【DESCRIPTION】

【Disclosure Title】

CERVICAL IMAGE GENERATING SYSTEM AND METHOD USING GENERATIVE AI MODEL

【Technical Field】

[1] The present disclosure relates to a system and method for generating a cervical image using a generative artificial intelligence (AI) model, and more particularly, to a system and method for generating a cervical image using a generative AI model to generate virtual positive cervical images based on a diffusion probabilistic model and a transfer learning technique.

【Background Art】

[2] Unless otherwise indicated herein, the materials described in this section are not prior art to the claims in this application and are not admitted to be prior art by inclusion in this section.

[3] In general, the uterus of a woman is largely divided into a body part (corpus) and a neck part (cervix), wherein the body part occupies about 75% of the uterus, and the neck part is a region connected to the vagina. Among them, cancer occurring in the cervix, which is the neck part of the uterus, is referred to as "cervical cancer".

[4] According to statistics from the Health Insurance Review & Assessment Service, more than 50,000 patients per year have visited hospitals for cervical cancer over the past five years. Among them, patients in their 40s account for about 25%, followed by patients in their 50s and 30s, each accounting for 20% or more. As such, according to cervical cancer incidence statistics, cervical cancer is one of the most

dangerous types of cancer for women worldwide.

[5] However, according to the 2020 cancer registration statistics of the National Cancer Center, the incidence of cervical cancer decreased from 16.7 to 14.2 per 100,000 persons in 2009 to 2013 compared with 2014 to 2018.

[6] Such a trend results in a continuous decrease in the number of positive image data necessary for training an artificial intelligence-based cervical cancer grading model, thereby causing a data imbalance problem between negative and positive image classes. Accordingly, in order to continuously enhance the performance of the artificial intelligence-based cervical cancer grading model, it is necessary to secure positive cervical cancer image data.

[7] Under such situation, it is necessary to continuously augment training data by generating virtual cervical images to increase the performance of the artificial intelligence-based cervical cancer grading model and improve the accuracy of cervical cancer diagnosis. In particular, in the case of positive cervical cancer images, it is necessary to secure such data because the incidence in Korea has decreased. Therefore, a virtual image generation technique may be effective.

[8] Regarding such AI-based cervical cancer diagnosis, the invention of "AI-Based Cervical Cancer Screening Service System (Korean Patent No. 10-2462975, published on November 8, 2022)" previously filed and registered by the applicant of the present disclosure proposes a method capable of solving the above-described problems by enhancing the accuracy, objectivity, and promptness of cervical cancer screening using an artificial intelligence training model.

[9] However, in order to more effectively utilize the artificial intelligence-based cervical cancer screening service system of the previously filed patent disclosure and to increase the performance of the artificial intelligence-based cervical cancer grading

model constructed for the screening service, there is a necessity to supplement the reduced number of positive image data to solve the data imbalance problem between negative and positive image classes and to generate virtual cervical images to augment training data.

[10] In this regard, Korean Patent No. 10-2041402 (published on Nov. 7, 2019) discloses a conventional technique related to a "Cervical Training Data Generation System and Cervical Training Data Classification Method", but the prior art does not relate to a method for generating a positive cervical image for generating virtual cervical images based on an artificial intelligence diffusion probabilistic model and a transfer learning technique intended by the present disclosure, but merely relates to a classification method for classifying cervical image data for constructing an AI training system related to the cervix, and thus it cannot solve the above-described problems.

[11] [Prior Art Documents]

[12] {Patent Documents}

[13] (Patent Document 1) Korean Patent No. 10-2462975 (November 8, 2022)

[14] (Patent Document 2) Korean Patent No. 10-2041402 (November 7, 2019).

【Disclosure】

【Technical Problem】

[15] The present disclosure has been devised to improve upon the conventional problems as described above, and its object is to provide a system and method for generating a cervical image using a generative AI model by solving a data imbalance problem between negative and positive image classes required for constructing an artificial intelligence-based cervical cancer grading model, generating virtual positive cervical images by applying an AI diffusion probabilistic model and a transfer learning

technique to these image data, and accordingly pursuing continuous performance enhancement of the artificial intelligence-based cervical cancer grading model.

[16] In addition, the technical problems are not limited to those described above, and it will be apparent that other technical problems may be derived from the following description.

【Technical Solution】

[17] According to an embodiment of the disclosure, a system for generating a cervical image using a generative artificial-intelligence (AI) model includes: a data collection unit configured to acquire and collect cervical image data; a data learning unit configured to train a generative AI model based on the cervical image data collected by the data collection unit; and an inference unit configured to infer input data using a cervical image generation model derived from the data learning unit to generate and output a virtual cervical image.

[18] According to an embodiment, the generative AI model may include a diffusion probabilistic model.

[19] According to an embodiment, the data collection unit may include: a camera configured to capture and acquire a cervical image; a cervical image interpretation unit configured to allow a medical professional to interpret the captured cervical image; and a database server storage unit configured to store interpreted image data received through a communication means.

[20] According to an embodiment, the data learning unit may include: a training dataset classification unit configured to classify image data received from the database server storage unit into a training dataset; a training dataset preprocessing unit configured to preprocess the training dataset; and a diffusion probabilistic model

training unit configured to train the diffusion probabilistic model based on the preprocessed data.

[21] According to an embodiment, the inference unit may include: an inference input unit configured to receive an input image or a prompt; an inference preprocessing unit configured to preprocess the input data; a cervical image generation model inference unit configured to apply the preprocessed data to a cervical image generation model trained using the diffusion probabilistic model; and an output unit configured to output a virtual cervical image generated by the generation model inference unit.

[22] According to an embodiment, the system may further include: an AI-based cervical cancer grading model training database configured to store a virtual positive cervical image generated and output from the inference unit and interpreted by a medical professional

[23] According to an embodiment of the present disclosure, a method of generating a cervical image using a generative artificial-intelligence (AI) model includes: a data collection step of acquiring and collecting cervical image data; a data learning step of training a generative AI model based on the cervical image data collected in the data collection step; and an inference step of inferring input data using a cervical image generation model derived from the data learning step to generate and output a virtual cervical image.

[24] According to an embodiment, the generative AI model may include a diffusion probabilistic model.

[25] According to an embodiment, the data collection step may include: a capture and acquisition step of capturing and acquiring a cervical image by a camera; a cervical image interpretation step of allowing a medical professional to interpret the captured cervical image; and a database server storage step of storing the interpreted image

data received through a communication means.

[26] According to an embodiment, the data learning step may include: a training dataset classification step of receiving image data from a database server storage unit and classifying the image data into a training dataset; a training dataset preprocessing step of preprocessing the training dataset; and a diffusion probabilistic model training step of training the diffusion probabilistic model based on the preprocessed data.

[27] According to an embodiment, the inference step may include: an inference input step of inputting an input image or a prompt to an inference input unit; an inference preprocessing step of preprocessing the input data; a cervical image generation model inference step of applying the preprocessed data to a cervical image generation model trained using the diffusion probabilistic model; and an output step of outputting a virtual cervical image generated in the generation model inference step by an output unit.

[28] According to an embodiment, the method may further include: a interpretation step of allowing a medical professional to determine whether a virtual positive cervical image generated and output in the inference step is an actual positive image; and a storage step of storing the image data in an AI-based cervical cancer grading model training database when the virtual positive cervical image is equivalent to the actual positive image after the interpretation step.

[29] According to an embodiment, the method may further include: a retraining step of retraining an AI-based cervical cancer grading model based on negative and positive image data stored in the AI-based cervical cancer grading model training database.

【Advantageous Effects】

[30] According to the present disclosure, there is an advantageous effect of

resolving the data imbalance problem between negative and positive image classes required for constructing an artificial intelligence-based cervical cancer grading model.

[31] According to the present disclosure, there is an advantageous effect of continuously enhancing the performance of an AI-based cervical cancer grading model by generating virtual positive cervical images using a generative AI model based on an AI diffusion probabilistic model and a transfer learning technique for negative and positive image data, and retraining the AI-based cervical cancer grading model.

[32] It should be understood that the effects of the present disclosure are not limited to the above-described effects, abut include all effects that can be inferred from the configuration of the disclosure described in the detailed description or the appended claims of the present disclosure.

【Description of Drawings】

[33] FIG. 1 is an overall block diagram of a system for generating a cervical image using a generative AI model of the present disclosure.

[34] FIG. 2 is a detailed block diagram of the data learning unit of FIG. 1.

[35] FIG. 3 is a detailed block diagram of the inference unit of FIG. 1.

[36] FIG. 4 is a flowchart of a process performed by a system for generating a cervical image using a generative AI model according to Examples 1 and 2 of the present disclosure.

[37] FIG. 5A shows an example of a virtual positive image generated by the system and method for generating a cervical image using a generative AI model according to Example 1 of the present disclosure.

[38] FIG. 5B shows an example of virtual positive images generated by the system and method for generating a cervical image using a generative AI model according to

Example 2 of the present disclosure..

[39]

【Mode for Carrying Out the Invention】

[40] Hereinafter, a system and method for generating a cervical image using a generative AI model according to an embodiment will be described in detail with reference to the accompanying drawings.

[41] For reference, in the following drawings, each component is omitted or schematically illustrated for convenience and clarity, the size of each component does not reflect the actual size, the same reference numerals refer to the same components throughout the specification, and reference numerals for the same components in individual drawings will be omitted. In addition, detailed descriptions of known functions and configurations that may unnecessarily obscure the gist of the present disclosure will be omitted.

[42] When an embodiment of the present disclosure is described with reference to FIGS. 1 to 5, as shown in FIG. 1, a system 1000 for generating a cervical image using a generative AI model of the present disclosure includes: a data collection unit 100 for acquiring and collecting cervical image data; a data learning unit 200 for training a generative AI model based on the cervical image data collected by the data collection unit 100; and an inference unit 300 for inferring input data using a cervical image generation model derived from the data learning unit 200 to generate and output a virtual cervical image.

[43] According to the present disclosure, a generative AI model is used to generate a virtual cervical image, in which the generative AI model uses a diffusion probabilistic model. Further, according to the present disclosure, a transfer learning technique is used to construct a cervical image generation model. In addition, although the diffusion

probabilistic model is used according to an embodiment of the present disclosure, other types of generative AI models, such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), or Autoregressive Models, may also be used without exclusion.

[44] The overall generation system according to the above-described features of the present disclosure is summarized as follows.

[45] That is, a cervical image captured by a camera 110 is interpreted by a reading unit 120 of a medical professional to identify whether the cervical image is negative or positive and to indicate a lesion, and is stored in a database server storage unit 130. A training dataset stored in the database server storage unit 130 is classified by a training dataset classification unit 210 and preprocessed by a training dataset preprocessing unit 220. Based on the preprocessed dataset, a diffusion probabilistic model is trained by a generative AI model training unit 230. Thereafter, an interference process is performed in the inference unit 300, in which an input image or prompt is input in an inference input unit 310 and preprocessed by an inference preprocessing unit 320 to generate inference data, and the preprocessed inference data is input to a trained cervical image generation model inference unit 330 to generate a virtual image through an output unit 340.

[46] In more detail with reference to FIG. 1, first, in the data collection unit 100, a cervical image is captured and acquired from a patient by the camera 110, and using various channels, such as a communication means, a medical professional determines whether the acquired cervical image is negative or positive through the cervical image reading unit 120, and identifies a lesion if it is positive. Then, the positive image with the lesion indicated as a result of the reading is stored in the database server storage unit 130.

[47] As described above, the data collection unit 100 according to an embodiment of the present disclosure may include the camera 110 for capturing and acquiring a cervical image, the cervical image reading unit 120 for allowing a medical staff to interpret the captured cervical image, and the database server storage unit 130 for storing the interpreted image data through the communication means.

[48] In addition, according to an embodiment of the present disclosure, as shown in FIG. 1, a learning process is performed in the data learning unit 200 based on the cervical image data collected by the data collection unit 100 described above. That is, the data learning unit 200 may include a training dataset classification unit 210 for classifying the image data received from the database server storage unit 130 into the training dataset, a training dataset preprocessing unit 220 for preprocessing the training dataset, and a diffusion probabilistic model training unit 230 for training a generative AI model (diffusion probabilistic model) based on the preprocessed data.

[49] In the above-described embodiment of the present disclosure, positive cervical image generation technique will be described with reference to FIG. 2.

[50] That is, as shown in FIG. 2, the present disclosure provides three representative cervical image generation techniques 131: (1) Virtual cervical images are generated in any desired number through an unconditional image generation technique 132; (2) Virtual cervical images are generated through cross-domain translation, such as converting a negative cervical image into a positive cervical image through an image translation technique 133; and (3) Conditional cervical images are generated according to various diseases and situations through a conditional image generation technique 134.

[51] In other words, as described above, a cervical image is captured through a colposcope (camera), interpreted by a specialist, and stored in a database along with

features such as negative or positive status and presence of a lesion, and the image stored in the database is preprocessed into training data suitable for the purpose in the three techniques introduced above. Thereafter, the preprocessed cervical image dataset is input as training data into a diffusion probabilistic model, which is one of the generative AI models. An input image or prompt is preprocessed according to the trained cervical image generation model, and input as the input for the trained cervical image generation model, and a virtual cervical image is generated through the inference process of the inference unit.

[52] In addition, according to an embodiment of the present disclosure, as shown in FIG. 1, in order to generate a virtual positive cervical image by the cervical image generation model 240 trained by the data learning unit 200 described above, input data may be transmitted to the inference unit 300, thereby generating the virtual positive cervical image. That is, the inference unit 300 may include an inference input unit 310, an inference preprocessing unit 320 for preprocessing the input data, a cervical image generation model inference unit 330 for applying the preprocessed data to the cervical image generation model trained using the diffusion probabilistic model, and an output unit 340 for outputting a generated virtual cervical image.

[53] In addition, according to an embodiment of the present disclosure, as shown in FIG. 4, the system may further include an AI-based cervical cancer grading model training database 500 configured to store the virtual positive cervical image generated and output by the inference unit 300 after interpretation by a medical staff. That is, if the generated and output virtual positive cervical image is evaluated by a medical professional as being comparable in quality to as an actual positive image, the image may be stored in the AI-based cervical cancer grading model training database 500 as image data for enhancing the performance of the AI-based cervical cancer grading

model constructed for more effective utilization in an AI-based cervical cancer screening service system.

[54] The following describes a method for generating a cervical image using a generative AI model according to an embodiment of the present disclosure.

[55] The method for generating a cervical image using a generative AI model of the present disclosure comprises: a data collection step S100 of acquiring and collecting cervical image data; a data learning step S200 of training a generative AI model based on the cervical image data collected in the data collection step S100; and an inference step S300 of inferring input data using the cervical image generation model derived from the data learning unit 200 to generate and output a virtual cervical image.

[56] The data collection step S100 may include an image capture step S110 of capturing and acquiring a cervical image by the camera 110, a cervical image interpretation step S120 of interpreting the captured cervical image by a medical professional, and a database server storage step S130 of storing the interpreted image data received through a communication means.

[57] In addition, the data learning step S200 may include a training dataset classification step S210 of classifying image data received from the database server storage unit 130 into a training dataset, a training dataset preprocessing step S220 of preprocessing the training dataset, and a diffusion probabilistic model training step S230 of training the diffusion probabilistic model based on the preprocessed data.

[58] In addition, the inference step S300 may include an inference input step S310 of inputting an input image or prompt into the input unit 310, an inference preprocessing step S320 of preprocessing the input data, a cervical image generation model inference step S330 of applying the preprocessed data to the cervical image generation model trained by the diffusion probabilistic model, and an output step S340

of outputting the virtual cervical images generated in the generation model inference step S330 by the output unit 340.

[59] According to an embodiment of the present disclosure, the method may further include an interpretation step S400 in which a medical professional determines whether the virtual positive cervical image generated and output by the inference unit 300 is equivalent to an actual positive image, and a storage step S500 of storing the image data in the AI-based cervical cancer grading model training database 500 when the virtual positive cervical image is determined to be equivalent to the actual positive image after the interpretation step S400.

[60] According to an embodiment of the present disclosure, the method may further include a retraining step S600 of retraining the AI-based cervical cancer grading model based on the negative and positive image data stored in the AI-based cervical cancer grading model training database 500.

[61] Example 1 of the present disclosure employs an image translation technique 133 to generate a positive image based on a negative cervical image as shown in FIGS. 2 to 4, and Example 2 employs the conditional image generation technique 134 to generate a virtual positive cervical image based on a positive cervical image.

[62] Referring to FIG. 4, Examples 1 and 2 will be described. As shown in FIG. 4, the upper process of Example 1 employs the image translation technique 133 to classify a negative cervical image in the classification unit 210 and perform the image generation process, and the lower process of Example 2 employs the conditional image generation technique 134 to classify a positive cervical image in the classification unit 210 and perform the image generation process.

[63] More specifically, as shown in FIG. 4, the image translation technique 133 of Example 1 requires three pairs of inputs to be made into the training dataset. That is,

a pre-translation image is designated as a negative cervical image, the prompt is designated as "positive cervix", and a post-translation image is designated as a positive cervical image. After preprocessing these in the training dataset preprocessing unit 220 of the image translation technique 133, the generative AI model training unit 230 performs training. When the diffusion probabilistic model training is completed, the pre-translation image is designated as the negative image through the inference input unit 310 to input inference data, the prompt is designated as "positive cervix" and input, and then the inference data is preprocessed in the inference preprocessing unit 320. When the preprocessed inference data is used as an input for the diffusion probabilistic model, and inference is performed in the cervical image generation model inference unit 330, a virtual positive cervical image is generated and output through the output unit 340.

[64] In addition, the conditional image generation technique 134 of Example 2 in FIG. 4 collects and classifies positive cervical images from the database server storage unit 130, and the collected and classified positive cervical images are used as images for the training dataset, while the prompt is specified as "positive cervix". By preprocessing these as the training data in the training dataset preprocessing unit 220, the diffusion probabilistic model is trained by the generative AI model training unit 230. When the diffusion probabilistic model training is completed, the prompt is designated as "positive cervix" through the inference input unit 310 to input inference data, the number of images to be generated is specified, and then the inference data is preprocessed in the inference preprocessing unit 320. The preprocessed inference data is used as an input to the diffusion probabilistic model and the inference is performed in the cervical image generation model inference unit 330, thereby generating and outputting virtual positive cervical images through the output unit 340.

[65] In addition, after the processes of Examples 1 and 2 described above are completed, an interpretation step S400 is performed by a medical professional using an interpretation unit 400 to determine whether the generated virtual positive cervical image has the characteristics of an actual positive cervical image. The interpretation step S400 includes interpretation by a medical specialist, and if the generated virtual positive cervical image is determined to have the characteristics of an actual positive cervical image, the image data is stored in the AI-based cervical cancer grading model training database 500 (S500). Based on the stored positive cervical images, a retraining step S600 is performed using an AI-based cervical cancer grading model retraining unit 600, thereby enhancing the performance of the model.

[66] Meanwhile, the 'unconditional image generation technique' is not limited to a separate Example in the present disclosure, but is added merely for explanatory purposes to facilitate understanding of the present disclosure.

[67] FIG. 5A shows an example of a virtual positive image generated according to Example 1 of the present disclosure, and FIG. 5B shows an example of a virtual positive image generated according to Example 2 of the present disclosure

[68] Hereinafter, to facilitate understanding of the foregoing Examples of the present disclosure, the diffusion probabilistic model and the transfer learning technique, which are types of generative AI models related to the present disclosure, will first be described in detail, and other types of generative AI models will be described briefly thereafter.

[69] <Generative AI Models>

[70] Machine learning models may be broadly classified into discriminative models and generative models according to their functions. A discriminative model generally performs a task of mapping high-dimensional input data to low-dimensional label data,

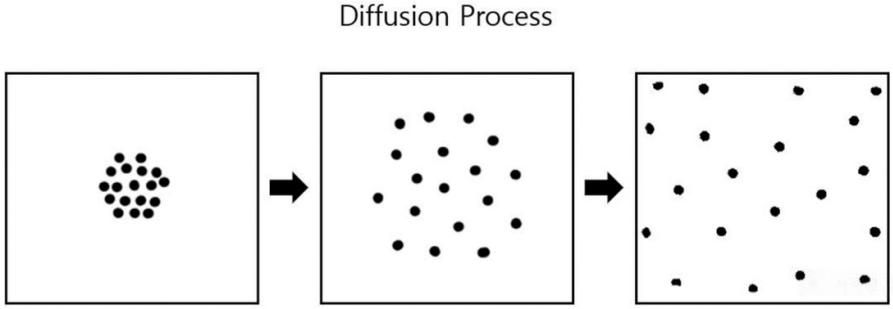
whereas a generative model performs a task of generating high-dimensional data from relatively low-dimensional data.

[71] Here, the types of generative AI models for generating the images include Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Autoregressive Models, Diffusion Models, etc., which will be briefly described below.

[72] First, the generative AI model used in the present disclosure uses the diffusion probabilistic model and is trained by the transfer learning technique.

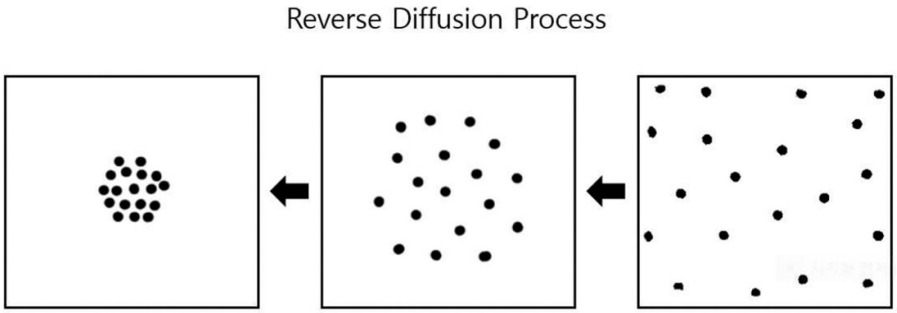
[73] <Diffusion Probabilistic Model>

[74] The diffusion probabilistic model is based on the idea of Langevin dynamics, which describes a phenomenon in which molecules initially concentrated in a particular region gradually become uniformly distributed throughout an entire space through a diffusion process, as described below.



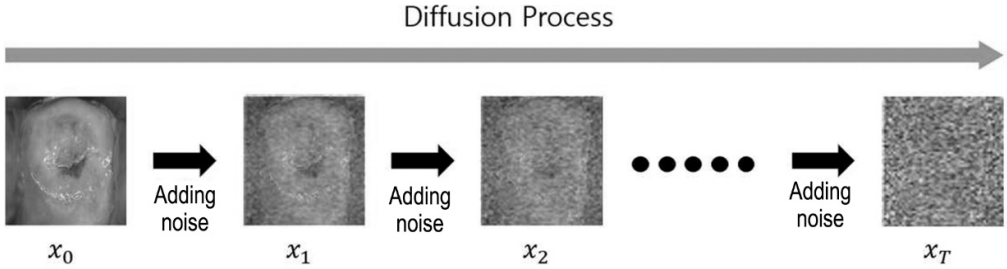
[75]

[76] The movement of each molecule follows a Gaussian distribution, and may be represented by a normal distribution defined by a mean and standard deviation. If the movement of each molecule can be calculated at every time step, the diffusion process can be reversed.



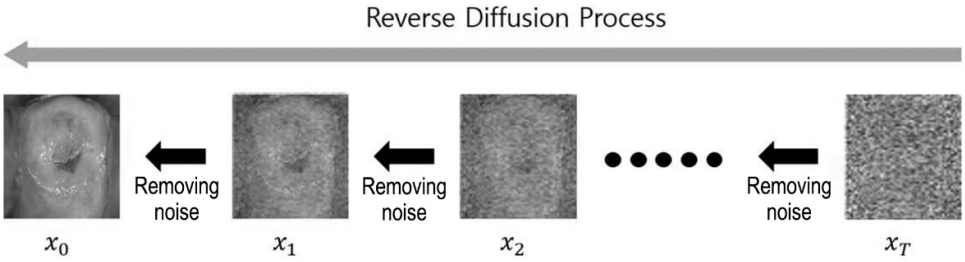
[77]

[78] By applying this concept directly to the pixel values of an image, noise values following a normal distribution are added to the pixel values of the image, just as the movement of molecules is modeled as noise following a normal distribution.



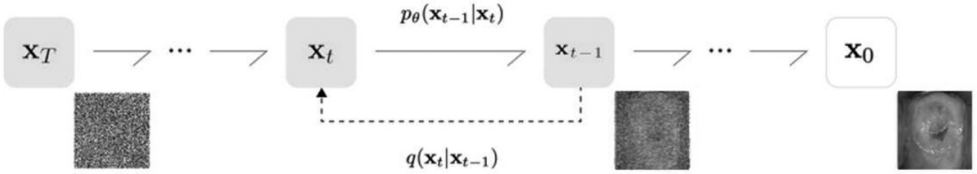
[79]

[80] x_0 denotes an original image. x_1 denotes an image generated by adding noise to all pixel values of the original image. In the same manner as the molecular diffusion process, noise is added to all pixel values of the image at each time step t. The image obtained after T time steps is a completely noisy image. By analogy to the molecular diffusion process, x_0 represents a state in which molecules are clustered together, whereas x_T represents a state in which the molecules are uniformly distributed throughout the entire space. Furthermore, as described above, if the noise added at each time step can be estimated, the diffusion process can be reversed. In the case of molecules, the state in which the molecules are uniformly distributed throughout the entire space can be reversed to a state in which the molecules are gathered together in a single region.



[81]

[82] In the case of the above images, if the noise added to the pixel values of the image at each time t can be calculated, it is possible to reconstruct the input image x_0 from the noisy image x_T. This process may be expressed by the following equations:



[83]

[84] The input image becomes x_0 on the far right, and the noisy image becomes x_T. The process is divided into forward translation and reverse translation. The forward translation is a process in which the input image turns into a noise image, and the reverse translation is a process in which the input data is reconstructed from the noise image. Therefore, by reconstructing the input image from the nosy image, the diffusion probabilistic model parameterizes the reverse translation and trains it using a deep learning model, and generates the input image from the noise image through the trained reverse translation. Thus, the diffusion probabilistic model can be said to be a parameterized Markov chain trained to generate an image after a finite time. It has the Markov property that the current state (t) depends on the previous state (t-1). The objective of the diffusion probabilistic model is to train the reverse translation such that the probability distribution of the reconstructed images approximates that of the input images. To this end, learning proceeds by updating the mean and standard deviation, which are parameters of noise generation probability distribution, during the reverse translation. In addition, since different values are sampled from the Gaussian

probability distribution each time noise is generated, the generated image varies accordingly. Furthermore, the resulting image generated from the reverse translation varies depending on the training data.

[85] <Diffusion Probability Model Training>

[86] In the present disclosure, the generative AI model learns patterns and features of existing data by using a neural network similar to neurons in the human brain. Then, the model can generate new data that match the learned patterns and features. For example, a generative AI model trained on a cervical image dataset can generate virtual cervical images similar to the trained cervical images.

[87] As described above in Examples 1 and 2, the generative AI model of the present disclosure employs three techniques, such as the unconditional image generation technique 132, the conditional image generation technique 134, and the image translation technique 133. That is, although it is not presented as a separate example in the present disclosure, the unconditional image generation technique 132 generates virtual cervical images using only a cervical image dataset. In addition, the image translation technique 133, which is adopted in Example 1 of the present disclosure, generates cervical images through techniques such as style transfer, image restoration, domain translation, and spatial transformation. Further, the conditional image generation technique 134, which is adopted in Example 2 of the present disclosure, generates cervical images based on specific cervical characteristics.

[88] The differences between the unconditional image generation technique 132 and the conditional image generation technique 134 are as follows. For example, the unconditional image generation technique 132 can generate a large number of cervical images because it can generate the images without input data, and the conditional image generation technique 134 can generate cervical images tailored to specific

conditions. For examples, there are positive cervical images, negative cervical images, and cervical images in which white lesions are clearly visible.

[89] <Transfer Learning>

[90] In addition, in the present disclosure, a diffusion probabilistic model is trained using a transfer learning technique. Transfer learning refers to using a model trained to achieve a certain purpose for another task. It is a technique that utilizes the knowledge of a model already trained on a different dataset for a new task or dataset, and has the advantage of enabling high performance even with a small dataset and enabling the creation of a model specialized for a target task and domain. Transfer learning is divided into two stages, i.e., a pre-training stage and a fine-tuning stage. In the pre-training stage, a model is trained on a large-scale dataset to learn general features. For example, when training an image recognition model, a large dataset such as ImageNet is used to learn general features of various images (e.g., edges, textures, etc.). In the fine-tuning stage, the pre-trained model is fine-turned for a specific task. This is a process of adapting the model to a specific domain using a small dataset. That is, the pre-trained model is adjusted to suit the generation of cervical images. In this process, by using a cervical image dataset and retraining the last few layers of the model, high performance can be achieved even with few data and resources.

[91] <Details of Diffusion Probability Model Training>

[92] As shown in FIG. 2, first, the unconditional image generation technique 132 collects cervical images from the database server storage unit 130 and preprocesses the collected cervical images as the training data. Based on the pre-processed cervical image dataset, the diffusion probabilistic model training unit 230 trains the basic algorithm of the diffusion probabilistic model.

[93] In addition, as shown in FIG. 2, second, the image translation technique 133

forms pairs of three elements: a pre-translation image, a prompt with conditions, and a post-translation image, and preprocesses them as the training data. The diffusion probabilistic model training unit 230 trains a diffusion probabilistic model based on the preprocessed dataset through an Image-to-Image algorithm.

[94] In addition, as shown in FIG. 2, thirdly, the conditional image generation technique 134 sets a condition including a specific situation or case as a prompt, forms pairs of two elements: the prompt and an image that matches the condition, and preprocesses them as the training data. The diffusion probabilistic model training unit 230 trains a diffusion probabilistic model based on the preprocessed dataset through a Text-to-Image algorithm.

[95] <Details of Inference for Diffusion Probability Model>

[96] As shown in FIG. 3, first, the unconditional image generation technique 302 can generate virtual cervical images by specifying the number of images to be generated using the diffusion probabilistic model trained on a cervical image dataset.

[97] In addition, second, the mage translation technique 303 is a technique for converting an input image into another image having a specific attribute or style. A virtual image is generated based on an input image 311 and a prompt 310. For example, a negative cervical image is converted into a virtual positive cervical image based on the negative cervical image and the prompt "positive cervix". For example, image translation techniques include style transfer, image restoration, domain translation, or spatial transformation. Style transfer converts a given image into an image having a specific style. Such a style includes race, physician, and the like. When characteristics of a cervix differ for each race or a method of capturing a cervical image differs for each physician, a cervical image may be generated through the style transfer technique. Image restoration refers to restoring a damaged or incomplete image. When

a cervical image captured using a camera contains noise or has been damaged, it can be converted into a complete image. Domain translation refers to converting an image from one domain to another domain. For example, a negative cervical image is converted into a positive cervical image, or a positive cervical image is converted into a negative cervical image. Finally, spatial transformation refers to changing the position or appearance of a specific object. For example, an image in which a transformation zone of a cervix is not visible is converted into an image in which the transformation zone is visible. Alternatively, an image in which an external os of a cervix is not visible is converted into an image in which the external os is visible.

[98] In addition, the third conditional image generation technique 304 can generate virtual negative cervical images by training the diffusion probabilistic model based on negative cervical images. Alternatively, virtual positive cervical images can be generated by training the diffusion probabilistic model based on positive cervical images. Such a generation technique is referred to as a conditional image generation technique. The condition is referred to as a prompt 310, and the prompt is provided in text form. For example, in the conditional image generation model, when "negative cervix" is entered as the prompt and N images to be generated are designated (312), N negative cervical images are generated. In addition, images can be variously generated based on all visual features of a cervix (e.g., images can be generated by learning all conditions such as a positive cervical image, a cervical image including a specific lesion, or a cervical image in which an external os of a cervix is not visible).

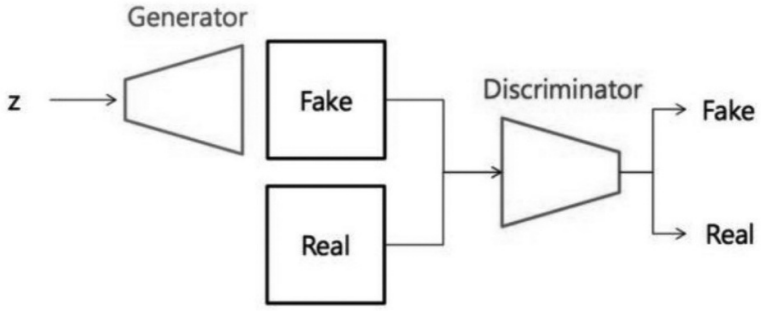
[99] As described above, virtual cervical images are generated based on three principal techniques. As specific inputs for each technique, the unconditional image generation technique 302 uses the number of images to be generated (312) as an input, the image translation technique 303 uses the pre-translation image 311 and the

prompt 310 as inputs, and the conditional image generation technique 304 uses the prompt 310 and the number of images to be generated (312).

[100] Meanwhile, Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), and Autoregressive Models among the generative AI models will be described.

[101] <Generative Adversarial Networks (GANs)>

[102] Generative Adversarial Networks are models composed of two neural networks: a generator and a discriminator. The generator and the discriminator compete with each other to generate data. The generator generates new data, and the discriminator determines whether the data is real or fake.



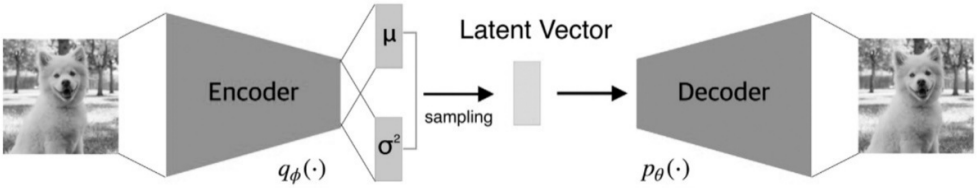
[103]

[104] The generator receives the generated z and is trained to create data similar to real data, and the discriminator is trained to distinguish between real data and fake data generated by the generator. The generator is trained to learn the distribution of the input data and reproduce this distribution so that there is no difference from the distribution of the original data. The discriminator distinguishes whether the data is real or fake and estimates the probability for each. Generating data that approaches the distribution of real data is the ultimate goal of a Generative Adversarial Network, and the generator attempts to generate fake data that is close to real data so that the discriminator cannot identify it as fake. Through this process, the performance of the generator and the discriminator is gradually improved, and the ultimate goal is to train the discriminator so that it can no longer distinguish between real data and fake data.

[105] < Variational Autoencoders (VAEs)>

[106] The variational autoencoder is a generative AI model that learns a compressed representation of training data as a probability distribution, and is used to create new sample data by sampling variations from the learned representation. First, the basic concept of an autoencoder is as follows. The process of encoding original data into latent variables suitable for a particular purpose is called encoding, and the process of restoring encoded data to its original form is called decoding. A neural network composed of an encoder and a decoder is called an autoencoder. While most autoencoders learn discrete latent-space models, variational autoencoders learn continuous latent-variable model. Instead of a single encoding vector in the latent space, the variational autoencoder models two different vectors: a mean vector and a standard deviation vector.

[107]



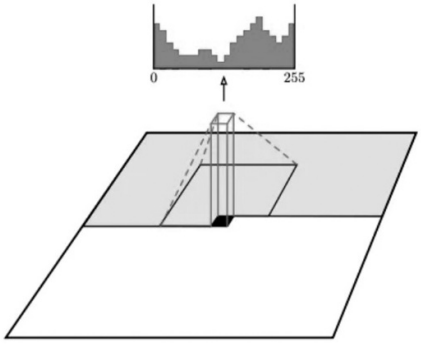
[108] The input dog photo is connected to an encoder network. The encoder compresses the input image and converts it into a low-dimensional latent vector. An important point here is that the encoder does not simply convert the input image into a single vector, but estimates two parameters: the mean and variance. These parameters define a probability distribution in the latent space. The latent vector is sampled based on the mean and variance obtained from the encoder. The sampled latent vector is a random vector drawn from a normal distribution, and a random sampling process is added in this process. Because of this randomness, the variational autoencoder can operate as a generative AI model rather than merely performing simple compression. The sampled latent vector is provided to a decoder network to

restore an image similar to the original image. The decoder receives the latent vector and restores it back to high-dimensional image data. Finally, the image output from the decoder is very similar to the original input image. However, because the latent vector is randomly sampled, it is not completely identical to the original.

[109] <Autoregressive Models>

[110] The term “autoregression” means a model that regresses on itself. This means predicting the next pixel value based on previous pixel values. An autoregressive model generates an image by two processes: establishing a pixel sequence and predicting each pixel based on previous pixels.

[111]



[112] The image is expressed as a two-dimensional array. An autoregressive model flattens a two-dimensional image into a one-dimensional sequence and sequentially processes each pixel. After generating the first pixel, the second pixel is predicted and generated based on that pixel. In this process, the value of the next pixel is calculated based on information from the previously generated pixels. To this end, the model estimates a probability distribution for the next pixel using information of previously generated pixels and samples a new pixel value according to the distribution. Repeating this process until all pixels have been generated yields the final image. In addition, an image is generated on a pixel basis using a recurrent neural network or a convolutional neural network.

[113] As described above, according to the present disclosure, in order to effectively

perform an AI-based cervical cancer screening service, a problem of data imbalance between negative and positive image classes required to construct an AI-based cervical cancer grade classification model can be solved, and further, according to the present disclosure, the performance of the AI-based cervical cancer grading model can be continuously enhanced by generating virtual positive cervical images for negative and positive image data based on a generative AI model using an AI diffusion probabilistic model and a transfer learning technique, and retraining the AI-based cervical cancer grading model using the generated virtual positive cervical images.

[114] Although preferred embodiments of the present disclosure have been described above with reference to the accompanying drawings, the configurations shown in the specification and drawings are merely embodiments of the present disclosure and do not represent all technical aspects of the present disclosure. Accordingly, it should be understood that various equivalents and modifications capable of replacing them may be made without departing from the scope of the present disclosure. Therefore, the embodiments described above should be understood as illustrative and not restrictive in all respects, and the scope of the present disclosure is defined by the appended claims rather than the detailed description. Accordingly, all changes or modified forms derived from the meaning and scope of the claims and their equivalent concepts should be construed as being included in the scope of the present disclosure.

[115]

[116] [Reference Numerals]

[117] 100: data collection unit

[118] 110: camera (image capturing unit)

[119] 120: cervical image reading unit

[120] 130: database server storage unit

[121] 131: image generation technique selection unit

[122] 132: unconditional image generation technique selection unit

[123] 133: image translation technique selection unit

[124] 134: conditional image generation technique selection unit

[125] 143: condition setting unit

[126] 144: condition setting unit

[127] 200: data learning unit

[128] 210: training dataset classification unit

[129] 220: training dataset preprocessing unit

[130] 230: generative AI model training unit (diffusion probabilistic model)

[131] 240: cervical image generation model

[132] 300: inference unit

[133] 301: image generation inference technique selection unit

[134] 302: unconditional image generation inference technique selection unit

[135] 303: image translation technique inference selection unit

[136] 304: conditional image inference generation technique selection unit

[137] 310: inference input unit (input image or prompt)

[138] 311: image input unit

[139] 312: generated image count setting unit

[140] 320: inference pre-processing unit

[141] 330: cervical image generation model inference unit

[142] 340: virtual positive cervical image generation output unit

[143] 400: medical staff interpretation unit for generated virtual (positive) image

[144] 500: AI-based cervical cancer grading model training database

[145] 600: AI-based cervical cancer grading model retraining unit

[146] 1000: cervical image generation system using generative AI model

【CLAIMS】

【Claim 1】

A system for generating a cervical image using a generative artificial-intelligence (AI) model, the system comprising:

a data collection unit configured to acquire and collect cervical image data;

a data learning unit configured to train a generative AI model based on the cervical image data collected by the data collection unit; and

an inference unit configured to infer input data using a cervical image generation model derived from the data learning unit to generate and output a virtual cervical image.

【Claim 2】

The system of claim 1, wherein the generative AI model comprises a diffusion probabilistic model.

【Claim 3】

The system of claim 2, wherein the data collection unit comprises:

a camera configured to capture and acquire a cervical image;

a cervical image interpretation unit configured to allow a medical professional to interpret the captured cervical image; and

a database server storage unit configured to store interpreted image data received through a communication means.

【Claim 4】

The system of claim 2, wherein the data learning unit comprises:

a training dataset classification unit configured to classify image data received from the database server storage unit into a training dataset;

a training dataset preprocessing unit configured to preprocess the training dataset; and

a diffusion probabilistic model training unit configured to train the diffusion probabilistic model based on the preprocessed data.

【Claim 5】

The system of claim 2, wherein the inference unit comprises:

an inference input unit configured to receive an input image or a prompt;

an inference preprocessing unit configured to preprocess the input data;

a cervical image generation model inference unit configured to apply the preprocessed data to a cervical image generation model trained using the diffusion probabilistic model; and

an output unit configured to output a virtual cervical image generated by the generation model inference unit.

【Claim 6】

The system of any one of claims 1 to 5, further comprising: an AI-based cervical cancer grading model training database configured to store a virtual positive cervical image generated and output from the inference unit and interpreted by a medical professional.

【Claim 7】

A method of generating a cervical image using a generative artificial-

intelligence (AI) model, the method comprising:

a data collection step of acquiring and collecting cervical image data;

a data learning step of training a generative AI model based on the cervical image data collected in the data collection step; and

an inference step of inferring input data using a cervical image generation model derived from the data learning step to generate and output a virtual cervical image.

【Claim 8】

The method of claim 7, wherein the generative AI model comprises a diffusion probabilistic model.

【Claim 9】

The method of claim 8, wherein the data collection step comprises:

a capture and acquisition step of capturing and acquiring a cervical image by a camera;

a cervical image interpretation step of allowing a medical professional to interpret the captured cervical image; and

a database server storage step of storing the interpreted image data received through a communication means.

【Claim 10】

The method of claim 8, wherein the data learning step comprises:

a training dataset classification step of receiving image data from a database server storage unit and classifying the image data into a training dataset;

a training dataset preprocessing step of preprocessing the training dataset; and

a diffusion probabilistic model training step of training the diffusion probabilistic model based on the preprocessed data.

【Claim 11】

The method of claim 8, wherein the inference step comprises:

an inference input step of inputting an input image or a prompt to an inference input unit;

an inference preprocessing step of preprocessing the input data;

a cervical image generation model inference step of applying the preprocessed data to a cervical image generation model trained using the diffusion probabilistic model; and

an output step of outputting a virtual cervical image generated in the generation model inference step by an output unit.

【Claim 12】

The method of any one of claims 7 to 11, further comprising:

a interpretation step of allowing a medical professional to determine whether a virtual positive cervical image generated and output in the inference step is an actual positive image; and

a storage step of storing the image data in an AI-based cervical cancer grading model training database when the virtual positive cervical image is equivalent to the actual positive image after the interpretation step.

【Claim 13】

The method of claim 12, further comprising: a retraining step of retraining an AI-based cervical cancer grading model based on negative and positive image data stored in the AI-based cervical cancer grading model training database..