-trained first encoder and a pre-trained second encoder, wherein the first encoder is based on a convolutional neural network, and the second encoder is based on a convolutional neural network;

inputting the first fundus-image initial sample into the first encoder, and performing, with the first encoder, feature extraction on the first fundus-image initial sample to obtain the first fundus-image initial feature data having the first data-source feature; and

inputting the second fundus-image initial sample into the second encoder, and performing, with the second encoder, feature extraction on the second fundus-image initial sample to obtain the second fundus-image initial feature data having the second data-source feature.

5. The method for fundus-image sample expansion of claim 4, wherein converting the first fundus-image initial feature data into the second fundus-image expansion feature data having the second data-source feature, and converting the second fundus-image initial feature data into the first fundus-image expansion feature data having the first data-source feature comprise:

determining a pre-trained first transcoder and a pre-trained second transcoder, wherein the first transcoder is based on a residual network, and the second transcoder is based on a residual network;

inputting the first fundus-image initial feature data into the first transcoder, and converting, with the first transcoder, the first fundus-image initial feature data into the second fundus-image expansion feature data having the second data-source feature; and

inputting the second fundus-image initial feature data into the second transcoder, and converting, with the second transcoder, the second fundus-image initial feature data into the first fundus-image expansion feature data having the first data-source feature.

6. The method for fundus-image sample expansion of claim 5, wherein performing image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source, and performing image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source comprise:

determining a first decoder and a second decoder, wherein the first decoder is based on a deconvolutional neural network and corresponds to the second encoder, and the second decoder is based on a deconvolutional neural network and corresponds to the first encoder;

inputting the first fundus-image expansion feature data into the first decoder, and performing, with the first decoder, image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source; and

inputting the second fundus-image expansion feature data into the second decoder, and performing, with the second decoder, image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source.

7. The method for fundus-image sample expansion of claim 6, wherein training the first encoder, the second encoder, the first transcoder, the second transcoder, the first decoder, and the second decoder comprising:

constructing a first discriminator and a second discriminator, wherein the first discriminator is configured to determine whether an input image is from the first fundus-image data source, and the second discriminator is configured to determine whether an input image is from the second fundus-image data source;

forming a first generative adversarial network by sequentially connecting the first encoder, the first transcoder, the second decoder, and the second discriminator, and forming a second generative adversarial network by sequentially connecting the second encoder, the second

transcoder, the first decoder, and the first discriminator; and

training jointly, with a same loss function, the first generative adversarial network and the second generative adversarial network.

8. A device for fundus-image sample expansion, comprising:

an initial-sample obtaining module, configured to obtain a first fundus-image initial sample and a second fundus-image initial sample, wherein the first fundus-image initial sample is based on a first fundus-image data source, and the second fundus-image initial sample is based on a second fundus-image data source;

a feature-extraction module, configured to perform feature extraction on the first fundus-image initial sample to obtain first fundus-image initial feature data having a first data-source feature, and perform feature extraction on the second fundus-image initial sample to obtain second fundus-image initial feature data having a second data-source feature;

a feature-data conversion module, configured to convert the first fundus-image initial feature data into second fundus-image expansion feature data having the second data-source feature, and convert the second fundus-image initial feature data into first fundus-image expansion feature data having the first data-source feature;

an image-restoration module, configured to perform image restoration on the first fundus-image expansion feature data to obtain a first fundus-image expansion sample corresponding to the first fundus-image data source, and perform image restoration on the second fundus-image expansion feature data to obtain a second fundus-image expansion sample corresponding to the second fundus-image data source.

9. The device of claim 8, wherein the initial-sample obtaining module is configured to: collect fundus images, and obtain data source information of the fundus images;

for each of the fundus images, determine, according to the data source information, whether data source of the fundus image is the first fundus-image data source, the second fundus-image data source, or a fundus-image data source to-be-determined;

determine a fundus image whose data source is the first fundus-image data source as the first fundus-image initial sample, and determine a fundus image whose data source is the second fundus-image data source as the second fundus-image initial sample; and

input a fundus image whose data source is the fundus-image data source to-be-determined into a pre-trained fundus-image classification model, and determine, according to an output result of the fundus-image classification model, the fundus image as the first fundus-image initial sample, the second fundus-image initial sample, or a noise sample.

10. The device of claim 8, wherein the initial-sample obtaining module is configured to:
determine that the first fundus-image data source is a fundus-image data set captured by using a near-infrared light as a light source, and determine that the second fundus-image data source is a fundus-image data set captured by using a red-free light as a light source.

11. The device of claim 8, wherein the feature-extraction module is configured to:
determine a pre-trained first encoder and a pre-trained second encoder, wherein the first encoder is based on a convolutional neural network, and the second encoder is based on a convolutional neural network;
input the first fundus-image initial sample into the first encoder, and perform, with the first encoder, feature extraction on the first fundus-image initial sample to obtain the first fundus-image initial feature data having the first data-source feature; and
input the second fundus-image initial sample into the second encoder, and perform, with the second encoder, feature extraction on the second fundus-image initial sample to obtain the second fundus-image initial feature data having the second data-source feature.

12. The device of claim 8, wherein the feature-data conversion module is configured to:
determine a pre-trained first transcoder and a pre-trained second transcoder, wherein the first transcoder is based on a residual network, and the second transcoder is based on a residual network;
input the first fundus-image initial feature data into the first transcoder, and convert, with the first transcoder, the first fundus-image initial feature data into the second fundus-image expansion feature data having the second data-source feature; and
input the second fundus-image initial feature data into the second transcoder, and convert, with the second transcoder, the second fundus-image initial feature data into the first fundus-image expansion feature data having the first data-source feature.

13. The device of claim 8, wherein the image-restoration module is configured to:
determine a first decoder and a second decoder, wherein the first decoder is based on a deconvolutional neural network and corresponds to the second encoder, and the second decoder is based on a deconvolutional neural network and corresponds to the first encoder;

input the first fundus-image expansion feature data into the first decoder, and perform, with the first decoder, image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source; and

input the second fundus-image expansion feature data into the second decoder, and perform, with the second decoder, image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source.

14. The device of claim 8, wherein training the first encoder, the second encoder, the first transcoder, the second transcoder, the first decoder, and the second decoder comprising:

constructing a first discriminator and a second discriminator, wherein the first discriminator is configured to determine whether an input image is from the first fundus-image data source, and the second discriminator is configured to determine whether an input image is from the second fundus-image data source;

forming a first generative adversarial network by sequentially connecting the first encoder, the first transcoder, the second decoder, and the second discriminator, and forming a second generative adversarial network by sequentially connecting the second encoder, the second transcoder, the first decoder, and the first discriminator; and

training jointly, with a same loss function, the first generative adversarial network and the second generative adversarial network.

15. An electronic device, comprising:

a processor; and

a memory, configured to store fundus-image sample expansion programs of the processor which, when executed by the processor, cause the processor to:

obtain a first fundus-image initial sample and a second fundus-image initial sample, wherein the first fundus-image initial sample is based on a first fundus-image data source, and the second fundus-image initial sample is based on a second fundus-image data source;

perform feature extraction on the first fundus-image initial sample to obtain first fundus-image initial feature data having a first data-source feature, and perform feature extraction on the second fundus-image initial sample to obtain second fundus-image initial feature data having a second data-source feature;

convert the first fundus-image initial feature data into second fundus-image expansion feature data having the second data-source feature, and convert the second fundus-image initial feature data into first fundus-image expansion feature data having the first data-source feature; and

perform image restoration on the first fundus-image expansion feature data to obtain a first fundus-image expansion sample corresponding to the first fundus-image data source, and perform image restoration on the second fundus-image expansion feature data to obtain a second fundus-image expansion sample corresponding to the second fundus-image data source.

16. The electronic device of claim 15, wherein the processor configured to obtain the first fundus-image initial sample and the second fundus-image initial sample is configured to:

collect fundus images, and obtain data source information of the fundus images;

for each of the fundus images, determine, according to the data source information, whether data source of the fundus image is the first fundus-image data source, the second fundus-image data source, or a fundus-image data source to-be-determined;

determine a fundus image whose data source is the first fundus-image data source as the first fundus-image initial sample, and determine a fundus image whose data source is the second fundus-image data source as the second fundus-image initial sample; and

input a fundus image whose data source is the fundus-image data source to-be-determined into a pre-trained fundus-image classification model, and determine, according to an output result of the fundus-image classification model, the fundus image as the first fundus-image initial sample, the second fundus-image initial sample, or a noise sample.

17. The electronic device of claim 15, wherein the first fundus-image data source is a fundus-image data set captured by using a near-infrared light as a light source, and the second fundus-image data source is a fundus-image data set captured by using a red-free light as a light source.

18. The electronic device of claim 15, wherein the processor configured to perform feature extraction on the first fundus-image initial sample to obtain the first fundus-image initial feature data having the first data-source feature, and perform feature extraction on the second fundus-image initial sample to obtain the second fundus-image initial feature data having the second data-source feature is configured to:

determine a pre-trained first encoder and a pre-trained second encoder, wherein the first encoder is based on a convolutional neural network, and the second encoder is based on a convolutional neural network;

input the first fundus-image initial sample into the first encoder, and perform, with the first encoder, feature extraction on the first fundus-image initial sample to obtain the first fundus-image initial feature data having the first data-source feature; and

input the second fundus-image initial sample into the second encoder, and perform, with the second encoder, feature extraction on the second fundus-image initial sample to obtain the second fundus-image initial feature data having the second data-source feature.

19. The electronic device of claim 15, wherein the processor configured to convert the first fundus-image initial feature data into the second fundus-image expansion feature data having the second data-source feature, and convert the second fundus-image initial feature data into the first fundus-image expansion feature data having the first data-source feature is configured to:

determine a pre-trained first transcoder and a pre-trained second transcoder, wherein the first transcoder is based on a residual network, and the second transcoder is based on a residual network;

input the first fundus-image initial feature data into the first transcoder, and convert, with the first transcoder, the first fundus-image initial feature data into the second fundus-image expansion feature data having the second data-source feature; and

input the second fundus-image initial feature data into the second transcoder, and convert,

with the second transcoder, the second fundus-image initial feature data into the first fundus-image expansion feature data having the first data-source feature.

20. The electronic device of claim 15, wherein the processor configured to perform image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source, and perform image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source is configured to:

determine a first decoder and a second decoder, wherein the first decoder is based on a deconvolutional neural network and corresponds to the second encoder, and the second decoder is based on a deconvolutional neural network and corresponds to the first encoder;

input the first fundus-image expansion feature data into the first decoder, and perform, with the first decoder, image restoration on the first fundus-image expansion feature data to obtain the first fundus-image expansion sample corresponding to the first fundus-image data source; and

input the second fundus-image expansion feature data into the second decoder, and perform, with the second decoder, image restoration on the second fundus-image expansion feature data to obtain the second fundus-image expansion sample corresponding to the second fundus-image data source.

21. The electronic device of claim 15, wherein training the first encoder, the second encoder, the first transcoder, the second transcoder, the first decoder, and the second decoder comprising:

constructing a first discriminator and a second discriminator, wherein the first discriminator is configured to determine whether an input image is from the first fundus-image data source, and the second discriminator is configured to determine whether an input image is from the second fundus-image data source;

forming a first generative adversarial network by sequentially connecting the first encoder, the first transcoder, the second decoder, and the second discriminator, and forming a second generative adversarial network by sequentially connecting the second encoder, the second transcoder, the first decoder, and the first discriminator; and

training jointly, with a same loss function, the first generative adversarial network and the

second generative adversarial network.

22. A non-transitory computer readable storage medium, storing fundus-image sample expansion programs which, when executed by a processor, cause the processor to execute any of claims 1 to 7.