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Image Inpainting Approach with Deep Learning

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Abstract

Image inpainting technology plays an important role in the process of digitalizing ancient literature. It helps to recover the partially missing or stained characters and has shown remarkable success in the field of image inpainting. In this paper, we propose a new CNN model using the idea of edge recovery and optimize this model with spatial attenuation mask and conditional labelling to improve performance. Experiments show better results than the previous works in character image inpainting. Image inpainting is nothing but the art of repairing the old and deteriorated image, has been around for many years, and now it has gained popularity due to various latest technologies in the image processing. To development of this model, Image inpainting is necessary to repair the damaged regions or to remove unnecessary objects to improve image quality for other post-processing tasks To evaluate image inpainting quality is the initial goal of the proposed method.

Keywords—Feature extraction, Convolutional Neural Network, Generative Adversarial Network, EdgeConnect

1. INTRODUCTION

Image inpainting is a technique used in image processing and computer vision to remove unwanted objects or fill in missing parts of an image. The process involves reconstructing the missing or damaged parts of an image based on the surrounding pixels or information from other similar images. It's often used in photo editing, video processing, and computer graphics to improve the visual quality of images or videos. Image inpainting can be also used to remove unwanted objects from an image, such as wires, poles, or even people. It can also be used to fill in missing parts of an image, such as cracks, scratches, or damaged areas. The process involves analyzing the surrounding pixels and using algorithms to predict what the missing or damaged parts should look like. There are different types of image inpainting techniques, such as patch-based methods, exemplar-based methods, and deep learning-based methods, each with its own strengths and weaknesses. Image inpainting has many practical applications, such as in the restoration of old photos, the removal of watermarks, and the enhancement of medical images.

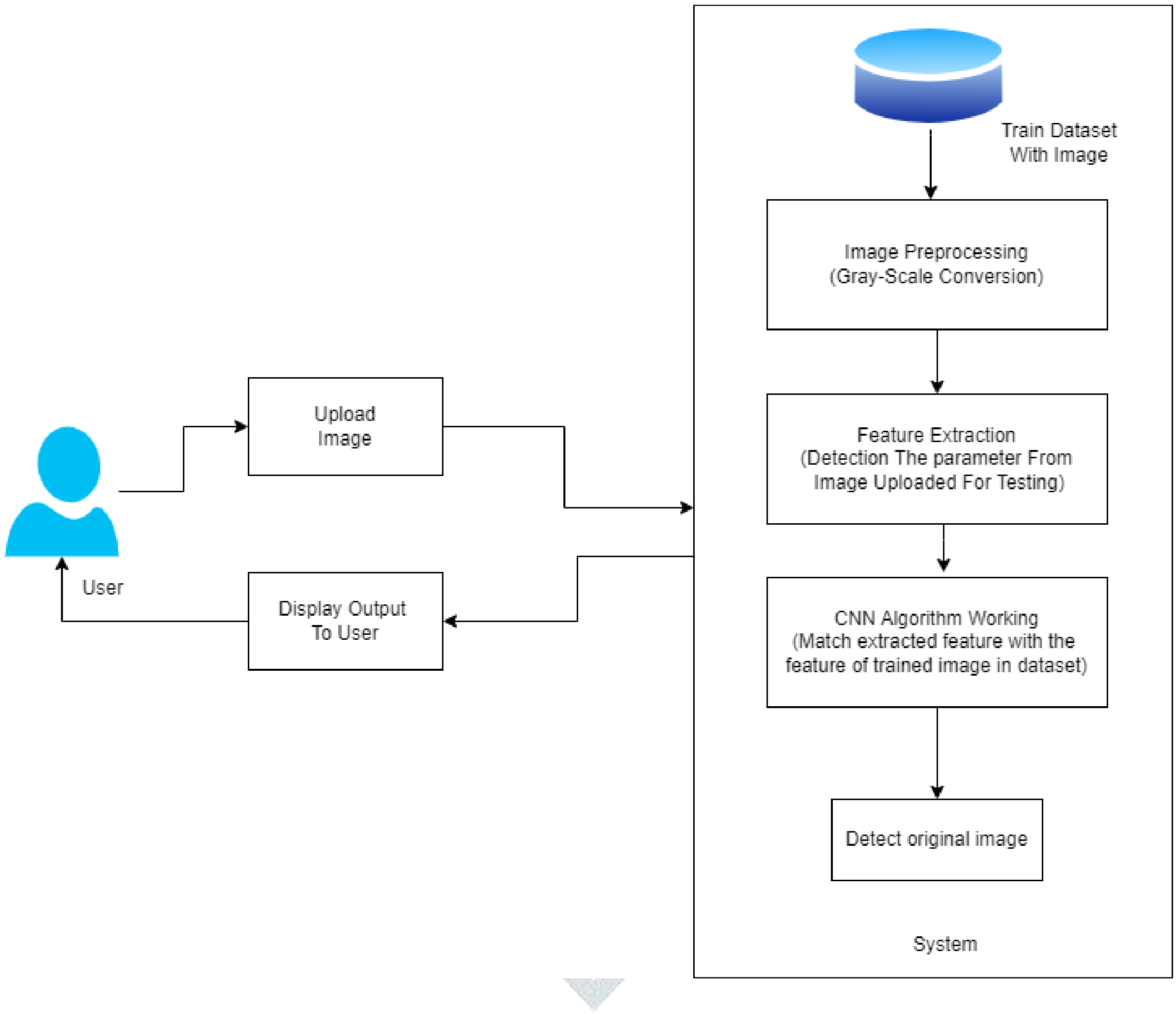
Image inpainting uses CNN algorithm which is a deep learning-based approach to image processing that involves training a neural network to predict the missing or damaged parts of an image. The network is trained on a large dataset of images, where the input is an image with missing or damaged parts, and the output is the reconstructed image. The CNN algorithm uses convolutional layers to extract features from the input image and then uses these features to predict the missing or damaged parts. The process involves optimizing the network's parameters to minimize the difference between the predicted and actual images. CNN-based image inpainting has shown promising results in generating high-quality images with realistic textures and details. However, it requires a large amount of training data and computational resources to achieve good results.

CNN stands for Convolutional Neural Network, which is a type of deep learning algorithm that is commonly used in image processing and computer vision tasks. CNNs are designed to automatically learn features from images, such as edges, shapes, and textures, and use these features to classify or segment images. CNNs consist of multiple layers of interconnected nodes, including convolutional layers, pooling layers, and fully connected layers. The convolutional layers perform feature extraction by convolving filters over the input image, while the pooling layers reduce the spatial size of the feature maps. The fully connected layers perform classification or regression tasks based on the extracted features. CNNs have been used in many applications, including image recognition, object detection, and image segmentation.

THE MAIN OBJECTIVES OF THIS SYSTEM ARE:

1) To fill in missing or corrupted parts of an image.
2) Convert the blur image into the clear image.
3) Restore old or damaged photographs.

2. SYSTEM MODEL DIAGRAM:



(Figure 1: System Model Diagram)

3. WORKING PROCESS:

1) Collect a dataset of damaged photographs with missing or corrupted regions.
2) Preprocess the dataset by cropping the damaged regions and resizing the images to a common size.
3) Train a deep neural network to predict the missing pixels based on the context of the surrounding pixels.
4) Fine tune the network on a smaller dataset of photographs that are similar to the ones we want to store.
5) Use the trained network to inpaint the missing regions of the damaged photographs.
6) Post-process the inpainted images to remove any artifacts or distorations.
7) Evaluate the quality of the results using metrics such as peak signal-to-noise ratio (PSNR).

4. LITERATURE SURVEY:

Table-1: Literature Survey on Recent Image Inpainting Methods

Ref. No.	Paper Title and Publication Details	Pre-processing	Feature Extraction and Classification	Accuracy	Post Processing	Research Gap Identified
[1]	An Iterative Image Inpainting Method Based on Similarity of Pixels Values Uğur Erkan, Serdar Enginoğlu, Dang N. H. Thanh. 6th International Conference on Electrical and Electronics Engineering (ICEEE), (2019)	Should able to fill the corrupted area	To evaluate the inpainting quality, Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM) metrics are used	85%	It proposes the method in which every iteration step is surrounded by the boundary pixel values which are having the corrupted regions.	The use of edge information in boundary values or the division of the defective region into multiple parts can give better result
[2]	Deep Two-Stage HighResolution Image Inpainting Andrey Moskalenko, Mikhail Erofeev and Dmitriy Vatolin. Creative Commons License Attribution 4.0 International (2020)	Filling missing parts in an image.	GIMP plugin that implements the method, which appears in the repository	80%	Making the almost resolution of the image, independent without the need for retraining	Train a new model using the proposed method, but in an end-to-end manner with dynamic shift size
[3]	Pixel-wise Dense Detector for Image Inpainting Ruisong Zhang, Weize Quan, Baoyuan Wu, Zhifeng Li and Dong-Ming Yan. It is published by John Wiley & Sons Ltd.(2020)	Adversarial loss and reconstruction loss are combined with tradeoff weights, which are difficult to time	Novel detectionbased generative framework for image inpainting which adopts min-max strategy	**75%**	Balances the weight of the adversarial loss and reconstruction loss automatically rather than manual operation	This framework may extend to other conditional generative tasks, e.g., image synthesis and image denoising
[4]	Zoom-to-Inpaint: Image Inpainting with High Frequency Details Soo Ye Kim, Kfir Aberman, Nori	The proportion of Neural Networks which helps to	Constitutes a frameworkagnostic approach for enhancing	**65%**	Provides qualitative and quantitative	The approach outperforms all other methods for small masks

	Kanazawa, Rahul Garg, Neal Wadhwa, Huiwen Chang, Nikhil Karnad, Munchurl Kim, Orly Liba. arXiv:2012.09401v1 [cs.CV] 17 Dec 2020	reconstruct low frequency which is more better than the high frequency	highfrequency detail		evaluations along with an ablation analysis to show the effectiveness of the approach	but not for large masks
[5]	Exploration of Image Inpainting approaches and challenges: A Survey Rishitha Reddy, B. Lakshmi Priya , P. Vinuthna , K. Priyatham Reddy , D. Sritha Reddy. International Journal of Computer Engineering in Research Trends(2022)	The various usefulness includes image quality improvement, coding and transmission without wires, image restoration, etc	Presents a survey of the majority image inpainting techniques and summarizes them	**80%**	Comparisons that include the benefits and drawbacks of each method.	Researchers must focus more on developing algorithms that can deal with both simple and complicated structures in the future.
[6]	Generative Image Inpainting with Contextual Attention Jiahui Yu, Zhe Lin, Jimei Yang, Xiaohui Shen, Xin Lu, Thomas S. HuangarXiv:1801.07892v2 [cs.CV] 21 Mar 2018	Ineffectiveness of convolutional neural networks in explicitly borrowing orcopying information from faraway spatial locations.	The contextual attention module significantly improves image inpainting resultsby learning feature representations for explicitly matching and attending to relevant background patches	**85%**	The model is a feedforward, fully convolutional neural network which can processimages with multiple holes at arbitrary locations and with variable sizes during the test time.	Extend the method to very high-resolution inpainting applicationsusing ideas similar to progressive growing of GANs
[7]	Guidance and Evaluation: Semantic-Aware Image Inpainting for Mixed Scenes Liang Liao, Jing Xiao, Zheng Wang, Chia-Wen Lin and Shin'ichi Satoh, arXiv:2003.06877v3 [cs.CV] 10 Jul 2020	Completing a corrupted image with correct structures and reasonable textures for a mixed scene	Semantic Guidance and Evaluation Network (SGENet) to iteratively refurbish the structural priors	**90%**	A novel SGE-Net with semantic segmentation guided scheme was proposed	Should focus more on the investigating the impact of segmentation accuracy on image inpainting
[8]	PEPSI : Fast Image Inpainting with Parallel Decoding Network Min-cheol Sagong, Yong-goo Shin, Seung-wook Kim, Seung Park, Sung-jea Ko, CVF, 2019	The existing method requires numerous computational resources due to its two-stage process for feature encoding.	Presents Novel network structure, which is commonly kmown as PEPSI: parallel extendeddecoder path for semantic inpainting	**82%**	By using PEPSI method there can be a reduction of convolution operations, which can be helpful to apply on the limited hardware	By reducing the parameters of the network, which can help to apply the restricted hardware systems.
[9]	StructureFlow: Image Inpainting via Structure-aware Appearance Flow Yurui Ren, Xiaoming Yu, Ruonan Zhang Thomas H. Li, Shan Liu Ge Li, 11 Aug 2019	The fine grained structures are unable to reconstruct using the maximum image	The appearance flow was used to sample features from relative regions	**83%**	It proposes a twostage model which splits the inpainting task into two parts: structure	The structureaware framework for recovering corrupted images with meaningful structures and vivid textures

		inpainting methods			reconstruction and texture generation	should be more efficient
[10]	EdgeConnect: Generative Image Inpainting with Adversarial Edge Learning Kamyar Nazeri, Eric Ng, Tony Joseph, Faisal Z. Qureshi, Mehran Ebrahimi, arXiv:1901.00212v3 [cs.CV] 11 Jan 2019	Almost all the methods not work well to reconstruct the reasonable structures.	A two stage adversarial model EdgeConnect is used	**75%**	Implements a good approach using EdgeConnect for reproducing filled regions.	Should work on fully convolutional generative model that can be extended to very highresolution inpainting applications with an improved edge generating system
[11]	A critical survey of state-ofthe-art image inpainting quality assessment metrics Muhammad Ali Qureshi, Mohamed Deriche, Azeddine Beghdad, Asjad Amin, ELSEVIER, 2017	The quality assessment of inpainting images continues to be a complex and challenging problem.	A performance comparison of different metrics in terms of correlation performance and computational complexity is defined	**85%**	A new technique of which is the description of existing metrics their good and bad performance on real images from public image dataset is provided	Video inpainting is a challenging problem when there is a need to remove and track undesired objects in videos or movies
[12]	Research into an Image Inpainting Algorithm via Multilevel Attention Progression Mechanism Peng Li and Yuantao Chen, 3 March 2022	Structual disorder and blurred texture details	Proposed method compressed the high-level features into Multiscale compact features according to scale size	**85%**	Produce higher quality repair results compared with classic main stream methods	Improve the complexity of the algorithm and its running time

5. ALGORITHMIC SURVEY

Table-2: Algorithmic Survey of Research Studies

Sr. No	Paper Title	Algorithms Used	Time Complexity	Accuracy	Advantages
[1]	An Iterative Image Inpainting Method Based on Similarity of Pixels Values Uğur Erkan, Serdar Enginoğlu, Dang N. H. Thanh. 6th International Conference on Electrical and Electronics Engineering (ICEEE), 2019	Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity (SSIM)	-	95%	The proposed inpainting method gives an outstanding performance to fill the corrupted areas and to remove objects.
[2]	Generative Image Inpainting with Contextual Attention Jiahui Yu, Zhe Lin, Jimei Yang, Xiaohui Shen, Xin Lu, Thomas S. Huang. arXiv:1801.07892v2 [cs.CV] 21 Mar 2018	Training the dataset	-	90%	The contextual attention module significantly improves image inpainting results by learning feature representations for explicitly matching and attending to relevant background patches
[3]	Research into an Image Inpainting Algorithm via Multilevel Attention	Image Inpainting Algorithm via multilevel	-	90%	Accurate pixel-level reconstruction of image

	Progression Mechanism Peng Li and Yuantao Chen, 3 March 2022	attention progression mechanism			
[4]	Robust Algorithm for Exemplar-based Image Inpainting Wen-Huang Cheng, ChunRobust Algorithm for Exemplar-based Image Inpainting Wen-Huang Cheng, Chun	Exemplar-based inpainting algorithm	-	85%	Adapt any image contents of different characteristics
[5]	A Convolution Based Image Inpainting	[A] PDE Alorithm [B]Texture Synthesis [C]Convolutional-Filter Based	-	80%	1. PDE Algorithm is helpful to connect edges or isophotes. 2. Texture Synthesis Algorithm helps to fill damaged or missed regions 3. Inpaint an image by convolving the neighborhood of damaged pixels with proper kernel

6. RESULTS AND DISCUSSION:

Based on our research, image inpainting with deep learning has shown great potential for filling in missing image information. However, there is still much work to be done in terms of improving speed and accuracy. Some of challeneges of image inpainting with deep learning include finding ways to handle complex image structures and textures, improving the ability to fill in large missing regions, and reducing the computational cost of the process. With continued research and development, deep learning-based image inpainting has the potential to be an important tool for a wide range of applications, from image editing to medical imaging.

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3. Pixel-wise Dense Detector for Image Inpainting; Ruisong Zhang, Weize Quan, Baoyuan Wu, Zhifeng Li and Dong-Ming Yan; Published by John Wiley & Sons Ltd, 2020

4. Zoom-to-Inpaint: Image Inpainting with High Frequency Details; Soo Ye Kim, Kfir Aberman, Nori

Kanazawa, Rahul Garg, Neal Wadhwa, Huiwen Chang, Nikhil Karnad, Munchurl Kim, Orly Liba; arXiv:2012.09401v1 [cs.CV] , 17 Dec 2020

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