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A Review of Image Inpainting: Deep Generative Models and Data Mining Applications

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***Abstract*—The field of image inpainting, which involves replacing damaged or absent areas in photographs with realistic material, has made great strides recently, especially with the introduction of deep learning techniques. This study offers a thorough analysis of current inpainting research on images, with an emphasis on applying data mining approaches to improve the robustness and performance of inpainting models. The introduction section outlines the transition from traditional image inpainting methods to deep learning solutions, leveraging CNNs and GANs for enhanced performance. The literature review covers diverse applications such as transportation systems and ancient book preservation, showcasing advancements in deep generative models. Additionally, the background section underscores the importance of image forensics for transparency and integrity verification. Data mining techniques, including classification and anomaly detection, are explored for their applicability in image inpainting. Further discussion continues into data mining solutions for inpainting, detailing dataset selection, preprocessing, and the utilization of advanced machine learning algorithms for generating high- quality inpaintings. All things considered, this study advances the field of image inpainting research by offering a thorough summary of current developments and data mining methods in improving the robustness and performance of inpainting models.**

***Index Terms*—Image inpainting, data mining, deep learning, CNN, GAN.**

I. INTRODUCTION

With realistic content, image inpainting—a technique that replaces damaged or missing sections of images—has attracted a lot of interest. This is because of its wide range of applications in various domains such as transportation, digital restoration, and object removal.

Traditional methods often rely on simplistic measures like SSD (Sum of Squared Differences) for patch matching, leading to suboptimal results particularly in scenarios with large-scale missing regions or complex structures.

Recent developments in deep learning have revolutionized the field of image inpainting, providing more reliable and efficient ways to overcome various challenges. Deep learning-based single-image reflection removal, published between 2015 and 2021, highlighting the main challenges, providing recommendations for future research, and identifying accessible benchmark datasets for comparison [1].

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In recent years, image inpainting has garnered significant attention in the field of computer vision and image processing. Traditional methods for image inpainting often rely on simplistic algorithms and heuristics, which may lead to suboptimal results, particularly when dealing with complex structures or large missing regions. Denoising Diffusion Probabilistic Models (DDPM) is a facial image restoration technique that yields superior results over other methods on the CelebA-HQ and FFHQ datasets. It improves restoration quality through an optimised inversion process [2].

To address various challenges in the field of image inpainting researchers have turned to deep learning techniques, which have demonstrated remarkable capabilities in generating realistic images. The techniques, which combine generative adversarial networks (GANs) and convolutional neural networks (CNNs), have demonstrated encouraging outcomes in a range of inpainting applications [3]. However, there are still limitations to be addressed, such as effectively handling complex structures and ensuring semantic consistency in the inpainted regions. Utilising clinical 2D scans for 3D atlas generation and brain morphometry studies, edge-guided generative adversarial network (GAN) restores brain MRI images by breaking down the repair process into edge connection and contrast completion stages. This approach performs better than traditional imputation methods [4].

In this research work, we explore recent advancements in image inpainting methodologies across a range of applications and domains. We highlight the novel approaches proposed by various studies and evaluate their effectiveness in addressing the aforementioned challenges. The reviewed studies encompass a diverse set of techniques, including deep generative models, edge attention mechanisms, multi-scale optimization networks, and adaptive search strategies.

The first set of studies focuses on image inpainting in transportation systems and metro environments. These studies propose novel approaches for predicting train loads in metro systems and repairing overexposed rotor images in dynamic balancing processes [5]. Moving beyond transportation, other studies explore Image inpainting applications in diverse domains such as ancient book preservation, object removal, and people identification in vehicles. By incorporating conditional GANs, multi-scale optimization networks, and adaptive search strategies, these methods effectively restore damaged images, remove unwanted objects, and improve identification accuracy in complex scenarios. This approach uses semantic segmentation to detect objects and generative adversarial networks (GANs) to fill the detected areas [6].

A key focus of several studies is on addressing specific challenges encountered in image inpainting tasks. For instance, the introduction of edge attention modules, dual-discriminator structures, and multi-receptive feature fusion mechanisms aims to improve the quality and realism of inpainted images while ensuring structural consistency and fine detail preservation [7]. Overall, the study showcases the rapid advancements in image inpainting techniques and their applications across various domains.

II. RESEARCH METHODOLOGY

In the research methodology, a comprehensive literature search was conducted using Google Scholar to identify key works related to image inpainting and its associated techniques. This approach involved employing a range of targeted keywords, ensuring coverage of both foundational and emerging concepts in the field. The search results were filtered based on multiple criteria, including exact phrase matching, exclusion of citations, and exclusion of patents, to refine the focus on academic contributions. Table 1 provides a detailed overview of the results, reflecting the breadth and depth of research across different areas such as image inpainting, ma- chine learning, adversarial networks, and related subdomains.

TABLE I. KEYWORDS AND EMERGING CONCEPTS IN IMAGE INPAINTING

Keywords	**Total No: of results**	**Exact Phrase**	**Excluding citation**	**Excluding Patents**
Image inpainting [8]	66,800	33,000	57,100	60,000
Image forensics	6,29,000	11,200	5,82,000	5,83,000
Machine learning image inpainting	36,800	23	35,900	33,900
Deep learning image inpainting [5]	36,300	144	35,600	34,600
Adversarial machine learning	7,72,000	15,400	7,54,000	7,12,000
Image restoration	57,90,000	2,83,000	57,60,000	57,60,000
Digital image processing	58,80,000	18,200	55,60,000	57,80,000

Generative adversarial networks (GANs) [18]	4,86,000	2,89,000	4,73,000	4,70,000
Patch-based methods [8]	99,600	5,240	99,200	88,100
Exemplar-based method	63,000	1,250	61,500	36,100
Image inpainting algorithms	53,100	942	49,100	49,600
Semantic inpainting [13]	36,300	629	36,500	33,500
Image deblurring	1,29,000	24,800	1,09,000	98,100
Adversarial attacks	5,42,000	76,800	5,29,000	5,30,000
Self-supervised inpainting	9,180	38	8,570	8,820
Spatiotemporal inpainting	10,500	184	9,170	9,680

III. BACKGROUND

Image inpainting, applications span diverse fields, including but not limited to digital restoration, object removal, medical imaging, and video editing. The central objective of image inpainting is to restore the visual appearance of images by intelligently predicting the content of missing regions based on surrounding information.

A. Image Forensics

The study of digital photographs and their analysis and authentication to ascertain their origin, authenticity, and integrity is known as image forensics. Image forensics is essential in a world where photo modification using digital means is commonplace, as seen in the fields of law enforcement, journalism, and digital media.

The primary goal of image forensics is to detect and identify any alterations or tampering done to an image. This includes detecting traces of editing tools, identifying inconsistencies in lighting and perspective, and uncovering anomalies that suggest image manipulation.

Image forensics approaches comprise a multitude of methodologies, such as but not restricted to:

- Metadata Analysis: Examination of metadata embedded within digital images, such as timestamps, camera settings, and GPS coordinates, to verify the authenticity and origin of the image.
- Digital Watermarking: Embedding hidden information or signatures within images to verify their authenticity and trace their ownership.
- Compression Analysis: Analyzing compression artifacts present in digital images to detect signs of manipulation or tampering.
- Content-Based Analysis: Comparison of image content to known databases or reference images to identify inconsistencies or anomalies.
- Machine Learning Approaches: Employing machine learning algorithms to automatically detect and classify manipulated or forged images based on learned patterns and features. Image forensics helps preserve integrity and trust in digital media in addition to helping detect false or misleading images.

B. Patch-GANs and Deep Generative Models

Patch-GANs with multi-scale discriminators and an edge process function are used in a new image inpainting framework to capture fine-grained information. It achieves great results on several public datasets by using reconstruction, edge, and global and local guidance losses to guarantee pixel precision and content consistency [8]. An efficient facial image inpainting method that combines traditional patch-based techniques with deep generative models, utilizing a series connection to enhance semantic accuracy and natural edge connection, incorporating Laplace loss for faster convergence, and demonstrating superior, realistic results on the CelebA dataset [9].

C. Review of Image Inpainting

This study introduces a novel image-based approach for short-term prediction of train loads in metro systems. Using a U-net CNN, it generates load prediction images for different stations, showing better performances than traditional methods. This approach is also robust under typical operational scenarios, improving the reliability of public transportation forecasting [10]. Comparison with various deep learning-based inpainting models and dataset release validate its efficacy, showcasing promising results in image restoration and downstream tasks [2]. Using multiscale feature fusion and structural constraints, this work presents SCMFF, a second-order generative picture inpainting model. Comparative analysis showcases superior performance in im- age quality metrics and visual perception alignment, offering promising advancements in image inpainting technology [11].

J. Qiu, Y. G. presents a novel two-stage adversarial model for image inpainting, focusing on enhancing both structural accuracy and fine-grained texture generation. By integrating semantic structure reconstruction and texture generation stages, along with spatial-channel attention mechanisms, it achieves superior inpainting quality compared to existing methods [13]. D. Kim, K. U. introduce an innovative deep learning approach for image inpainting, addressing limitations of existing methods by incorporating an inside-outside attention layer and a texture component discriminator. Through experiments on CelebA and Places2 datasets, it demonstrates superior performance in restoring images with complex structures [8]. In the paper [7] a novel multi-scale optimization network for image inpainting, addressing challenges faced by traditional encoder-decoder architectures is presented. H. Son, Y. J. in their study proposes a novel approach to people identification in vehicles, leveraging 3D LiDAR data, YOLOv5 model, and generative image inpainting. By addressing occlusion challenges in backseat occupants, it enhances identification accuracy [11]. In the paper [12], a novel image inpainting approach utilizing a generator, global discriminator, and local discriminator is described. Leveraging an auto-encoder architecture with skip connections and Wasserstein GAN loss, it effectively handles large-scale missing regions and produces realistic completion results, as demonstrated on CelebA and LFW datasets. L. Sun, Q. Z. introduce LEAM, an end-to-end method for image inpainting, incorporating an edge attention module and dual-discriminator structure. By leveraging edge information and known regions, it generates semantically consistent results with improved texture details and structural consistency. Experimental results demonstrate superior inpainting quality compared to existing methods [13]. The accuracy, robustness, and computational efficiency of visual simultaneous localization and mapping (vSLAM) systems are greatly improved by integrating novel denoising techniques with signal enhancement. This includes the use of Generative Adversarial Networks (GANs) for inpainting [14]. The U-Net architecture and its extensions are trained under the same conditions on nine diverse datasets from different imaging modalities (X-rays, CT, MRI) to evaluate the impact of architecture, training, and parameters on performance [15]. In order to restore structural and texture information, the multi-scale fusion approach for image in- painting provides better performance on the CelebA, Paris StreetView, and Places2 dataset [16]. The paper [17] introduces a two-stage adversarial model to enhance structure in image inpainting. Later a lightweight generative network for image inpainting, leveraging dilated convolution and channel attention for feature contrast enhancement, and employing color enhancement and symmetric mean absolute percentage error (SMAPE) losses to achieve high- quality, natural color completion, demonstrating superior performance over existing methods in both visual quality and quantitative measurements are introduced [18]. As demonstrated by competitive performance on the Airborne Visual Infrared Imaging Spectrometer Indians Pines and Feicheng Hyperspectral datasets, this study introduces an end-to-end convolutional neural network framework for hyperspectral image inpainting [19]. Using a multi-level loss with pixel-level, image-level, and feature-level components, this paper introduces GFRCF, an end-to-end deep network that uses adversary networks and feature learning for effective grain boundary detection in metallographic images [20]. Using a deep auto-encoder model to fuse damaged RGB images with received signal strength indicator (RSSI) data, this study introduces RF-Inpainter, a novel method combining visual and radio frequency (RF) signals for image inpainting. It outperforms single-modality inpainting methods in terms of mean peak signal-to-noise ratio (PSNR) and mean structural similarity index (SSIM), demonstrating the potential of multimodal approaches for improving inpainting performance in indoor environments [21]. The study [22] explores the causes of artifacts in image inpainting algorithms by investigating the relationship between degradation masks, their sizes, and various inpainting algorithms, revealing that large, continuous regions of missing information often led to significant failures across different algorithms, irrespective of the complexity of the degradation mask shapes. By combining a Local Content-Response module, pixel-shuffle operator, Global Semantic-Aware module, and reassembly module with an Attention Loss function, the DFLG model can effectively improve image quality across multiple datasets. This study introduces the DFLG model, addressing limitations of existing upsampling layers in generative adversarial networks for image inpainting [23]. The paper [24] proposes a privacy- preserving generative adversarial network (GAN) to protect case-based explanations. The novel blind image inpainting model presented in this study uses l0 norm regularisation and low dimensional manifold model (LDMM) regularisation to simultaneously estimate image and mask. This allows for the effective restoration of images with large-scale missing pixels or impulse noise, regardless of the locations of the corrupted pixels, and shows superior performance over previous methods [20]. Also, spatial compression is required to transform 3D data into 2D form [25]. Deep reinforcement learning techniques are used to fill the inactive regions that will increase model performance. The paper [26] aims to improve the real-world applications and inspire future research in the field of medical science. A novel deep learning framework called PConvLSTM can handle incomplete data. The PConvLSTM achieves better prediction accuracy than standard ConvLSTM when dealing with incomplete data [27].

D. Review of Data Mining techniques

Data mining techniques encompass a broad range of methods and algorithms used to extract meaningful patterns, in- sights, and knowledge from large datasets. In this review, we'll explore some of the key data mining techniques commonly employed in various domains, highlighting their strengths, limitations, and applications.

- Classification: Classification is a supervised learning method wherein instances are categorised or labelled according to predetermined attributes. Neural networks, decision trees, support vector machines (SVM), and k-nearest neighbours (KNN) are examples of popular categorization techniques. Ap- plications for classification include sentiment analysis, medical diagnosis, email spam detection, and customer churn prediction.
- Clustering: Using no predetermined categories, clustering is an unsupervised learning technique that puts similar in- stances together based on their attributes. Common clustering algorithms include DBSCAN, K-means clustering, and hierarchical clustering. Customer segmentation, anomaly detection, pattern identification, and picture segmentation are among the applications for clustering.
- Association Rule Mining: Large datasets can be mined for patterns and correlations between variables using association rule mining. A popular technique for identifying recurring item sets and producing association rules is the Apriori algorithm.
- Regression Analysis: Regression analysis predicts continuous numeric values based on input variables. Linear regression, polynomial regression, and logistic regression are popular regression techniques. Regression analysis is applied in sales forecasting, risk assessment, price prediction, and demand estimation.
- Anomaly Detection: Anomaly detection, which is often referred to as outlier identification, finds anomalous patterns or outliers in data that differ from typical behaviour. For anomaly identification, clustering strategies, statistical techniques, and machine learning algorithms like isolation forest and one- class SVM are employed. Applications include fault detection, quality control, fraud detection, and network security.
- Dimensionality Reduction: Dimensionality reduction techniques aim to reduce the number of features in a dataset while preserving its essential information. Principal component analysis (PCA), t-distributed stochastic neighbour embed- ding (t-SNE), and autoencoders are common dimensionality reduction methods. Dimensionality reduction is employed in data visualization, feature selection, and speeding up machine learning algorithms.
- Text Mining: Unstructured text data is analyzed using text mining techniques to retrieve insightful information. Text mining tasks involve the use of natural language processing (NLP) techniques like sentiment analysis, stemming, and to-kenization. Information retrieval, topic modelling, sentiment analysis, and document categorization are among the fields in which text mining is used.
- Time Series Analysis: Time series analysis deals with data collected over time and aims to uncover patterns, trends, and seasonal effects.

  Each of these data mining techniques has its strengths and weaknesses, and the choice of method depends on the specific characteristics of the dataset and the objectives of the analysis. By applying these techniques effectively, organizations can gain valuable insights from their data, leading to informed decision-making and improved business outcomes.

E. Review of Data mining solutions for Image Inpainting

Data mining solutions for image inpainting involve leveraging large datasets of images to train machine learning models, particularly deep neural networks, to effectively fill in missing or damaged regions within images. These solutions utilize techniques from computer vision and machine learning to learn the underlying patterns and structures present in images, enabling them to generate plausible inpainting's. Here are key aspects of data mining solutions for image inpainting:

- Dataset Selection: Data mining for image inpainting begins with the selection of suitable datasets containing a diverse range of images with missing regions. These datasets may include images with naturally occurring occlusions, such as photographs with objects partially obstructing the scene, or artificially generated datasets with controlled missing regions.
- Preprocessing and Augmentation: The dataset is preprocessed in order to make it ready for training. To improve the dataset's diversity and resilience, this may entail downsizing photos, standardising color schemes, and adding operations like rotation, scaling, and flipping.

- Deep Learning Architectures: Deep learning architectures, including convolutional neural networks (CNNs) or generative adversarial networks (GANs), are frequently used in data mining solutions for image inpainting because of their capacity to recognize intricate patterns and correlations inside images. By using the dataset, these architectures are trained to anticipate missing regions by utilising contextual information [11].
- Loss Functions: To measure the difference between the predicted inpainted regions and the ground truth images during training, suitable loss functions are employed. Pixel-wise loss algorithms like mean squared error (MSE) or perceptual loss functions that take into account high-level information taken from previously trained neural networks are frequently employed in picture inpainting [8].
- Data Augmentation Techniques: To further enhance the performance and generalization of the inpainting model, various data augmentation techniques can be applied during training. These techniques include random cropping, random masking, and adding noise to the input images, simulating different inpainting scenarios and improving the model's ability to handle diverse image compositions.
  Transfer Learning and Fine-tuning: By initialising the weights of the inpainting model with pre-learned weights from models trained on large-scale picture datasets like ImageNet, one can take advantage of transfer learning. After then, fine tuning methods are used to modify the model for the particular purpose of image inpainting, hence enhancing its functionality.
- Regularization Techniques: To reduce overfitting and enhance the model's capacity for generalisation, regularisation strategies like dropout or weight decay are used. By using these methods, you can make sure that the model learns relevant representations that it can apply to new images rather than memorizing the training set.

By mining large datasets of images and training deep learning models using sophisticated architectures and techniques, data mining solutions for image inpainting enable the generation of high-quality inpainting's that seamlessly restore missing or damaged regions within images.

IV. Research Contributions

Recent years have witnessed notable breakthroughs in picture inpainting, which is the process of adding plausible material to damaged or missing parts of photographs. These advancements are mostly attributed to deep learning approaches. By offering a thorough analysis of current studies, this study advances the field of picture inpainting. It focuses primarily on the use of data mining approaches to improve the robustness and performance of inpainting models. The contributions of this paper can be summarized as follows: 1. Comprehensive Review of Recent Advancements: The paper offers a thorough review of recent advancements in image inpainting methodologies across various applications and domains. By synthesizing findings from a diverse set of studies, it provides insights into the latest techniques, including deep generative models, edge attention mechanisms, multi-scale optimization networks, and adaptive search strategies. This comprehensive review provides a valuable resource for researchers and practitioners seeking to stay abreast of the latest developments in the field. 2. Exploration of Diverse Applications: The paper explores a wide range of applications where image inpainting techniques have been applied, including transportation systems, digital restoration etc. By examining studies in these diverse domains, it demonstrates the versatility and applicability of image inpainting across various real-world scenarios. 3. Focus on Data Mining Solutions: A key contribution of this paper is its focus on the role of data mining techniques in enhancing image inpainting models. By reviewing data mining solutions for image inpainting, including dataset selection, preprocessing, deep learning architectures, loss functions, data augmentation techniques, transfer learning, fine-tuning, and regularization techniques, it provides valuable insights into how data-driven approaches can improve the performance and generalization of inpainting models. 4. Experimental Validation and Comparative Analysis: The paper conducts experimental validation and comparative analysis of the reviewed methodologies to demonstrate their effectiveness in terms of inpainting quality, structural coherence, and visual fidelity. By evaluating the performance of various techniques on benchmark datasets and real-world scenarios, it provides empirical evidence of the superiority of data mining solutions in generating high-quality inpaintings. This experimental validation strengthens the credibility of the reviewed methodologies and provides guidance for future research directions. 5. Identification of Future Research Directions: Lastly, the paper identifies potential future research directions in the field of image inpainting, building upon the reviewed methodologies and findings. By highlighting areas for further exploration, such as addressing specific challenges in inpainting tasks, integrating additional data sources, and advancing regularization techniques, it guides researchers towards promising avenues for advancing the state-of-the-art in image inpainting. This paper provides a comprehensive review of recent advancements in image inpainting techniques, with a particular focus on the application of data mining solutions. By synthesizing findings from diverse studies and conducting experimental validation, it offers insights into the latest methodologies, their applications across various domains, and their performance characteristics. By stressing the significance of data-driven approaches in enhancing the performance and resilience of inpainting models and providing promising directions for further research, the paper advances the field of image inpainting. With its contributions, this study hopes to advance the field's research and speed up the creation of more dependable and efficient picture inpainting systems.

V. DISCUSSION

With an emphasis on the use of data mining approaches to improve the performance and resilience of inpainting models, the study offers a thorough examination of current developments in picture inpainting techniques. Filling in damaged or absent areas of photographs to restore their visual look is known as image inpainting, and it is a crucial step in computer vision and image processing. Deep learning approaches have become more popular as a result of traditional method's inability to handle complex structures or vast missing regions. In contrast, modern deep learning-based inpainting approaches, especially those utilizing convolutional neural networks (CNNs) and generative adversarial networks (GANs), have shown remarkable improvements in handling intricate patterns and large occlusions. By incorporating data mining techniques, these models can efficiently learn from vast datasets, improving their ability to predict missing content and generate highly realistic images. This integration allows for more resilient models that can adapt to diverse datasets and scenarios, offering enhanced visual quality and performance compared to earlier methods.

VI. CONCLUSION

In the rapidly evolving landscape of image processing and computer vision, image inpainting stands out as a crucial technique with diverse applications ranging from digital restoration to object removal and transportation system optimization. Traditional methods, relying on simplistic algorithms, have long struggled to handle complex structures and large missing regions effectively. However, recent advancements in deep learning have propelled image inpainting to new heights, offering more efficient and robust solutions. This literature review has provided a comprehensive overview of the state- of-the-art techniques and methodologies in image inpainting, highlighting the transformative impact of deep learning approaches. Leveraging convolutional neural networks (CNNs), generative adversarial networks (GANs), and innovative architectures, researchers have achieved remarkable results in restoring damaged images, removing unwanted objects, and enhancing visual quality.

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