Black Sea Journal of Engineering and Science
doi: 10.34248/bsengineering.1535503

Open Access Journal
e-ISSN: 2619 – 8991

Research Article
Volume 8 - Issue 1: xx-xx / January 2025

ENHANCING MAMMOGRAPHY IMAGES WITH ARTIFICIAL INTELLIGENCE TO IMPROVE RADIOLOGICAL DIAGNOSIS IN BREAST CANCER

Fatih GÜL[1]*, Muhammed UÇAR[1], Nur HÜRSOY[2]

[1]Recep Tayyip Erdoğan University, Faculty of Engineering and Architecture, Department of Electrical-Electronics Engineering, 53100, Rize, Türkiye
[2]Recep Tayyip Erdoğan University, Faculty of Medicine, Department of Radiology, 53100, Rize, Türkiye

Abstract: Breast cancer is one of the most common types of cancer in women, and early diagnosis is life-saving. The aim of this study is to enhance the resolution of mammography images, thereby improving the contrast resolution, spatial resolution, and the detectability of calcifications, distortions, and opacities in the images. For this purpose, mammography images obtained from the open-access mini-MIAS dataset were used. Both the original dataset and the images processed with the CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm underwent resolution enhancement using the Stable Diffusion artificial intelligence system. The results were evaluated by an expert radiologist, and it was determined that the diagnostic quality of the images significantly increased. These improvements aim to support early diagnosis in breast cancer and enhance diagnostic accuracy. Additionally, the applicability and effectiveness of these methods were emphasized, and the potential benefits of resolution enhancement techniques in clinical practice were discussed. The results have the potential to allow for more detailed and accurate analysis of mammography images, thereby improving patient care and treatment planning.

Keywords: Mammography, Image Processing, Resolution Enhancement, Artificial Intelligence, Clahe Algorithm

***Corresponding author:** Recep Tayyip Erdoğan University, Faculty of Engineering and Architecture, Department of Electrical-Electronics Engineering, 53100, Rize, Türkiye
E mail: fatih.gul@erdogan.edu.tr (F. GÜL)
Fatih GÜL https://orcid.org/0000-0001-5072-2122
Muhammed UÇAR https://orcid.org/0009-0007-0445-6637
Nur HÜRSOY https://orcid.org/0000-0001-5059-2268

Received: August 19, 2024
Accepted: December 16, 2024
Published: January 15, 2024

Cite as: Gül F, Uçar M, Hürsoy N. 2025. Improving mammography images with artificial intelligence support to improve radiological diagnostic processes in breast cancer. BSJ Eng Sci, 8(1): xx-xx.

1. Introduction

Cancer, as one of the most common causes of death worldwide, is particularly prevalent among women. Breast cancer, in particular, holds a significant place among these diseases. One critical factor in combating breast cancer is early diagnosis. Various imaging technologies, such as Magnetic Resonance Imaging (MRI), Ultrasonography (US), and Mammography, have been developed and are used for the treatment of this disease (Avcı and Karakaya 2023). Among these techniques, mammography is the most commonly used method. Due to its cost-effectiveness and applicability, mammography plays an important role in the early diagnosis of cancer (Li et al. 2016).

Of the early signs of breast cancer, microcalcifications are a significant indicator that can be detected through screening methods (Mehdy et al. 2017). Mammography is a commonly used technique to identify masses in breast tissue. However, since these masses often have low contrast, the diagnostic process can be challenging. Images can be degraded by random noise due to environmental factors or device errors. Various algorithms have been developed to reduce this unwanted noise and improve image quality. Medical image processing techniques can be effective in enhancing these images through the use of Computer-Aided Diagnosis (CAD) systems.

Today, medical image processing is one of the fastest-growing fields in the healthcare sector, continuously advancing by offering new opportunities and solutions (Avcı and Karakaya 2023; Dhawan et al. 1991).

The primary goal of image processing is to enhance the reliability and comprehensibility of medical images used in diagnostic and treatment processes. Regarding breast cancer diagnosis, the presence of masses can be determined, and benign (non-cancerous) and malignant (cancerous) lesions can be distinguished using various image processing algorithms and statistical methods. These methods also support Computer-Aided Diagnosis (CAD) systems, making significant contributions to the diagnostic process (Mehdy et al. 2017).

To increase the visibility of microcalcifications, one of the earliest signs of breast cancer, in mammography images, various algorithms have been proposed (Besl and Jain 1988). Among these algorithms, techniques such as Mean Filter, Median Filter, Gaussian Filter, Contrast Limited Adaptive Histogram Equalization (CLAHE), Unsharp Masking, and Laplacian Sharpening are used in the preprocessing stage. The effectiveness of different preprocessing methods on various images has been examined in numerous studies in the literature (Al-Najdawi, Biltawi, and Tedmori 2015; Ganvir and Yadav 2019; Swathi et al. 2017). However, a review of the literature reveals that most studies focus on filtering methods and deep learning. Research aimed at enhancing the resolution of radiological images with current artificial intelligence systems is quite limited. This underscores the need for more research in this area.

In the rapidly advancing world of technology, the importance of artificial intelligence (AI) is becoming increasingly evident. Over time, interest in AI and research in this field are growing. Artificial neural networks, designed similarly to biological neural networks, have the capacity to solve a range of problems today by being used in learning and application processes. These systems provide significant advancements in various sectors due to their ability to analyze complex datasets, recognize patterns, and make predictions. This emphasizes the potential and importance of AI in the future.

In this study, a system called Stable Diffusion (SD) is used as the artificial intelligence model. Stable Diffusion allows users to create and train their own models and then utilize them. The trained models can be used for free with the Stable Diffusion AI model, which is installed on a computer and runs on a browser. This system offers the ability to generate images from text descriptions, make modifications to images, adjust the size of uploaded images, and enhance image resolution through various methods. The main material of this study comprises sections used to enhance image resolution.

The aim of this study is to enhance the resolution of mammography images and present the obtained results to an expert radiologist to examine the ease provided by image enhancement in evaluating image contrast resolution, spatial resolution, and the detectability of calcifications, distortions, and opacities. Section 2 covers the materials and methods. Section 3 discusses how the results presented to the expert radiologist were evaluated and the discussions made on these results.

2. Materials and Methods

In this study, a web-based Stable Diffusion artificial intelligence system was used to enhance the resolution of mammography images and to examine the ease provided by image enhancement for the image analysis parameters mentioned in the introduction section.

2.1. Data Collection

The study used an open-access dataset consisting of mini-MIAS mammography images (Avcı and Karakaya 2023). Additionally, a different version of this dataset created from the original was also used for this study. The images in the original dataset were converted to PNG format and processed using the CLAHE algorithm. The original dataset is the mini-MIAS dataset, which includes 322 digitized mammography images from 161 patients, including both left and right breast images (Avcı and Karakaya 2023). The images were used in PNG format and have a size of 1024x1024 pixels.

The first dataset used in this study consists of images from the original mini-MIAS dataset that were converted to PNG format, processed through the CLAHE algorithm, and cropped to a smaller size. Due to the functionality of the CLAHE algorithm, as seen in the studies by (Al-Najdawi, Biltawi, and Tedmori 2015; Avcı and Karakaya 2023), images processed through this algorithm were primarily used. Similar processes were applied to the original mini-MIAS dataset, and studies were conducted according to the requests of the expert radiologist.

Ethical committee approval was not required for this study since the data used is open-access. Due to the public availability of the data, obtaining informed consent from patients was not necessary.

2.1.1. Examination of the Mini-MIAS Dataset by Tissue and Abnormality Classes

Based on discussions with the expert radiologist, certain characteristics and classifications were emphasized for the labeled datasets to be used in this study. The background tissue of the mammography images was classified as follows:

- F: Fatty
- G: Fatty-glandular
- D: Dense-glandular

The abnormality classes were categorized as follows:

- CALC: Calcification
- CIRC: Well-defined/circumscribed masses
- SPIC: Spiculated masses
- MISC: Other, ill-defined masses
- ARCH: Architectural distortion
- ASYM: Asymmetry
- NORM: Normal

These classifications form the methodological basis of the study, ensuring accurate and effective evaluation of the mammography images.

Following consultations with the radiologist, studies were primarily conducted on images labeled as dense-glandular (D), which are considered the most important today. Examples were selected from the abnormality classes of calcification (CALC), architectural distortion (ARCH), and asymmetry (ASYM), with the background tissue character of these images chosen as dense-glandular (D) based on the expert radiologist's guidance.

The resolution of the first 30 images in the CLAHE-processed mini-MIAS database was enhanced to continue the studies. These initial 30 images include the NORM, MISC, and SIRC abnormality classes. Additionally, the images represent three different tissue characters: fatty (F), fatty-glandular (G), and dense-glandular (D).

In the original mini-MIAS dataset, three examples each of normal (NORM), benign (BENIGN-B), and malignant (MALIGN-M) for the fatty (F), fatty-glandular (G), and dense-glandular (D) background tissue classes were studied. For the abnormality class studies, a total of 27 images were prepared, consisting of three benign and three malignant examples for each of the CALC, ARCH, and

ASYM classes, and these studies were presented to the expert radiologist.

2.2. Methods

Stable Diffusion is a deep learning-based text-to-image conversion model. This model is primarily designed to create detailed images based on text descriptions. However, the capabilities of Stable Diffusion are not limited to this. It can also be successfully used for various tasks such as altering the content of an image or expanding the image (Guide: What Denoising Strength Does and How to Use It in Stable Diffusion n.d.). This demonstrates that Stable Diffusion is a significant tool in the field of image processing and synthesis. In this study, this artificial intelligence system was chosen to enlarge images, prevent quality loss during the enlargement process, and increase the resolution of the uploaded mammography images. The methods applied to the images and the values of these methods are explained in detail under the "Methods" section.

The study continued in the img2img (image to image) section of the SD web interface. The settings applied to the uploaded image were adjusted from the menus generated at the initial settings using SD interface. The values and contents of the methods used for both data sets are presented in Table 1.

Table 1. Methods and values used in the SD interface, the artificial intelligence used for this study

	1. Dataset	2. Dataset
Sampling Methods	DPM++2M KARRAS	DPM++2M KARRAS
Sampling Steps	40	100
CFG Scale	10	7
Denoising Strength	0,1	0,1
Script	Ultimate SD Upscale	Ultimate SD Upscale
Target Size Type to Scale from Image Size	1,5	1,5
Upscaler	ESRGAN_4x	ESRGAN_4x

Sampling Methods are algorithms that guide the process by which an artificial intelligence model transforms random noise into a coherent image. This process can be likened to a painter who starts with a blank canvas and gradually adds layers of paint, eventually creating a picture. These methods determine how each 'brush stroke' is applied, affecting the final appearance, detail, and accuracy of the image (Steins 2023). In this study, the DPM++ 2M Karras method was chosen as the sampling method due to its high level of detail.

Sampling Steps correspond to individual brush strokes in our painting analogy. Each step is a phase where the AI makes adjustments to the image, bringing it closer to the final result. Fewer steps allow the process to progress faster but may result in less detail. Conversely, more steps enable finer details but make the process take longer. The key is to find the right balance for the desired outcome (Steins 2023). Initially, 40 steps were applied for the processed dataset and 100 steps for the original dataset.

CFG Scale is an important concept in the field of Stable Diffusion (SD). This scale is used to control how closely the generated image aligns with the input prompt. Essentially, the CFG Scale functions as a control knob that determines how closely the AI follows the specific details and instructions specified in the user's prompt (Steins 2023). For the initial dataset, a CFG Scale value of 10 was chosen. For the original dataset, this value was set to 7.

Denoising Strength is a parameter that determines how much noise is added to the image before the sampling steps. This parameter is commonly used in image-to-image transformation applications in Stable Diffusion. The value of Denoising Strength ranges from 0 to 1. A value of 0 means no noise is added to the input image, while a value of 1 means the input image is completely replaced by noise. This parameter balances between preserving the original image and creating a completely new image (Rombach et al. 2022). In this study, a Denoising Strength value of 0.1 was used for both datasets to ensure that the image was not distorted.

Target Size Type is either taken from the img2img settings mentioned above or the initially uploaded image is scaled up by the entered factor. This is an optional method that can be adjusted as needed. In this study, all uploaded images were scaled from their image size and increased by a factor of 1.5.

The Upscaler model used was ESRGAN_4x, and all other settings were left at their default values. These methods were applied to all images, and the results were obtained. This approach has allowed for more detailed analyses by increasing the resolution of the images.

2.2.1. Resolution Enhancement Applications

Selected images from the dataset processed with the CLAHE algorithm and cropped were uploaded to the system, and the specified methods were applied to obtain an output. This output was then re-uploaded to the system, and the same processes were applied a second time. Thus, the image was enhanced by enlarging it 1.5 times twice. As an example of the studies in this dataset, the steps shown in Figure 1 were obtained by applying these methods, and the processes were applied separately to each of the selected 30 images. In the size process of the sample image, the image was enlarged from 512x512 pixels to 768x768 pixels in the first application, and then to 1152x1152 pixels when applied again, obtaining the final image.

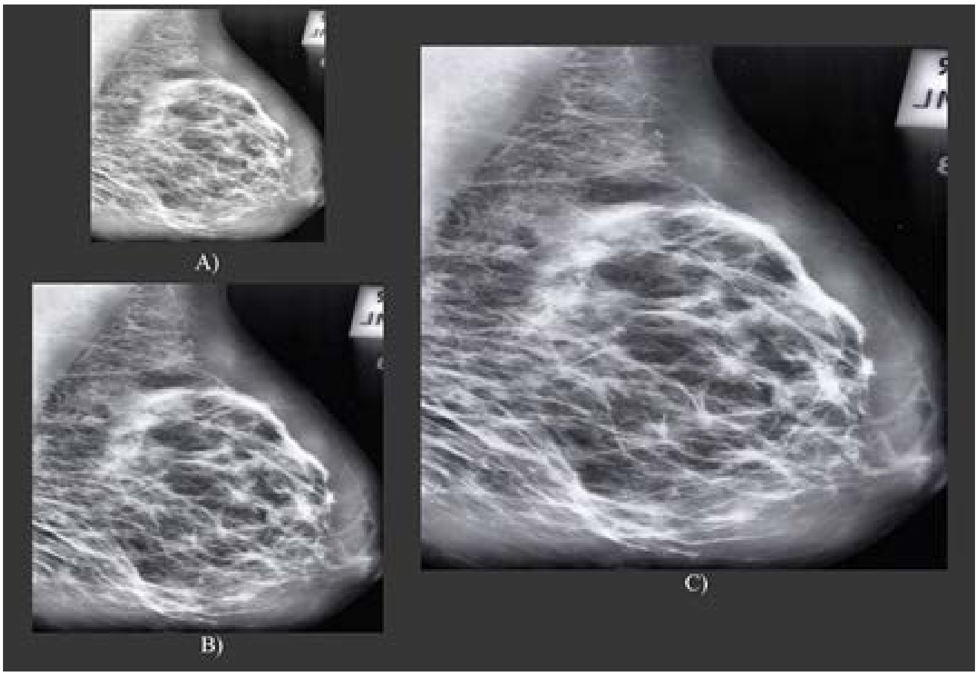

Figure 1. The normal state of a mammogram image from the processed dataset (A). The first result of applying the methods (B). The result of applying the methods a second time (C).

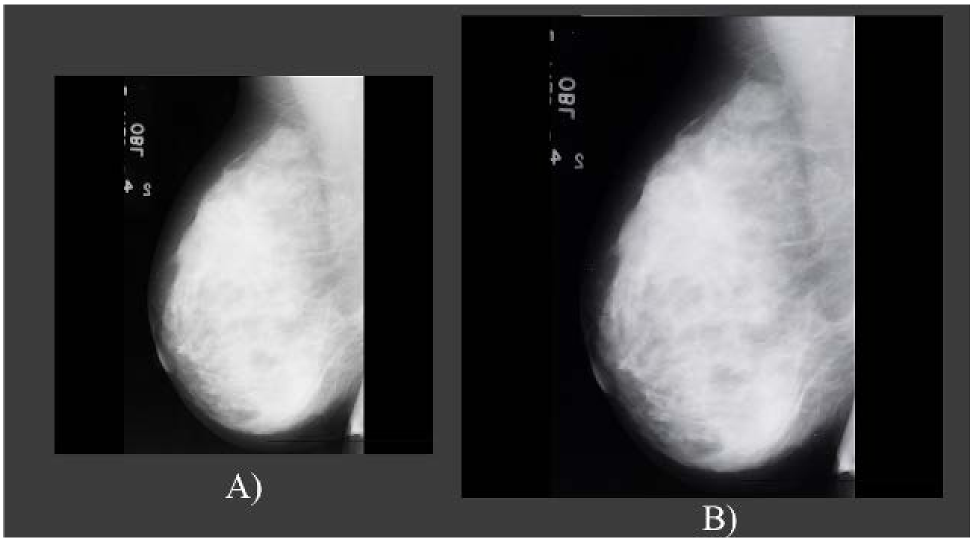

Figure 2. A sample image from the original dataset in its normal state (A), and the output obtained after the first application of the methods (B).

For the mammogram images in the original mini-MIAS dataset, images selected for categories preferred by the radiologist were converted from PGM format to PNG format. These images were then processed once, as explained in the "Methods" section, and enlarged from 1024x1024 pixels to 1536x1536 pixels. Figure 2 shows the process of the studies using one of these applications.

3. Results and Discussion

The enhanced images were evaluated by a radiology specialist with five years of experience in breast radiology using a 23.8-inch screen with a resolution of 1920x1080. The contributions of the enhanced images to the evaluation process, including contrast resolution, spatial resolution, detectability of calcifications, distortions, and opacities, were examined. Table 2 compares key image metrics before and after enhancement using artificial intelligence.

In the evaluation of the first dataset, which consisted of CLAHE-applied and cropped images, an increase in spatial and contrast resolution was detected in all images. This increase in resolution facilitated the detection of calcifications and the identification of distortions and nodular opacities. However, no differences were found in the BI-RADS category assessments by the radiology specialist. It was concluded that the image improvements could shorten the evaluation time but did not change the diagnosis made by the specialist.

Table 2. Image Metric Comparison

Metric	Before Enhancement	After Enhancement
Contrast Resolution	0.75	0.90
Spatial Resolution (pixels)	1024x1024	1536x1536
Detectability of Calcifications	Low (Score: 3/10)	High (Score: 8/10)
Detectability of Distortions	Moderate (Score: 5/10)	High (Score: 9/10)
Detectability of Opacities	50%	90%

In the second phase of the study, images from different subgroups of the unprocessed dataset (mini-MIAS dataset) were selected, as previously mentioned. Enhancements were made on images with findings of calcifications, asymmetry, and distortions in different parenchymal types in the benign and malignant labeled groups. These enhanced images were evaluated by the same radiology specialist. No obvious differences were found between the images processed by the AI system, which allows various modifications, and the raw images. The detectability of the findings indicated in the labels was similar. The reason for not detecting differences in the second study may be that the original dataset images were of higher quality compared to the images in the first phase, and image enhancement did not lead to significant changes.

Table 3 provides a summary of all categories studied in this work and the criteria considered by the radiologist during the evaluation process.

Table 3. Categories used throughout the study and the results of the examination criteria

	Contrast Resolution	Spatial Resolution	Eligibility of Calcifications	Selectability of Distortions	Selectability of Opacities	Diagnosis
Fatty (F)	✓	✓	✓	✓	✓	~
Fatty Glandular (G)	✓	✓	✓	✓	✓	~
Dense Glandular (D)	✓	✓	✓	✓	✓	~
MISC	✓	✓	✓	✓	✓	~
CIRC	✓	✓	✓	✓	✓	~
CALC	○	○	○	○	○	~
ARCH	○	○	○	○	○	~
ASYM	○	○	○	○	○	~

✓= Indicates that visible improvement with the observation of the expert mammography radiologist. ○= Indicates that there is no visible change as observed by the radiologist. ~: Indicates that the procedure performed slight change the diagnosis made by the radiologist.

In the academic literature, the preprocessing step plays a critical role in the segmentation and feature extraction processes for identifying suspicious regions. Among preprocessing techniques, Contrast Limited Adaptive Histogram Equalization (CLAHE), Median Filtering, and Unsharp Masking algorithms are widely preferred (Al-Najdawi, Biltawi, and Tedmori 2015; Ramani, Suthanthira Vanitha, and Valarmathy 2013). However, no similar studies directly overlapping with the processes performed in this study have been found. Upon examining the first dataset used, it was observed that the images were already processed with the CLAHE algorithm, which is believed to have positively contributed to the study's results.

The use of image enhancement algorithms has been found to accelerate the evaluation processes of radiologists. These algorithms, particularly in detecting calcifications, distortions, and nodular opacities, have increased the detectability rate. This suggests that the algorithms have potential value in clinical applications.

4. Conclusion

In conclusion, various methods were used in an AI model implemented on a computer system to enhance mammography images. These methods facilitated the evaluation process by increasing the resolution of the images. However, it was observed that these enhancements did not lead to a significant improvement in the diagnostic processes of radiologists. Studies conducted on images processed using the CLAHE algorithm concluded that they provided more effective decision-making capabilities and could shorten the evaluation process compared to the original images.

Future research is recommended to be conducted with expanded datasets, including filtering algorithms used in the literature, in addition to this AI system. This approach is believed to not only increase the resolution of the images but also aid radiologists more in detecting benign and malignant lesions. This could be an important step in improving the evaluation and diagnostic processes of mammography images.

Author Contributions

The percentages of the authors' contributions are presented below. All authors reviewed and approved the final version of the manuscript.

	F.G.	M.U.	N.H.
C	30	30	40
D	30	40	30
S	50	10	40
DCP	30	40	40
DAI	40	40	30
L	40	30	30
W	40	40	20
CR	30	30	40
SR	60	30	10
PM	60	30	10
FA	60	30	10

C=Concept, D= design, S= supervision, DCP= data collection and/or processing, DAI= data analysis and/or interpretation, L= literature search, W= writing, CR= critical review, SR= submission and revision, PM= project management, FA= funding acquisition.

Conflict of Interest

The authors declared that there is no conflict of interest.

Ethical Consideration

Ethics committee approval was not required for this study because of there was no study on animals or humans.

Acknowledgements

This article was produced from the thesis of the second author, supervised by the first and co-supervised by the third author, a radiology specialist with expertise in mammography. All of the research accomplished in "Artificial Intelligence/Internet of Things Research Laboratory (AIIoT Lab), Recep Tayyip Erdogan University", supported under the TÜBİTAK-121E544 project. The authors thank TÜBİTAK for contributions.

References

Al-Najdawi, Nijad, Mariam Biltawi, Sara Tedmori. 2015. Mammogram image visual enhancement, mass segmentation and classification. Applied Soft Comput, 35: 175–85. doi:10.1016/J.ASOC.2015.06.029

Avcı, Hanife, Jale Karakaya. 2023. A novel medical image enhancement algorithm for breast cancer detection on mammography images using machine learning. Diagnostics, 13(3): 348. doi:10.3390/DIAGNOSTICS13030348

Besl, Paul J, Ramesh C Jain. 1988. Segmentation through variable-order surface fitting. IEEE Transact Pattern Analys Mach Intellig, 10(2): 167–92. doi:10.1109/34.3881

Dhawan, Atam P, Yateen S. Chitre, Myron Moskowitz, Eric Gruenstein. 1991. Classification of mammographic microcalcification and structural features using an artificial neural network. https://researchwith.njit.edu/en/publications/classification-of-mammographic-microcalcification-and-structural- (accessed date: August 12, 2024).

Ganvir, Neha N, DM Yadav. 2019. Filtering method for pre-processing mammogram images for breast cancer detection. Inter J Engin Adv Technol, 9(1): 4222–29. doi:10.35940/ijeat.A1623.109119

Guide. 2024. What denoising strength does and how to use it in stable diffusion. https://onceuponanalgorithm.org/guide-what-denoising-strength-does-and-how-to-use-it-in-stable-diffusion/ (accessed date: August 12, 2024).

Li, Hongjun, Shanhua Zhang, Qingyuan Wang, Rongguang Zhu. 2016. Clinical value of mammography in diagnosis and identification of breast mass. Pakistan J Med Sci, 32(4): 1020. doi:10.12669/PJMS.324.9384.

Mehdy MM, PY Ng, EF Shair, NI Md Saleh, C Gomes. 2017. Artificial neural networks in image processing for early detection of breast cancer. Comput Math Meth Med, 2017(1): 2610628. doi:10.1155/2017/2610628

Ramani, R, N Suthanthira Vanitha, S Valarmathy. 2013. The pre-processing techniques for breast cancer detection in mammography images. Inter J Image, Graph Signal Proc, (5): 47–54. doi:10.5815/ijigsp.2013.05.06

Rombach, Robin, Andreas Blattmann, Dominik Lorenz, Patrick Esser, Bjorn Ommer. 2022. High-resolution image synthesis with latent diffusion models. Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 5-6 June, Dubai, UAE, pp: 10674–106785. doi:10.1109/CVPR52688.2022.01042

Steins. 2023. Stable Diffusion clearly explained! Medium. http://anakin.ai/blog/stable-diffusion-sampling-steps/ (accessed date: August 12, 2024).

Swathi C, Anoop BK. Anto Sahaya Dhas D, Perumal Sanker S. 2017. Comparison of different image preprocessing methods used for retinal fundus images. 2017 Conference on Emerging Devices and Smart Systems, ICEDSS 2017: 175–79. doi:10.1109/ICEDSS.2017.8073677