ijamrsd.com JAMRSD ISSN: 2583-6404
Journal of Advanced Multidisciplinary Research Studies and Development
Peer Reviewed Referred Journal Bi-monthly Open Access

IMAGE INPAINTING: USING HYBRID DEEP LEARNING GENERATIVE MODEL FOR IMAGE RESTORATION AND RECONSTRUCTION

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Abstract
Image inpainting is an important technique in the field of image processing and computer vision that focuses on restoring missing, damaged, or unwanted regions of an image. The objective of image inpainting is to reconstruct the missing parts in such a way that the final image appears natural and visually consistent with the surrounding areas. Traditional inpainting methods rely on basic algorithms that copy information from neighboring pixels, but these techniques often fail when dealing with large or complex missing regions.In recent years, deep learning has significantly improved the performance of image inpainting. Deep learning models such as Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) can learn complex image patterns, textures, and structures from large datasets. These models analyze the surrounding context of the damaged area and generate realistic content to fill the missing regions automatically. As a result, deep learning-based inpainting methods produce more accurate and visually appealing results compared to traditional approaches.Image inpainting using deep learning has many practical applications, including photo restoration, object removal, image editing, medical image reconstruction, and film post-production. This technology helps improve image quality and enables automatic restoration of damaged images. Therefore, deep learning-based image inpainting has become an important research area in modern computer vision and image processing.

Keywords: Image Inpainting, Deep Learning, Convolutional Neural Network, Generative Model, Image Restoration Introduction.

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Introduction:

Image inpainting is a technique used to restore or reconstruct missing, damaged, or unwanted parts of an image. The main goal of image inpainting is to fill the missing regions in such a way that the completed image looks natural and visually consistent with the surrounding areas. Traditional image inpainting methods mainly rely on manual editing or basic algorithms that copy information from nearby pixels, but these approaches often fail when the missing area is large or complex.

With the advancement of deep learning, image inpainting has become more accurate and efficient. Deep learning models, especially Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), are capable of understanding complex patterns, textures, and structures present in images. These models learn from large datasets of images and can generate realistic content to fill the missing regions automatically. By analyzing the context around the missing area, deep learning models can predict the most suitable pixels and create visually coherent results.

Image inpainting using deep learning has many practical applications. It is widely used in photo restoration, object removal, image editing, medical image reconstruction, and film or video post-production. For example, it can remove unwanted objects from photographs, repair old damaged photos, or fill missing parts of images in digital media. Due to its ability to produce high-quality and realistic results, deep learning-based image inpainting has become an important research area in the field of computer vision and image processing.

Literature Review:

1. Depth-Image-Based Rendering (DIBR) for 3D-TV

- Published in SPIE, May 2024.
- Method used: Deep Learning and Image Processing.
- The study focuses on image inpainting to repair damaged image areas.
- Deep learning improves image reconstruction and drawing performance.

2. Reference-Guided Texture and Structure Inference for Image Inpainting

- Research from NIT Goa, IEEE Xplore (2023).
- Method used: Deep Learning.
- Uses reference images to fill missing textures and structures.
- Still faces challenges in complex scenes and large missing areas.

3. Damaged Image Repair using Masks with Computer Vision Inpaint Method

- Published in IEEE Xplore, 2023.
- Method used: Deep Learning.
- Uses masks to detect damaged regions in images.
- The system automatically repairs missing parts of images.

4. Image Inpainting via Generative Multi-Column CNN

- Published in 2022.
- Method used: CNN-based Deep Learning.
- Uses multi-column CNN architecture for inpainting.
- Produces better and more realistic reconstructed images.

5. Deep Learning-based Image Inpainting Methods

- Published in Applied Sciences Journal, 2023.
- Method used: CNN, GAN, and Autoencoder models.
- The study explains different deep learning architectures used for image inpainting.
- These models help to reconstruct missing image regions with realistic textures.
- The research also compares single-stage and multi-stage inpainting models.

6. Image Inpainting using Generative Adversarial Networks (GAN)

- The method uses GAN architecture for generating realistic images.
- GAN consists of two networks: Generator and Discriminator.
- The generator fills missing parts of an image, while the discriminator checks image quality.
- This technique produces high-quality and visually consistent results.
- GAN models are widely used in object removal and photo restoration.

7. Deep Learning-Based Image and Video Inpainting Survey

- This research reviews different deep learning techniques for image inpainting.
- Methods include CNN, GAN, Variational Autoencoders, and Diffusion models.
- These techniques help to restore damaged areas with realistic content.

- The study also discusses datasets, evaluation metrics, and challenges

Methodology:
In That Project We Are Use Two Methods
1.GAN
2. CNN

1. Generative Adversarial Network (Gans):
GAN (Generative Adversarial Network) is a deep learning technique used to fill missing or damaged parts of an image automatically. It generates realistic image content so that the repaired area looks natural.

1. What is GAN?
GAN consists of two neural networks that work together:

1. **Generator (G)**
   - The generator tries to create or fill the missing part of the image.
   - It generates a new image that looks similar to the real image.
2. **Discriminator (D)**
   - The discriminator checks whether the image is real or generated by the generator.
   - It acts like a judge and gives feedback to the generator.

Both networks compete with each other to improve the quality of the generated image.

2. Working of GAN for Image Inpainting

Step 1:
An image with a missing or damaged region is given as input.

Step 2:
A mask identifies the missing part of the image.

Step 3:
The Generator network fills the missing area using learned patterns from training images.

Step 4:
The Discriminator network checks whether the filled image looks real or fake.

Step 5:
If the discriminator detects it as fake, the generator improves the generated image.

Step 6:
This process repeats many times until the generated image looks realistic.

2. CNN (Convolutional Neural Network)
CNN is a type of deep learning algorithm mainly used for image processing and computer vision tasks such as image classification, object detection, and image inpainting.
It helps computers understand and analyze images automatically.

1. What is CNN?
A Convolutional Neural Network is a neural network that learns important features from images like edges, shapes, textures, and patterns.
It processes images using convolution filters to extract useful information.

2. Main Layers of CNN

1. Convolution Layer

- This layer applies filters (kernels) to the input image.
- It extracts features like edges, colors, and textures.

2. ReLU Layer (Activation Function)

- ReLU means Rectified Linear Unit.

- It introduces non-linearity and helps the network learn complex patterns.

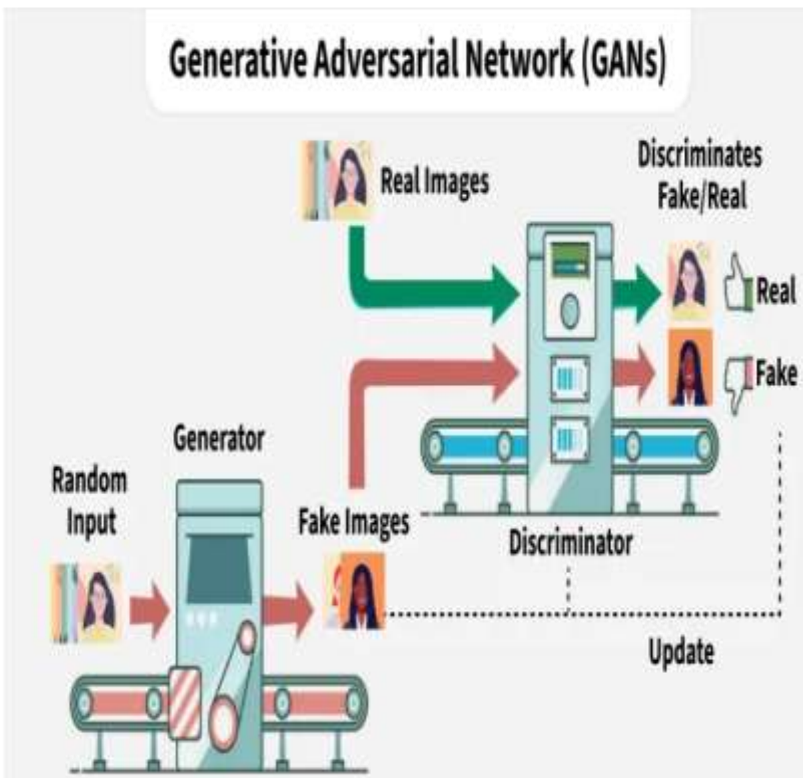
3. Pooling Layer
- Pooling reduces the size of the feature map.
- It helps to reduce computation and overfitting.
- Example: Max Pooling.

4. Fully Connected Layer
- This layer connects all neurons together.
- It makes the final prediction or output.

3. Working of CNN

Step 1: Input image is given to the CNN.
Step 2: Convolution layer extracts important features.
Step 3: Activation function (ReLU) improves learning.
Step 4: Pooling layer reduces image size and complexity.
Step 5: Fully connected layer processes features and produces final output.

System Architecture:



Architecture of Generative Adversarial Network (GAN)

The GAN architecture consists of two main neural networks that work against each other to generate realistic images.

1. Generator (G)
- The Generator creates new images.
- It takes random input (noise vector) as input.
- Using deep learning layers, it generates a fake image.

- The goal of the generator is to produce images that look like real images.

Function:
Generate realistic images from random data.

2. Discriminator (D)

- The Discriminator acts like a classifier or judge.
- It receives two types of images:
  - Real images from the dataset
  - Fake images created by the generator
- It checks whether the image is real or fake.

Function:
Identify whether an image is original or generated.

3. Working Process of GAN Architecture

Step 1:
Random noise is given as input to the Generator.
Step 2:
The generator produces a fake image.
Step 3:
Both real images and fake images are sent to the Discriminator.
Step 4:
The discriminator analyzes the images and decides Real or Fake.
Step 5:
If the discriminator detects a fake image, the generator updates its parameters to improve the image quality.
Step 6:
This process repeats until the generator produces very realistic images.

4. Architecture Flow (Based on the Diagram)

Random Input → Generator → Fake Image → Discriminator
Real Image → Discriminator
Discriminator → Real / Fake Decision
Generator and Discriminator update their parameters during training.

5. Role of GAN in Image Inpainting

In image inpainting, GAN:

- Generates missing parts of an image.
- Maintains texture and structure consistency.
- Produces high-quality reconstructed images.

Needs:

- Restoration And Preservation: Image Inpainting Fulfills The Need To Restore And Preserve Damaged Or Aging Visual Content, Allowing Historical Or Deteriorated Images To Be Recovered And Maintained For Posterity.
- Object Removal And Concealment: It Addresses The Necessity Of Removing Unwanted Objects Or Sensitive Information From Images, Ensuring Privacy, Security, And Aesthetic Appeal, Such As In Photo Editing And Data Anonymization.
- Visual Completion: Image Inpainting Is Essential For Seamlessly Completing Cropped Im- Ages, Enabling A Coherent Presentation Of Scenes That May Have Been Unintentionally Trun- Cated During Photography Or Post-Processing.

- Data Recovery: It Serves The Critical Purpose Of Recovering Lost Or Corrupted Visual Data In Cases Of Transmission Or Storage Errors, Safeguarding T Of Digital Images.

Database Description:

1. Dataset Overview:

We Can Choose Any Type Of Image

A.PNG

B.JPG

.PNG Image:- Size Refers To The Physical Dimensions Of The Image In Pixels. For Example A PNG Image With A Size Of 1024x768 Pixels Is 1024 Pixels Wide And 768 Pixels High.

Resolution Refers To The Number Of Pixels Per Inch(Ppi) Of The Image. For Example A PNG Image With A Resolution Of 300 Ppi Has 300 Pixels Per Inch.

.JPG Image:- Size Refers To The Physical Dimensions Of The Image In Pixels. For Example A Jpg Image With A Size Of 1024x768 Pixels Is 1024 Pixels Wide And 768 Pixels High Resolution Refers To The Number Of Pixels Per Inch (Ppi) Of The Image. For Example A Jpg Image With A Resolution Of 300 Ppi Has 300 Pixels Per Inch.

Flow Chart of Overall Model:

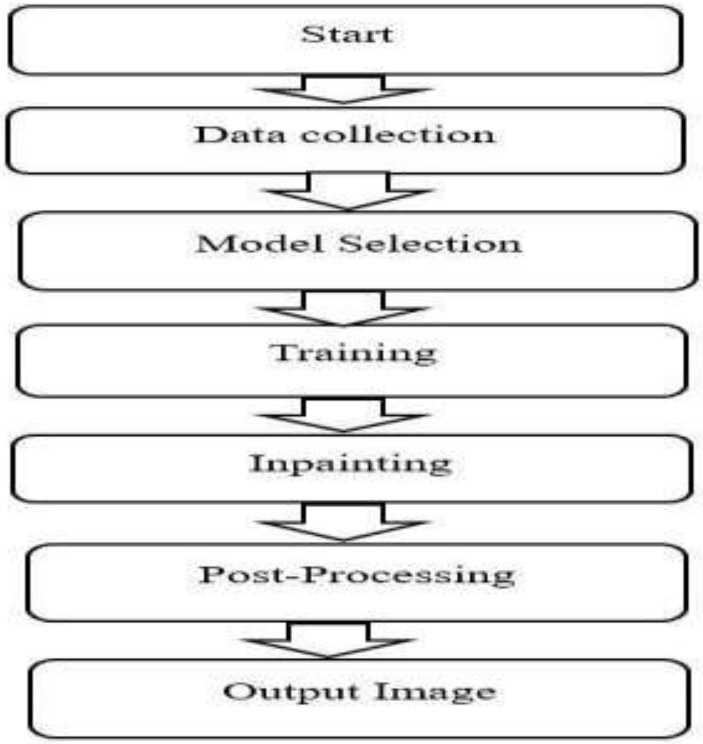
1. Data Collection: Gather A Dataset Of Images With Missing Portions Or Masks Along With Their Complete Version. Preprocessing: Resize, Normalize , And Preprocess The Images Additionally Create Masks To Identify The Regions To Be Inpainted.

2. Model Selection: Choose A Deep Learning Model Suitable For Image Inpainting Comon Models Include Convolutional Neural Network (CNNs) Like U-Net, Gans, Or More Recent Models Like Contextual Attention And Gated Convolutional.

3. Training: Train The Selected Model Using The Dataset. This Involves Optimizing The Models Parameters To Accurately Predict Missing Parts Of The Images.

4. Inpainting: Given A New Image With Missing Parts, Apply The Trained Model To Predict And Fill In The Missing Regions

5. Post-Processing: Refine The Inpainted Image To Ensure It Blends Seamlessly With The Rest Of The Image, Applying Techniques Like Smoothing Or Edge Enhancement.



Algorithms used (Methodology):
In That Project We Are Use Two Methods
1.GAN
2. CNN

1. Generative Adversarial Network (Gans): Generative Adversarial Networks(Gans) Are A Powerful Tool For Image Inpainting. A GAN Consists Of Two Neural Networks: A Generator And A Discriminator.

Generator: The Generator Network Creates Plausible Images Or Patches To Fill The Missing Parts Of An Image. It Takes The Incomplete Image As Input And Outputs A Completed Image, Attempting To Generate Realistic And Contextually Accurate Content For The Missing Regions

Discriminator: The Discriminator Network Evaluates The Generated Images Distinguishing Between Real Images (From The Training Set) And The Images Produced By The Generator. It Provides Feedback To The Generator On How Realistic The Inpainted Images Appear.

Result:
Result 1:

This is car image . In which unwanted part(iStock) of the image removed. using image inpainting algorithm. and we recover the image**.**

Result 2:

It shows Tuljabhavani Mata image. In which name removed using image inpainting algo- rithm. and we recover the image Green rectangular shows the massking of image.

Conclusion:

Image Inpainting Using Deep Learning Has Revolutionized The Field Of Digital Image Restoration By Providing Robust And Efficient Solutions For Reconstructing Missing Or Correpted Parts Of Images. Leaveraging Advancements In Convolutional Neural Network And Generative Adversarial Networks (Gans) Modern Inpainting Techniques Can Produce Highly Realistic And Contextually Accurate Results. These Deep Learning Models Excel In Understanding And Replicating Complex Patterns, Textures, And Semantic Content, Surpassing Traditional Methods In Both Performance And Quality. The Success Of Deep Learning In Image Inpainting Has Broad Applications, Including Photo Editing, Restoration Of Damaged Artworks, And Filling In Gaps In Visual Data For Scientific And Medical Imaging. Despite Ongoing Challenges Such As Handling Large Missing Regions And Ensuring Consistency With Surrounding Areas, Continuous Research And Improvements In Neural Network Architectures And Training Methodologies Promise To Further Enhance The Capabilities And Applications Of Image Inpainting Technologies.

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