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# Image Inpainting Using Deep Learning

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**Abstract**: **Image inpainting,** a critical task in computer vision, involves the art of replenishing missing or damaged regions within images. It's a process that hinges on the capabilities of deep learning, primarily through the utilization of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). The fundamental steps in implementing image inpainting encompass data collection and pre-processing, which entails assembling a dataset of images featuring gaps alongside their intact counterparts. The neural network architecture plays a pivotal role, with choices ranging from GANs to Auto-encoders, tailored to the specific task at hand. The models are trained by minimizing various loss functions, each contributing to specific training objectives. Inpainting algorithms must handle variable hole sizes and exhibit contextual understanding, ensuring generated content seamlessly blends with the surrounding context. Post-processing techniques can refine the generated inpaintings and evaluations are performed using quantitative metrics and qualitative assessments. Overall, deep learning-based image inpainting continues to advance, with practical applications in image restoration, object removal, and beyond.

**Keywords**: I Image inpainting, computer vision, Deep learning, Convolutional Neural Network, Generative Adversarial Network, dataset, Auto-encoders, image restoration, object removal.

## I. INTRODUCTION

Image inpainting is a challenging problem in image processing and computer vision. It involves reconstructing missing or damaged parts of an image, such as scratches, cracks, or occluded objects. Image inpainting has a wide range of applications, including image restoration, image editing, and object removal

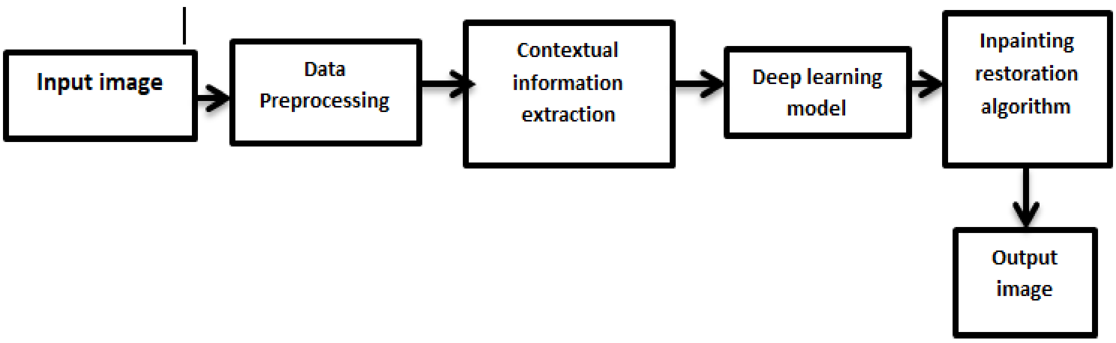


Fig. 1 A Basic block Diagram of Imageinpainting.

**Input image:** The original image that contains missing or damaged regions.

**Data pre-processing:** This image is then pre-processed, which means it's prepared for the deep learning model by resizing it, normalizing it, converting it to grayscale. Once the image is pre-processed, it's fed into the deep learning model.

**Contextual information and extraction:** Contextual information helps the inpainting model to make informed decisions about how to fill in the missing parts. For example, if a portion of an object is missing, understanding the shape and color patterns of the surrounding regions can guide the model in generating a plausible completion. Feature extraction involves capturing relevant information or features from the input data. In the case of image inpainting, this typically involves using a neural network to extract high-level features that represent important aspects of the image.

  

**Deep learning:** The deep learning model is made up of multiple layers of artificial neurons. These neurons are connected to each other in a complex web, and they're able to learn from the data that's passed through them. As the image data passes through the layers of the model, the neurons extract features from the image. These features could be things like edges, lines, or textures.

**Inpainting and restoration algorithm:** Aims to repair imperfections or distortions. These could be noise, scratches, blur, and color fading or other types of degradation. The goal is to bring the image back to its original state or a desired level of quality.

**Output image:** Finally we have to gate output image where we recover missing or damage region.

❖ **Types of image Inpainting:**

**TRADITIONAL INPAINTING METHODS:** There are numerous approaches to image inpainting. These techniques all have their own mathematical bases. These techniques are divided into groups based on the algorithms they employ to produce the intended results. The first of these approaches is the so-called traditional approach, which focuses solely on the aspects in the image that need to be fixed in order to attempt to fill in the missing portion of the main title picture.

a) **Patch-based Methods**: The techniques used in patch-based picture inpainting construct the filled region by utilizing the parts of the image that are still intact. The goal of this strategy is to get the highest level of patch similarity.

b) **Patch-based Texture Synthesis:** The goal of Zhou et al.'s method [1] is to fill the necessary area by using patch-based algorithms to create textures for the image inpainting technique. When putting this targeted strategy into practice, a road that starts rough and proceeds in detail is the goal. Targets and limits were established during the filling process to guarantee the newly produced region's integrity with the remainder of the image.

c) **Image Melding:** Using the picture melting technique, different qualities and information from one image can be transferred to another by creating a transition zone. Depending on the usage type, there are various uses for this procedure.

d) **Diffusion-based Method:** This technique essentially diffuses surrounding pixel information to fill in undesired items or missing areas in an image. A partial differential equation is used in the diffusion process. Such diffusion-based techniques are not limited to inpainting applications. These kinds of techniques are also available in fields like picture compression.

e) **Navier-Stokes Method:** Partial differential equations called Navier-Strokes equations are used to describe the motion of fluids. These formulas are employed in many various fields and sectors, including the modelling of weather patterns, ocean currents, and even the building of automobiles and airplanes.

f) **Fast Marching Method:** Ahmet created an inpainting method based on the rapid marching method in this 2004 paper. A filling procedure is created by beginning at the edges of a region where pixel information is absent and working your way inward. To compute the unknown pixel value as the weighted sum of the known pixels inside that border, only a tiny neighborhood of pixels is needed.

• **Deep learning Inpainting Methods:** Deep learning techniques have been applied to picture inpainting, as they have done to many other computer vision issues. When compared to traditional methods, deep learning techniques yield more successful solutions to complicated issues, which is why their use is increasing over time. The primary cause of this is the development of large-scale datasets and computing capacity that will facilitate the training of deep learning techniques.

a) **CNN-based Methods:** Thanks to their grid-like layer design, convolutional neural network structures are well-known for their exceptional performance in computer vision studies. These networks are also utilized in picture inpainting research, producing remarkable outcomes. Numerous buildings have been specifically created for inpainting projects.

b) **GAN-based Methods:** Numerous deep learning techniques have been tested over time, and analysis has shown that some techniques produce more fruitful outcomes than others. It may be concluded that approaches based on CNN and GAN perform better at assessing realistic outcomes in photos.

  

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c) **State-of-the-Art Method:** There were numerous cutting-edge techniques for image inpainting. It's crucial to remember that advances in computer vision and image processing can happen quickly, and it's possible that some have happened since then.

d) **Deep Image Prior:** The use of deep convolutional networks for picture production and restoration issues has grown significantly. Generally speaking, these networks perform well because they can extract realistic picture priors from datasets with a high number of images. To put it succinctly, image prior is a general term for information about an image that may be utilized to any type of image processing activity in order to improve results and select processing parameters.

- According our study Traditional image inpainting techniques are often based on diffusion or partial differential equations (PDEs). These techniques can be effective for small and simple missing regions, but they often fail to produce satisfactory results for large and complex missing regions. Deep learning has recently emerged as a promising new approach to image inpainting. Deep learning models can learn complex patterns in images and use this knowledge to generate realistic and plausible inpainting results. Deep learning-based image inpainting models have been shown to outperform traditional image inpainting techniques on a variety of datasets.

## II. LITERATURE SURVEY

1. Depth-image based rendering (DIBR), compression, and transmission for a new approach on 3D-TV. This paper published in May 2020. SPIE, vol. 5291 using deep learning method. In this paper Deep learning and image pre-processing method is used and result is image –inpainting tech. was utilized to automatically repair damaged areas with section data that has been preserved. The performance of image drawing has significantly improved in recent years due to the advancements in deep learning. This paper examines the primary techniques for picture inpainting automation.

2. Depth-image based rendering (DIBR), compression, and transmission for a new approach on 3D-TV. This paper published in May 2020. SPIE, vol. 5291 using deep learning method. In this paper Deep learning and image pre-processing method is used and result is image –inpainting tech. was utilized to automatically repair damaged areas with section data that has been preserved. The performance of image drawing has significantly improved in recent years due to the advancements in deep learning. This paper examines the primary techniques for picture inpainting automation.

3. In the 2023 IEEE Xplore document, "Damaged Image Repair using Masks with Computer Vision Inpaint Method," we see that an image- inpainting technique was employed to automatically repair the damaged parts by utilizing data from saved sections. The performance of drawing images has significantly improved with the advancement of deep learning in recent years. This paper examines the primary techniques for picture inpainting automation.

4. Image Mapping & Object Removal in Image Inpainting those paper published in 2016 and we learn the analysis proved that exemplar based Inpainting will produce best results for Inpainting the large missing region also these algorithms can inpaint both structure and textured image as well.

5. Image Inpainting via Generative Multi-Column Convolutional Neural Networks. This paper published in 2018. Result of this proposed a multi-column CNN architecture for inpainting tasks, which multiple scales of receptive

6. Object Removal from Digital Image in image Inpainting using Novel Framework this paper published in 2016. Result of this paper is the process of partitioning of an image is done by using segmentation.

## III. PROPOSED METHODE

GAN-based Image Inpainting: GAN-based image inpainting represents a powerful approach in the realm of deep learning, capable of reconstructing missing regions in images with impressive realism. Here's a breakdown of the method and how it works

Concept-
- A Generative Adversarial Network (GAN) consists of two main components: a generator and a discriminator.
- The generator aims to create realistic images that "fool" the discriminator.
- The discriminator tries to distinguish real images from those generated by the model.
- In image inpainting, the generator takes a partially masked image and the mask information as input.

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- It learns to fill in the missing regions by creating plausible content consistent with the surrounding image structure.
- The discriminator assesses the generated content, evaluating its realism and guiding the generator to improve its output.

**Training Process-**

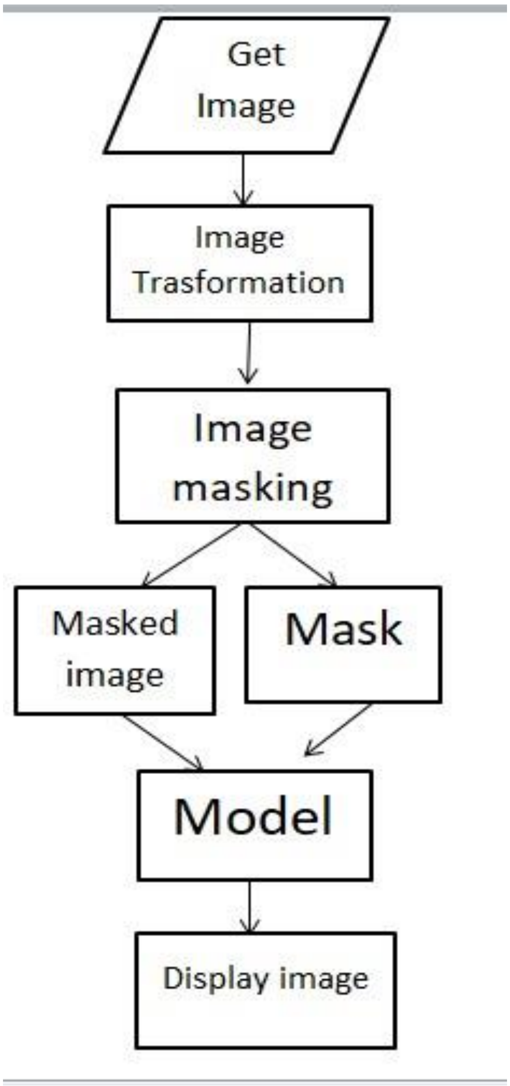
1. Input Preparation: Image with masked region and mask information fed to the generator.
2. Generator's Role: Creates inpainted image filling the missing region.
3. Discriminator's Role: Analyzes both the real image and the generated image.

I. Loss Calculation:

a. Adversarial Loss: Measures how well the generator fools the discriminator, encouraging realistic outputs.
b. Reconstruction Loss: Compares the generated content to the ground truth (if available) for pixel-wise accuracy.
c. Perceptual Loss: Assesses the naturalness of the generated image using pre-trained models.

II. Backpropagation: Gradients flow back to update generator and discriminator parameters.
III. Iteration: Process repeats, with the generator gradually improving its inpainting ability.

## IV. METHODOLOGY



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1. **Get Image:** The first step involves obtaining an image. This image can come from various sources, including a photograph or a video.

2. **Image Transformation:** The image undergoes a transformation process. The details of this transformation aren't provided in the image.

3. **Image Masking:** Next, an image mask is created. An image mask is a separate image that defines which parts of the original image will be kept and which parts will be discarded. Black areas in the mask correspond to areas that will be removed, while white areas correspond to areas that will be preserved.

4. **Masked Image:** The mask is then applied to the transformed image, resulting in a masked image. In the masked image, only the areas that were white in the mask remain.

5. **Model:** The masked image is then fed into a model. The type of model isn't specified in the image.

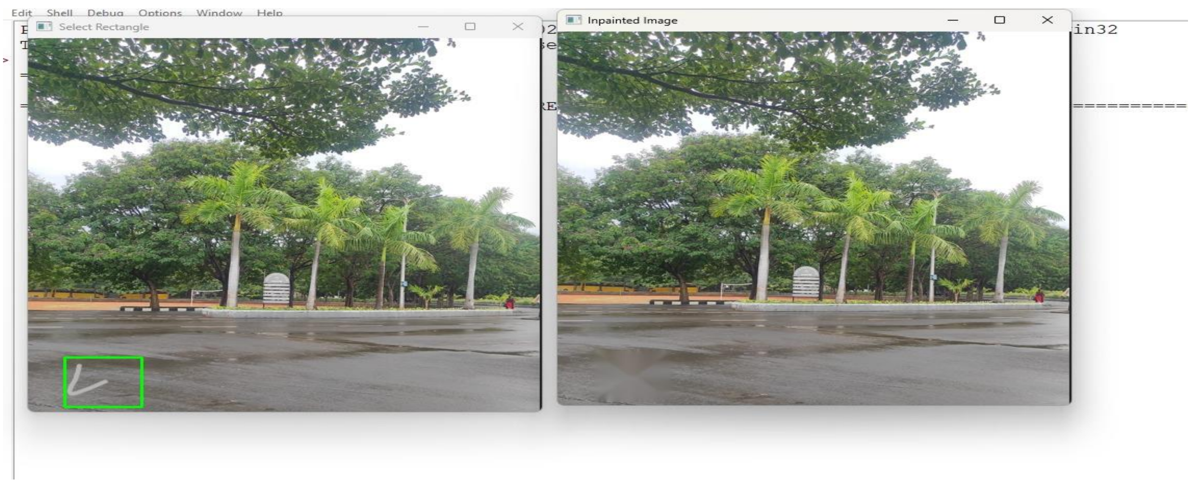
6. **Display Image:** Finally, the output from the model is displayed as an image.

## V. ALGORITHM

### 1. Generative Adversarial Networks :

Generative Adversarial Networks (GANs) are a type of deep learning model that can be used for image inpainting. GANs consist of two neural networks: a generator and a discriminator. The generator is responsible for generating new images, while the discriminator is responsible for distinguishing between generated images and real images. The GAN algorithm works by training the generator and discriminator simultaneously. The generator is trained to produce images that are indistinguishable from real images, while the discriminator is trained to distinguish between generated images and real images. This adversarial training process forces the generator to produce increasingly realistic images. To use GANs for image inpainting, the generator is trained to fill in the missing parts of an image, while the discriminator is trained to distinguish between inpainted images and real images. The generator is trained to minimize the loss function, which is a measure of how well the generated images can fool the discriminator. The discriminator is trained to maximize the loss function. The GAN algorithm for image inpainting is typically implemented as follows: The generator is initialized with a random image. The discriminator is given the generated image and a real image as input. The discriminator outputs a probability score for each image, indicating how likely it is that the image is real. The generator and discriminator are updated using their respective loss functions. Steps 2 and 3 are repeated until the generator is able to produce images that are indistinguishable from real images. Once the GAN is trained, the generator can be used to inpaint new images. To do this, the generator is given the incomplete image as input and outputs a complete image. Here are some examples of GAN-based image inpainting models: DeepFill PatchGAN Contextual Attention GAN (cGAN) Perceptual Adversarial Network (PAN) GAN-based image inpainting models have achieved state-of-the-art results on a variety of datasets. However, they can be computationally expensive to train and can be sensitive to the choice of hyperparameters.

## VI. RESULT




Result 1

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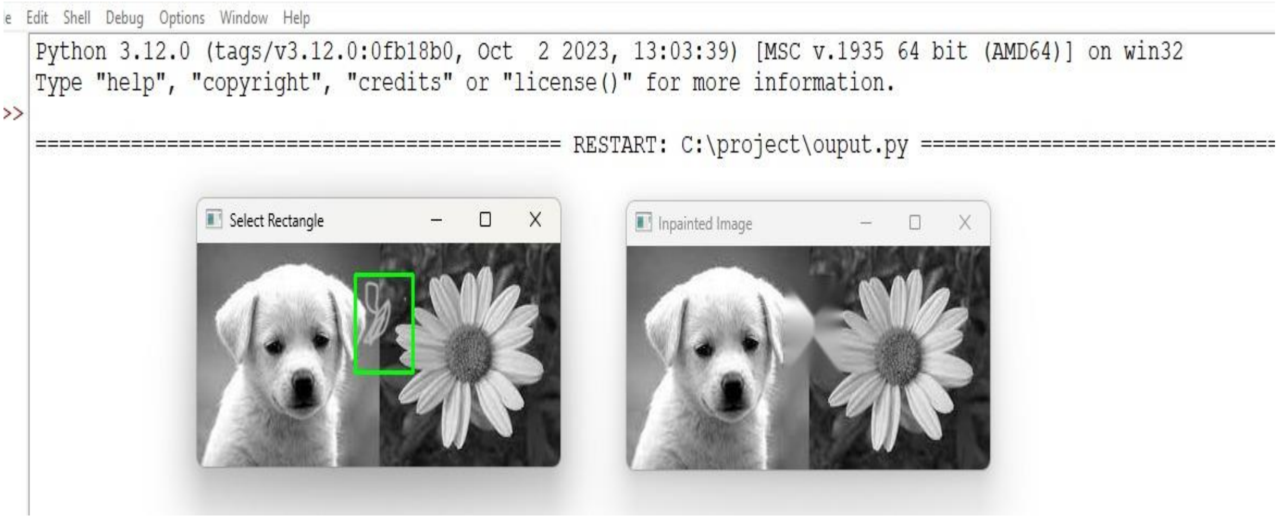


Result 2

## VII. CONCLUSION

Image inpainting has been successfully applied to dynamically selected image. The inpainted region like missing section in the center blends seamlessly with the surrounding image, demonstrating the effectiveness of this technique for image restoration.

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Group Members
1) Savali Magar
2) Aishwarya Waykule

## REFERENCES

[1]. "Image Inpainting Using Pre-trained Classification-CNN," Kerzhner, Yaniv, Adar Alad, and Yanov Romano, 2018.ICSEE proceedings. 'A survey on picture completion approaches in remote sensing images' Lakshmanan, V. and R. Gomathi, 2017. IEEE Xplore Press, Chennai, India, 4th International Conference on Signal Processing, Communication and Networking, Proceedings, Mar. 16–18, pp. 1-6.
[2]. Nermin Salem Doctor Mohamed Fawzy (2021) Future Engineering Journal, Vol. 2, No. 2, Article 1, "A Survey on Various Image Inpainting Techniques."
[3]. A saliency map and gray entropy-based image inpainting algorithm was presented by Zeng, J., X. Fu, L. Leng, and C. Wang in 2019. Arabian Journal of Engineering and Science.
[4] Sujita Pillai, Sanjay Khadagade, and others. 2017; "A Review of the Process of Digital Image Restoration." The International Journal of Computer Applications, Volume 158, Issue 7
[5]. "High-Resolution Image Inpainting using Multi-Scale Neural Patch Synthesis," Yang, Chao, Xin Lu, Zhe Lin, Eli Shechtman, Oliver Wang, and Hao Li, 2017. The IEEE Conference on Pattern Recognition and Computer Vision (CVPR).

DOI: 10.17148/IJIREEICE.2024.12531

[6]. "Context-Aware Semantic Inpainting," Li, Haofeng, Guanbin Li, Liang Lin, and Yizhou Yu and published in 2017. Preprint arXiv:1712.07778v1 arXiv.

[7]. "Structure-guided image inpainting using homography transformation," published in 2018 by PLiu, J., S. Yang, Y. Fang, and Z. Guo. IEEE Multimedia Transactions.

[8]. Wu, Xian, Peter Hall, and Kun Xu. 2017. "A Survey of Generative Adversarial Networks for Image Synthesis and Editing." Vol. 22, No. 6, Tsinghua Science and Technology

[9]. G.Sridevi and S. S. Kumar. "Fractional-order nonlinear diffusion based image inpainting for image reconstruction," 2019. Signal processing, systems, and circuits.

[10]. May 21, 2019 in revised form; accepted 24.08.2018, Alexandru Telea, Department of Mathematics and Computer Science, Eindhoven University of Technology, Den Dolech 2, Eindhoven 5600 MB, The Netherlands.

[11] "Energy-based Generative Adversarial Network," Zhao, J., M. Mathieu, and Y. LeCun, 2017. ICLR.

[12] Wu, Xian, Peter Hall, and Kun Xu. 2017. "A Survey of Generative Adversarial Networks for Image Synthesis and Editing." Vol. 22, No. 6, Tsinghua Science and Technology

  