International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 8.021 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 11, Issue 6, June 2023
DOI: 10.17148/IJIREEICE.2023.11625

Generating Realistic and Coherent Textures for Missing Regions in Images using DeepFill

Varsha C Parihar [1], Sai Prabhu K.B[2]

Assistant Professor, Department of Electronics & Communication, T.John Institute of Technology, Bengaluru, INDIA[1]

Assistant Professor, Department of Electronics & Communication, T.John Institute of Technology, Bengaluru, INDIA [2]

Abstract: DeepFill is a method that allows you to paint an image with a free-form mask using a generative adversarial network (GAN). This includes contextual awareness and gated convolution to generate realistic and consistent textures for missing regions. It can handle various remediation scenarios such as: B. Delete objects, complete faces, delete text, etc. User-guided repairs can also be supported with additional inputs such as sketches and colors. DeepFill is based on his Jiahui Yu et al article "Free-Form Image Inpainting with Gated Convolution" published at ICCV 2019. Image inpainting uses information from surrounding pixels to fill in missing or damaged areas of the image. Image restoration can be used for many purposes. B. Restore corrupted images, remove unwanted objects, create artistic effects, etc.

Keywords: Inpainting, DeepFill, Image Processing.

I. INTRODUCTION

Images can be inpainted using different techniques such as diffusion-based, patch-based and learning-based methods. Diffusion-based methods use partial differential equations to transfer pixel values from the boundary of the missing region to the interior. . Patch-based methods use an optimization algorithm to copy and paste similar patches from known regions to missing regions. Learning-based techniques use machine learning models such as: B. Deep neural networks. Use training data to learn the mapping of input images with missing regions to output images with filled regions.

Diffusion-based methods are a type of image inpainting technique that uses partial differential equations to transfer pixel values from the boundary of the missing region to the interior. Diffusion-based methods can remove noise and artifacts while preserving image continuity and smoothness. However, diffusion-based methods tend to blur edges and textures and lose image detail and structure.

Diffusion-based methods can be categorized into his two categories:

Isotropic and anisotropic. The isotropic diffusion method uses a constant diffusion coefficient in all directions. This means that the diffusion process is uniform and independent of image content. The anisotropic diffusion method uses a variable diffusion coefficient depending on local image features such as edges and gradients. This means that the diffusion process is adaptive and preserves image structure.

II. LITERATURE SURVEY

Diffusion-based methods include:

• Heat equation:
A simple isotropic diffusion method that uses the Laplacian to model the heat flow in the image. It can remove noise and fill in small gaps, but it also blurs edges and details1.

• Perona-Malik model:
A common anisotropic diffusion method that uses an edge-stop feature to control the diffusion coefficient. It can preserve edges and improve contrast, but it becomes numerically unstable and jaggy2.

• Global variation model:
An anisotropic diffusion method that uses a global variation regularization term to minimize image variation. It can preserve edges and remove noise, but it produces piecewise constant areas and loses fine detail3.

• Curvature-driven diffusion model:
An anisotropic diffusion method that uses a curvature term to determine the direction of diffusion. Edges and smooth regions can be preserved, but it also requires high computational complexity and complex implementation.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁘ Impact Factor 8.021 ⁘ Peer-reviewed / Refereed journal ⁘ Vol. 11, Issue 6, June 2023

DOI: 10.17148/IJIREEICE.2023.11625

Patch-based methods are a type of image inpainting technique that uses an optimization algorithm to copy and paste similar patches from known regions to missing regions. Patch-based methods can preserve image detail and structure and fill large gaps. However, patch-based methods are prone to image inconsistencies and repetitions, and are computationally and time-intensive.

Patch-based methods can be divided into two categories in his:

Example-based and learning-based. The example-based method finds the best matching patch from the source region for each patch in the target region using a similarity measure such as: B. Euclidean distance or normalized cross-correlation. Learning-based techniques use machine learning models such as: B. Deep neural networks. Use training data to learn the mapping of input images with missing regions to output images with filled regions.

Here are some examples of patch-based methods.

An example of the classical method of using a precedence term to determine the patch filling order based on the confidence term and the data term. It can handle textured and textured images, but it also suffers from blocking artifacts and edge misregistration1.

An instance-based method that combines diffusion and patch propagation to fill in missing regions. Edges and textures can be preserved, but also require manual intervention and parameter tuning.

• Patch Match:
A fast algorithm for finding approximate nearest neighbor fields from large image collections. Random initialization and propagation can be used to speed up the patch search process.

• Context Encoder:
A learning-based method that uses a convolutional neural network with an encoder/decoder architecture to process the image once. Although it can produce realistic images, it also tends to blur the results and lose detail.

• Makeover:
A learning-based method that uses probabilistic denoising and diffusion models as pre-generation for inpainting. It can produce high-quality, versatile output images for any restoration shape.

• DeepFill by Jiahui Yu et al. is a method by which a free-form mask can be applied to an image using a generative adversarial network (GAN). It is based on her two main components:
Contextual attention and gated convolution.

III.WORKING PROCEDURE

A method belonging to the category of adversarial methods for DeepFill image inpainting by Jiahui Yu et al. Generate realistic and consistent textures for inpainting using generative adversarial networks (GANs). It also incorporates context awareness and gated convolution to improve the performance and quality of inked images.

• Adversarial Repair of Medical Imaging Modalities by Karim Armanious et al. is a method to insert missing information into medical images using generative adversarial networks (GANs). It is based on two patch-based discrimination networks with additional stylistic and perceptual losses.

• The method can handle different types and sizes of masks, such as circular, square, and free-form masks, and various medical imaging modalities, such as MRI and CT. It also allows you to draw realistic and consistent details according to your surroundings and original modality.

• This method consists of her three main components:

Generator network, global discriminator network, and local discriminator network. A generator network takes an image with a mask as input and outputs a color image. A global discriminator network takes the entire image as input and predicts the relative reality of the colorized image compared to the original image. A local discriminator network takes as input patches around a colored region and predicts the relative reality of the colored patch compared to the original patch.

DOI: 10.17148/IJIREEICE.2023.11625

• This method also uses two additional losses.
Loss of style and loss of recognition. Style loss measures the difference between the feature map Gram matrix of the colored image and the original image that captures the style and texture information. Perceptual loss measures the difference between the feature maps of the colorized image and the original image before activation, capturing brightness consistency and texture recovery.

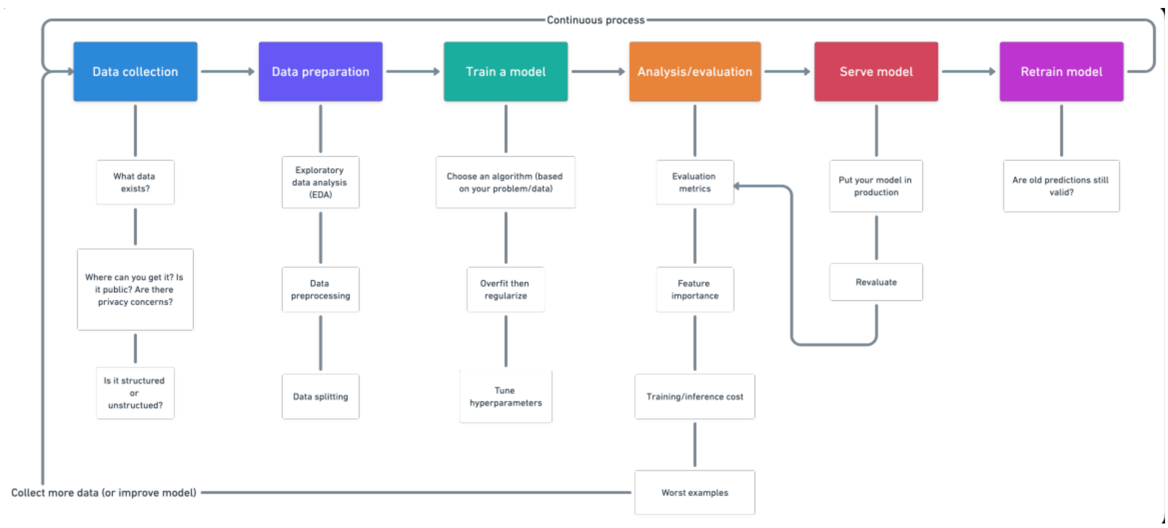
• This method is qualitatively and quantitatively superior to other natural imaging techniques in two different medical modalities.

MRI and CT
His DeepFill by Jiahui Yu et al. is a method to apply free-form masks to images using generative adversarial networks (GANs). It also incorporates context awareness and gated convolution to improve the performance and quality of inked images.

• Contextual awareness is a technique that allows the network to acquire information from remote spatial locations and generate missing regions. Large, irregular holes can be handled by finding similar patches in the source area and copying them to the target area.

Gated convolution is a technique that allows the network to dynamically control feature selection at each layer. A learnable gating mask that adapts to the input mask can be used to handle different hole shapes and positions.

His DeepFill by Jiahui Yu et al. can produce realistic and consistent results for a variety of repair scenarios, including object removal, face completion, and text removal. You can also perform user-guided repairs with additional inputs such as sketches and colors.



The main steps of the DeepFill algorithm are:

• Input:
The input consists of an image with a free-form mask that specifies the missing regions. Masks can be of any shape and size and can be user-created or randomly generated.

• Generator:
A generator network takes an input image with a mask as input and outputs a color image. A generator network consists of multiple gated convolution layers that dynamically control feature selection in each layer using learnable gate masks. Generative networks also use a contextual layer of attention that allows the network to inherit information from distant spatial locations to generate missing regions. The generator network minimizes the reconstruction loss, which measures the pixel-by-pixel difference between the colored image and the original image, and the inverse loss, which measures the difference between the real-world values determined by the discrimination network. are trained.

• Identifier:
A discrimination network takes an image as input and predicts a reality score that indicates how likely it is that the image is the actual image rather than the generated image. There are two identification networks.

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 8.021 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 11, Issue 6, June 2023
DOI: 10.17148/IJIREEICE.2023.11625

They are the global discriminator network and the local discriminator network. A global discriminator network takes the entire image as input and predicts its reality score. A local discriminator network takes as input a patch around a colored area and predicts its reality score. The discriminant network is trained to maximize the adversarial loss, which measures the difference in reality ratings between the original and painted images.

• Exit:
The output is a colorized image produced by a generator network that fills in missing areas with realistic and consistent textures.

Various image restoration methods can be used in medical imaging, depending on the type and size of the missing region, the modality and quality of the image, and the desired result and application. Here are some ways:

• Interpolation-based method:
These methods use interpolation techniques such as linear interpolation, cubic interpolation, and spline interpolation to estimate pixel values in missing regions based on neighboring pixels. Although these methods are simple and fast, they can produce blurry and unrealistic results, especially for large and complex defect regions1.

• Diffusion-based method:
These methods use diffusion techniques such as the heat equation, Perona-Malik model, total variation model, or curvature-driven diffusion model to transfer pixel values from the boundary of the missing region to the interior using partial differential equations. . While these methods can remove noise and artifacts and preserve image continuity and smoothness, they can also blur edges and textures and lose image detail and structure2. • Patch-based method:

These methods use patch-based techniques such as Criminisi et al., Bertalmio et al., PatchMatch, or ContextEncoder, and use optimization algorithms or machine-learning models to generate similarities from known regions to missing regions. Copy and paste patches. While these methods can preserve image detail and structure and fill large gaps, they can also introduce inconsistencies and repetitions in the image and require extensive computation and time3.

• Adversarial-based techniques:
These methods use adversarial techniques such as his DeepFill by Jiahui Yu et al., his ESRGAN by (GANs). Although these methods can provide high-quality and diverse results for different inpainting scenarios, they can also introduce artifacts, blurring, inconsistencies, and mode collapse4.

These are some of the methods that can be used for image restoration in medical imaging.

Advantages of the DeepFill method:

• Can handle free-form masks of arbitrary shape and position, but other methods may be limited to certain mask types such as: B. Rectangular mask or central mask. • Other methods may give blurry or repetitive results, but give realistic and varied results.

• User prompts such as sketches and colors can be integrated to control the healing process, but other methods may not support such inputs.

• The power of generative adversarial networks can be harnessed to improve the perceptual quality and fidelity of painted images, while other methods rely on per-pixel loss and perceptual loss that are not optimal for image generation. There is likely to be.

Deep fill flowchart

• The block diagram shows the major components and connections of the DeepFill algorithm. Input images with masks are fed to a generator network consisting of multiple controlled convolution layers and contextual attention layers. The output image of the generator network is fed to a global discriminator network and a local discriminator network to predict the real-world values of the whole image and colour patches, respectively. The generator and discriminator networks are trained with reconstruction and inverse losses, respectively.

• A message has been received. Below is a block diagram based on the DeepFill algorithm
The block diagram shows the main components and connections of the DeepFill algorithm. Input images with masks are fed to a generator network consisting of multiple controlled convolution layers and contextual attention layers. The output image of the generator network is fed to a global discriminator network and a local discriminator network to predict the

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
ISO 3297:2007 Certified ⧖ Impact Factor 8.021 ⧖ Peer-reviewed / Refereed journal ⧖ Vol. 11, Issue 6, June 2023
DOI: 10.17148/IJIREEICE.2023.11625

real-world value of the entire image and color patches, respectively. The generator and discriminator networks are trained with reconstruction and inverse losses, respectively.

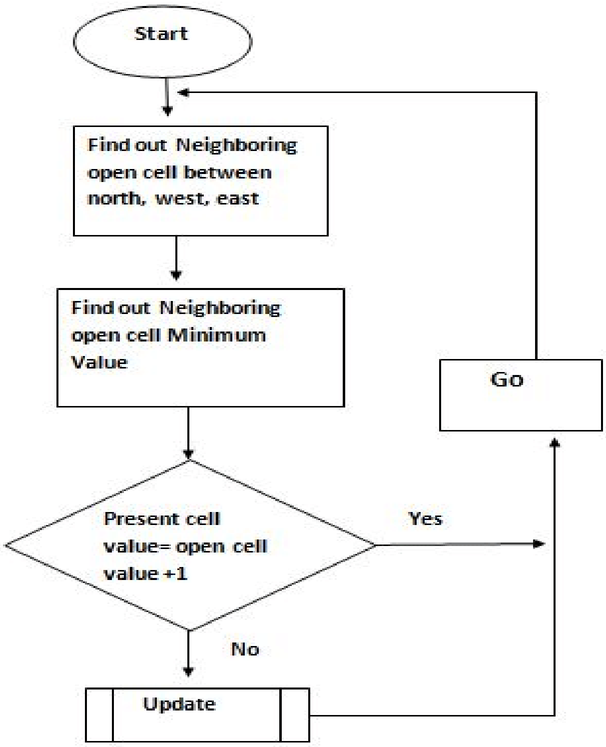
This flowchart shows the inputs, outputs, and intermediate steps of the DeepFill algorithm. The input is an image with a free-form mask that specifies the missing regions. The result is a painted image that fills in missing areas with a realistic and consistent texture. Intermediate steps include generator networks, global discriminator networks, local discriminator networks, reconstruction loss, and adversarial loss. A generator network takes an input image with a mask as input and outputs a colour image. A global discriminator network takes the entire image as input and predicts its reality score. A local discriminator network takes as input a patch around a coloured area and predicts its reality score. Reconstruction loss measures the difference in pixels.

Applications of the DeepFill method DeepFill algorithms can be used for different applications in different domains and scenarios such as:

• Edit a picture:
The DeepFill algorithm allows you to remove unwanted objects and people from your images. Wires, logos, watermarks, etc. It can also be used to fill in missing or damaged areas of the image such as scratches, smudges, and holes. It can also support user-guided repairs by controlling the repair process with additional inputs such as sketches and colours.

• Image recovery:
The DeepFill algorithm allows you to recover damaged or degraded images such as old photos, paintings and documents. It can also be used to improve the quality and resolution of low resolution images such as web images and thumbnails.

• Image compositing:
New images can be synthesized from existing images using the DeepFill algorithm. It can also be used to generate realistic and diverse images for data enhancement or artistic design by changing backgrounds, adding or removing elements, changing styles and textures, etc.



These are some of the applications of the DeepFill algorithm. See the web search results below for more examples and usage examples.

The DeepFill algorithm is a type of deep learning technique that can colour missing or damaged areas in an image by producing realistic and consistent content1. They are useful in medical imaging, such as restoring damaged or poor quality images, improving image quality, imputing missing data, and creating synthetic images for data augmentation234.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

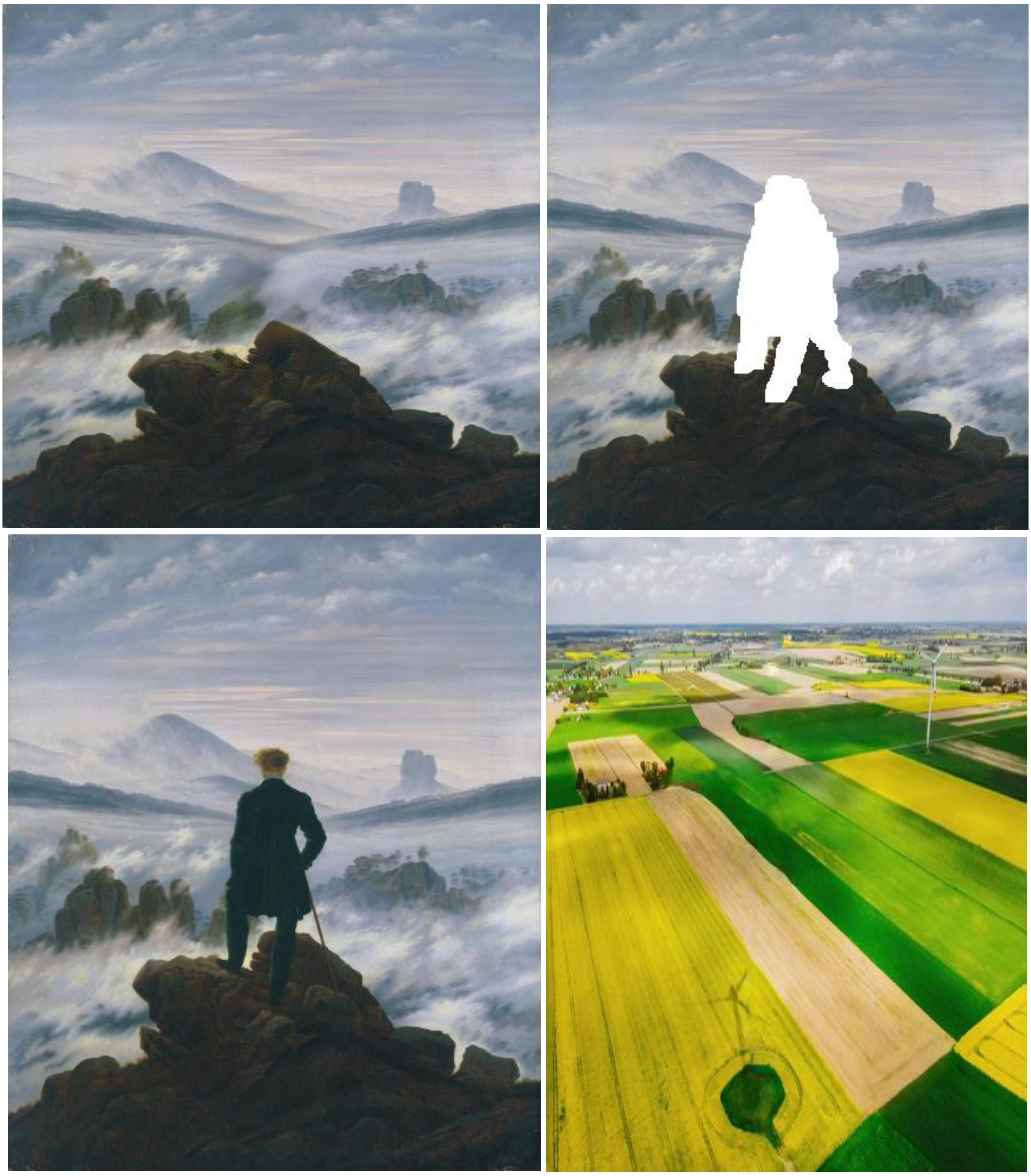
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁘ Impact Factor 8.021 ⁘ Peer-reviewed / Refereed journal ⁘ Vol. 11, Issue 6, June 2023

DOI: 10.17148/IJIREEICE.2023.11625

Medical imaging is the art of creating images of the internal structure of organs for clinical research, diagnosis, or surgical guidance. It involves various steps such as image acquisition, reconstruction, enhancement, segmentation, analysis and visualization5. Various imaging techniques can be used in medical imaging, including: B. Computed tomography (CT), X-ray, ultrasound, ultrasonography, radiography, etc.5.

RESULT

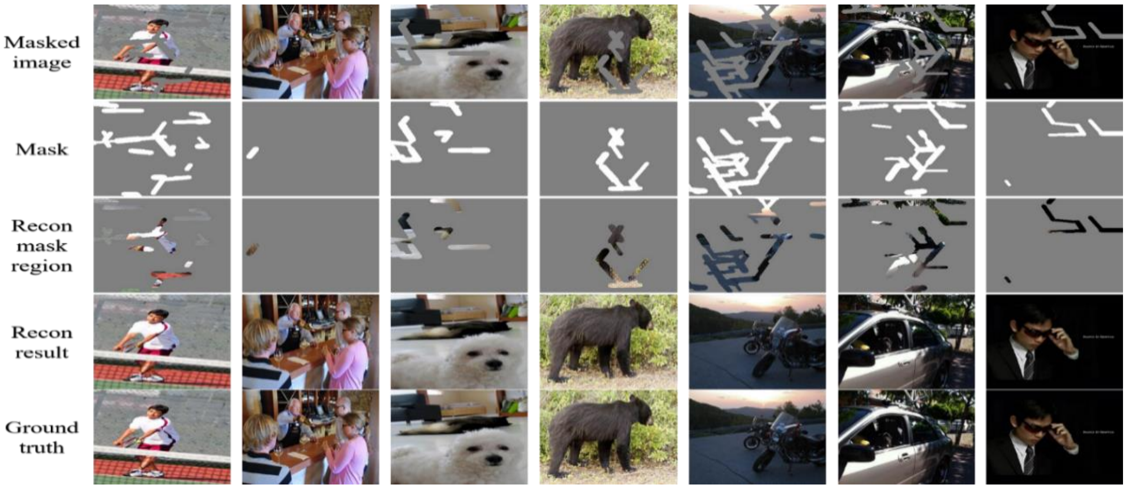


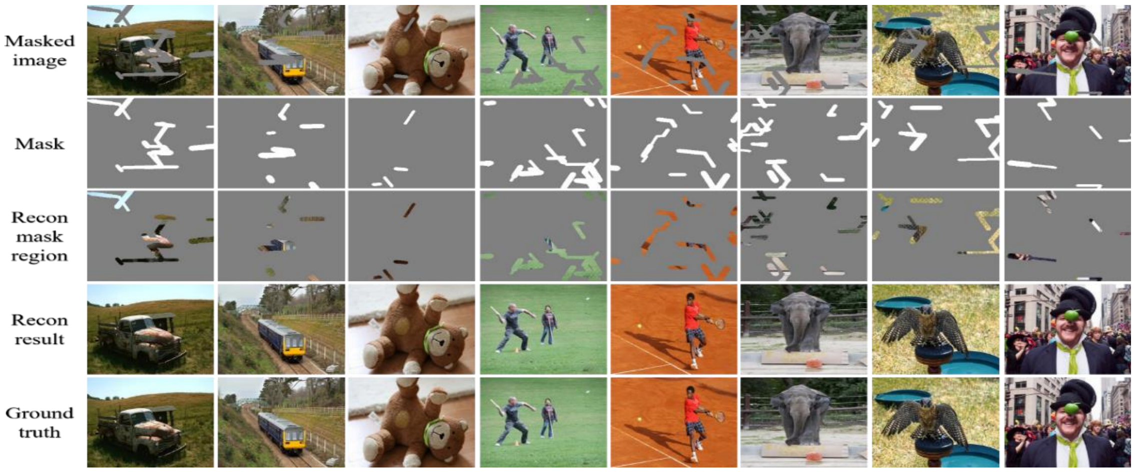
IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ∺ Impact Factor 8.021 ∺ Peer-reviewed / Refereed journal ∺ Vol. 11, Issue 6, June 2023

DOI: 10.17148/IJIREEICE.2023.11625





IV. CONCLUSION

The DeepFill algorithm, also known as Deep Image Prior (DIP), is a technique used to inpaint and perfect an image. It uses deep learning techniques to fill in missing or corrupted areas of the image, resulting in a visually pleasing and consistent finish. DeepFill algorithms are trained on large image datasets, allowing them to learn the underlying patterns, textures, and structures in the data. Using this knowledge, the algorithm generates content that fills the masked or missing areas of the image. The performance and quality of the DeepFill algorithm can vary based on various factors such as training data quality, network architecture, and training parameters. Therefore, results produced by the DeepFill algorithm may vary in realism and accuracy.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

ISO 3297:2007 Certified ⁝ Impact Factor 8.021 ⁝ Peer-reviewed / Refereed journal ⁝ Vol. 11, Issue 6, June 2023

DOI: 10.17148/IJIREEICE.2023.11625

To explore and experience specific examples and results of image creation using the DeepFill algorithm, we encourage you to refer to recent research papers, articles, or online resources that showcase its application. Additionally, you may find open-source implementations of DeepFill algorithms that you can experiment with to generate image interpolations. Overall, the DeepFill algorithm is a powerful tool for image creation and completion tasks, offering potential applications in areas such as image manipulation, restoration, and compositing.

REFERENCES

[1]. Machine Learning: Algorithms, Real-World Applications and Research Directions Iqbal H. Sarker SN Computer Science volume 2, Article number: 160 (2021)

[2]. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions

[3]. Iqbal H. Sarker SN Computer Science volume 2, Article number: 420 (2021)

[4]. Review of Deep Learning Algorithms and Architectures Publisher: IEEEAjay Shrestha; Ausif Mahmood All Authors

[5]. Deep Learning in Medical Imaging Mingyu Kim,1 Jihye Yun,1 Yongwon Cho,1 Keewon Shin,1 Ryoungwoo Jang,1 Hyun-jin Bae,1 and Namkug Kim1,2 Published online 2019 Dec 31. doi: 10.14245/ns.1938396.198 PMCID: PMC6945006 PMID: 31905454

[6]. Medical image analysis based on deep learning approach Muralikrishna Puttagunta and S. Ravicorresponding author Published online 2021 Apr 6. doi: 10.1007/s11042-021-10707-4 PMCID: PMC8023554 PMID: 33841033

[7]. Analysis of Algorithms in Medical Image Processing

[8]. Tina, Sanjay Kumar Dubey, Ashutosh Kumar Bhatt & Mamta Mittal Conference paper First Online: 20 August 2021

[9]. Image inpainting: A review Omar Elharrouss, Noor Almaadeed, Somaya Al-Maadeed, Younes Akbari

[10]. Image Inpainting : Overview and Recent Advances Publisher: IEEEReference Guided Image Inpainting using Facial Attributes Dongsik Yoon, Jeonggi Kwak, Yuanming Li, David Han, Youngsaeng Jin, Hanseok Ko Yu, J., Lin, Z., Yang, J., Shen, X., Lu, X., & Huang, T. S. (2018).

[11]. Generative image inpainting with contextual attention. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 5505-5514)1 Kumar, A., & Singh, A. (2020).

[12]. Image inpainting with contextual attention and partial convolution. In 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE3Gu et al., 2017

[13]. J. Gu, G. Yin, P. Huang, J. Guo, L. Chen An improved back propagation neural network prediction model for subsurface drip irrigation system Comput. Electr. Eng., 60 (2017), pp. 58-65, 10.1016/j.compeleceng.2017.02.016 View PDFView articleView in ScopusGoogle Scholar

[14]. Gupta et al., 2015 Kuo et al., 2018 Y. Kuo, H.Z. Li, D. Kifer Detecting outliers in data with correlated measures 2018 ACM Conference on Information and Knowledge Management (CIKM'18) (2018), pp. 22-26, 10.1145/3269206.3271798 View article Google Scholar

[15]. Kwak and Kim, 2017 S.K. Kwak, J.H. Kim Statistical data preparation: management of missing values and outliers Korean J. Anesthesiol., 70 (4) (2017), pp. 407-411, 10.4097/kjae.2017.70.4.407 View article View in ScopusGoogle Scholar

[16]. Lawrence, 1994 J. Lawrence Introduction to Neural Networks California Scientific Software Press, Nevada City (1994) Google Scholar

[17]. Liu et al., 2001 J. Liu, C.E. Goering, L. Tian A neural network for setting target corn yields Trans. ASAE, 44 (3) (2001), pp. 705-713, 10.2001/j.trans.2001.742104x View article View in ScopusGoogle Scholar

[18]. Liu et al., 2017 S. Liu, X. Wang, M. Liu, J. ZhuTowards better analysis of machine learning models: A visual analytics perspective Visual Inf., 1 (2017), pp. 48-56, 10.1016/j.visinf.2017.01.006 View PDFView articleView in ScopusGoogle Scholar

[19]. Matsumura et al., 2015 K. Matsumura, C.F. Gaitan, F. Sugimoto, A. Cannon, W.W. Hsieh Maize yield forecasting by linear regression and artificial neural networks in Jilin, ChinaJ. Agr. Sci., 153 (3) (2015), pp. 399-410, 10.1016/j.agrsci.2015.10.153 View article View in ScopusGoogle Scholar

[20]. Maya Gopal and Bhargavi, 2019a P.S. Maya Gopal, R. Bhargavi Optimum Feature subset for optimizing crop yield prediction using filter and wrapper approaches Appl. Eng. Agri., 35 (1) (2019), pp. 9-14, 10.13031/aea.12938 View article View in ScopusGoogle Scholar

[21]. Maya Gopal and Bhargavi, 2019b P.S. Maya Gopal, R. Bhargavi Performance evaluation of best feature subsets for crop yield prediction using machine learning algorithms Appl. Artificial Intelligence, 33 (7) (2019), pp. 621-642, 10.1080/08839514.2019.1592343 View PDF View in ScopusGoogle Scholar

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
ISO 3297:2007 Certified ⁜ Impact Factor 8.021 ⁜ Peer-reviewed / Refereed journal ⁜ Vol. 11, Issue 6, June 2023
DOI: 10.17148/IJIREEICE.2023.11625

BIOGRAPHY

Mrs Varsha C Parihar. Assistant Professor at T.John Institute of Technology and his research interest includes Digital electronics. He has more than 8 years of teaching experience

Mrs Varsha C Parihar has completed M.Tech in Digital electronics Systems from M S Ramaiah INSTITUTE OF TECHNOLOGY, Bengaluru under Visvesvaraya Technological University and Bachelor of Engineering [B.E] in Electronics and Communication from Pune University, Pune.

Mr. SAI PRABHU K.B. Assistant Professor at T.John Institute of Technology and his research interest includes VLSI design & embedded system design. He has more than 9 years of working experience which includes close to 7 years of IT working in research and embedded domains and 3 years of teaching.

Mr. SAI PRABHU K.B has completed M.Tech in VLSI Design and Embedded Systems from NITTE MEENAKSHI INSTITUTE OF TECHNOLOGY, Bengaluru under Visvesvaraya Technological University and Bachelor of Engineering [B.E] in Electronics and Communication from Visveswaraya Technological University, Belgaum.