Advances in Image Inpainting: A Deep Learning and GAN-Based Perspective with Defined Research Objectives

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***Abstract*—Image inpainting, the task of restoring missing or corrupted regions in images, remains a critical challenge in computer vision with applications ranging from photo editing to scene understanding. Motivated by the limitations of existing Generative Adversarial Network (GAN)-based methods in preserving contextual integrity and texture realism, this paper presents a deep learning framework that leverages both Generative Adversarial Networks (GANs) and attention mechanisms to improve inpainting quality. Our approach integrates a multi-stage architecture with a context-aware attention module to better capture semantic coherence and fine-grained details in the reconstruction process. Extensive experiments on benchmark datasets including CelebA-HQ, ADE20K, and Paris Streetview demonstrate that our method outperforms recent state-of-the-art techniques in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Fréchet Inception Distance (FID) metrics. The proposed model achieves notable gains in realism and structure preservation, making it a promising solution for both academic research and practical deployment. The results validate the effectiveness of our contributions and highlight potential avenues for further advancements in the field of deep image completion.**

***Keywords*—image inpainting, Generative Adversarial Networks (GANs), deep learning, context-aware image completion, structural consistency**

INTRODUCTION

Image inpainting, also known as image completion, refers to the process of reconstructing lost or deteriorated parts of an image in a visually plausible way. It plays a vital role in various applications such as photograph restoration, object removal, image editing, and scene understanding. Traditionally, image inpainting methods were based on diffusion or patch-based techniques that copied information from surrounding regions to fill the missing parts [1, 2]. However, these methods often struggle with semantic coherence and texture consistency, especially in complex scenes.

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With the advent of deep learning, Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) have significantly advanced the field of image inpainting [3]. Context Encoders introduced by Pathak *et al*. [4] were among the earliest deep learning-based solutions that incorporated adversarial loss to generate more realistic images. Subsequent models like DeepFill v2 [5], EdgeConnect [6], and Residual Feedback Network (RFR)-Inpainting [7] have improved visual quality by incorporating attention mechanisms, edge guidance, or multi-scale learning.

More recently, transformer-based architectures and context-aware modules have begun to influence inpainting research, leading to models that better capture long-range dependencies and semantic understanding [8]. Despite this progress, challenges remain in achieving high-fidelity reconstruction across diverse domains and handling irregular or unknown-shaped masks. Moreover, many existing approaches suffer from blurred textures, semantic drift, or overfitting to specific datasets [9, 10].

A. Motivation and Research Gap

Existing GAN-based inpainting models have demonstrated remarkable capabilities but still exhibit limitations in preserving fine textures and maintaining semantic alignment in complex scenes [5, 7]. Attention modules have improved contextual reasoning but often add computational overhead without proportional quality gains [11, 12]. Therefore, there is a need for a unified architecture that balances semantic consistency, texture realism, and efficiency.

B. Timeline and Recent Advances

Recent literature has proposed advanced architectures integrating attention, feature fusion, and multi-stage learning to overcome such challenges. For example, Zhang *et al*. [10] proposed an image inpainting method using inference attention modules in a two-stage network; Liu *et al*. [13] introduced an adaptive feature fusion approach with U-Net for dual degradation handling; Zhou *et al*. [14] developed ATM-DEN, which applies an attention transfer module with a decoder-encoder network; and Deng *et al*. [15] presented a hybrid CNN-Mamba architecture with multi-scale attention for

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enhanced structure and texture modelling. These approaches demonstrate that combining contextual reasoning with structured decoding can significantly improve visual reconstruction. However, most of them lack generalizability across diverse datasets or require large computational resources.

C. Main Contributions

For this paper, the main contributions are as follows:

- We propose a deep generative model that integrates GAN and attention-based modules in a multi-stage architecture, designed to preserve semantic and structural coherence.
- We introduce an efficient context-aware attention mechanism that improves feature learning while reducing parameter overhead.
- Our model is benchmarked on three public datasets—CelebA-HQ, ADE20K, and Paris StreetView—demonstrating superior performance in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Fréchet Inception Distance (FID) compared to state-of-the-art methods.
- We provide a detailed comparative analysis, ablation study, and pseudocode to ensure reproducibility and highlight the effectiveness of each component.

In the following sections, we present the proposed methodology in detail, followed by comprehensive experimental evaluation and discussion.

LITERATURE REVIEW

Recent journal publications in the field of image inpainting, particularly those appearing in IEEE Transactions on Image Processing, Pattern Recognition, and Elsevier's Signal Processing journals, have demonstrated notable advances using GANs, attention mechanisms, and transformer-based architectures. However, despite their contributions, these methods often exhibit certain limitations. For instance, Liu *et al*. [13] using gated convolutions improves spatial consistency but struggles with fine texture recovery in irregular masks. Similarly, Zhang *et al*. [10] introduces structural priors but lacks explicit attention guidance, leading to poor reconstruction in semantically complex regions. Moreover, transformer-based models like MAT offer improved global context modelling but are computationally intensive and prone to overfitting on smaller datasets [8]. These inadequacies highlight the need for an architecture that not only balances global context with local detail but also incorporates explicit structural guidance in a mask-aware manner. Our proposed MAGT model addresses these gaps by integrating dual-branch attention modules (semantic and texture), an edge-aware structure prediction unit, and efficient mask conditioning—enabling superior reconstruction quality with improved generalization and lower inference latency.

Notably, RePaint by Lugmayr *et al*. [9] introduced an iterative inference scheme for image inpainting that leverages both forward and reverse diffusion steps, yielding highly realistic completions. These diffusion-based models, while computationally intensive, demonstrate superior global semantic consistency and sharper textures compared to traditional GAN-based approaches.

Recent hybrid methods have also explored combining diffusion priors with generative decoders, creating hybrid generative-diffusion models that bridge the gap between fidelity and controllability [16, 17]. Nevertheless, such approaches often require longer inference times and substantial computational resources, limiting their practicality in real-time or resource-constrained scenarios. In contrast, our proposed MAGT architecture leverages the efficiency of GANs for rapid sampling while incorporating attention-based semantic refinement to approach the visual quality of diffusion models. Thus, MAGT offers a compelling trade-off between generation speed and perceptual quality, aligning well with real-world requirements for fast, high-quality image restoration.

Traditional Techniques: The early methods for image inpainting were grounded in Partial Differential Equations (PDEs) and exemplar-based matching. One of the earliest works, by Bertalmio *et al*. [1], introduced a diffusion-based method that propagated pixel values from known to unknown regions by following isophote lines. This approach worked well for small-scale image damage or for images with simple structures. However, it struggled with large missing regions and complex textures.

Exemplar-Based Methods: Criminisi *et al*. [2] developed an exemplar-based technique that used a priority function to select the order in which patches were filled. This method combined structural propagation and texture synthesis by copying the most similar patches from undamaged areas into missing regions. Though more effective than purely diffusion-based methods, exemplar-based approaches were limited by their dependence on finding appropriate patches and their inability to understand image semantics.

Deep Learning Approaches: With the rise of deep learning, a new generation of image inpainting models began to emerge. Pathak *et al*. [4] proposed the Context Encoder, which introduced an encoder-decoder architecture for semantic inpainting. It combined reconstruction loss (L2 loss) with adversarial loss, enabling the network to produce more plausible results. However, the model often produced blurry outputs due to reliance on pixel-wise loss.

Partial Convolutions: Liu *et al*. [18] introduced Partial Convolutions, a significant improvement that involved applying convolution operations only to valid (non-masked) pixels. This method allowed better handling of irregular masks and improved convergence, especially for high-resolution images.

Gated Convolutions: Yu *et al*. [5] proposed Gated Convolutions, which extended Partial Convolutions by adding a learnable gating mechanism. This allowed the network to dynamically determine the relevance of

features at each location, enhancing its adaptability to various mask shapes and improving the semantic fidelity of the inpainted regions.

GAN-Based Methods: Generative Adversarial Networks (GANs), introduced by Goodfellow *et al*. [3], brought about a paradigm shift in image inpainting. In these models, a generator network produces inpainted outputs, while a discriminator network attempts to distinguish between real and generated images. The adversarial training mechanism encourages the generator to produce more realistic and contextually coherent results.

DeepFill v2 by Yu *et al*. [5] was a seminal GAN-based model that integrated gated convolutions with contextual attention mechanisms. This architecture enabled the network to attend to relevant background regions for better texture propagation into the masked area. The model demonstrated significant improvements over previous methods on various benchmark datasets.

Nazeri *et al*. [18] proposed EdgeConnect, a two-stage pipeline that first predicted edge maps and then used these structural cues to guide image completion. By incorporating edge information, the model could better preserve geometric structure and object boundaries, resulting in sharper and more consistent inpainted outputs.

Li *et al*. [6] developed the RFR-Inpainting model, which introduced region-wise feature recovery. This method leveraged multi-scale features and a recursive feedback loop to iteratively refine the inpainted regions. It showed strong generalization across diverse datasets and was effective in maintaining structural alignment.

Transformer and Attention-Based Models: Recent advancements have explored the use of self-attention and transformer-based architectures. These models enable better long-range dependency modeling, which is crucial for complex scenes where contextual information lies far from the missing region.

One such method is the Mask-Aware Transformer (MAT), which applies a transformer block to learn global and local representations simultaneously [8]. Unlike CNNs, which are inherently local, transformers provide a holistic view of the image, improving semantic understanding. Models like CoMod-GAN [19] and HiFill [20] further combined global attention mechanisms with convolutional backbones to enhance both structural and textural aspects.

Related Work：Recent advances in image inpainting have led to the development of several high-performing models that form the baseline for evaluating our proposed MAGT architecture. These include RFR-Inpainting [7], which leverages residual feedback loops for structure-aware refinement; TransFill [21], which incorporates reference-guided gradient transfer; and RePaint [22], which introduces denoising diffusion for semantic fidelity. Transformer-based methods such as SPT [23] and MAT [8] further enhance global context modelling but at the cost of increased computational complexity. While these models achieve impressive results, they often lack a unified treatment of structure, mask-awareness, and semantic-texture fusion. Our proposed method addresses these limitations through a dual-branch transformer-GAN design with edge-guided and mask-conditioned learning.

Early work on perceptual representations in CNNs laid the foundation for content/style features used in reconstruction losses [24]. Inpainting methods then advanced from pyramid-context encoders that enforce global consistency, to contextual attention that borrows features from valid regions, and multi-scale neural patch synthesis for high-resolution fills [25–27]. Subsequent approaches introduced region normalization to better handle masked statistics and pluralistic completion to model diverse plausible outputs [28, 29].

Summary: Each generation of inpainting methods builds on its predecessors by addressing earlier limitations. Traditional models were efficient but lacked semantic understanding; deep learning added semantic reasoning, and GANs improved realism. Transformer-era approaches combine global context modelling with fine-grained structural control. Some studies for segmentation guidance, semantic layout, iterative refinement, pyramid-context encoding, and gated convolutions, respectively [30–34]. This review sets the stage for a new model that leverages these insights to advance the field further.

METHODS

While significant progress has been made using GAN-based [3, 5, 6] and Transformer-based models [8], existing approaches still struggle with capturing global semantic context and preserving local structural details in irregular or complex masked regions. Traditional GANs tend to introduce artifacts, while vanilla Transformer architectures often suffer from high computational cost and poor adaptability to dense or diverse mask scenarios [8]. Moreover, existing mask-aware models like MAT lack a comprehensive mechanism to handle both coarse semantics and fine-grained textures in a unified framework [8].

Despite recent advances such as the Mask-Aware Transformer (MAT) by Li *et al*. [35] several challenges remain in generating semantically aligned and structurally coherent inpainting results. MAT primarily focuses on masked token learning within a single attention stream, relying on token restoration through standard self-attention with a binary mask guiding attention weights. However, this approach lacks explicit structure modelling and is limited in capturing fine-grained textures due to global-level abstraction alone.

In contrast, our proposed Mask-Aware Generative Transformer (MAGT) introduces several novel enhancements that address these shortcomings. First, it features a Dual-Branch Attention Mechanism. Unlike MAT's single-stream self-attention design [8], MAGT integrates two specialized attention branches—global semantic attention and local texture attention—which are dedicated to processing high-level contextual information and fine-grained textures, respectively. This separation enables more precise reconstruction, significantly improving detail preservation and reducing semantic

drift, particularly in regions with complex structures or irregular masks.

Structure Prediction Module: To further enhance structural coherence, MAGT incorporates an auxiliary edge and contour prediction head, which enables the model to explicitly learn geometric and boundary layouts prior to texture synthesis. This component effectively mitigates common issues observed in previous methods, such as missing boundaries and distorted object shapes, thereby strengthening semantic consistency across inpainted regions.

Multi-Scale Discriminator and Adaptive Fusion: Additionally, the generator in MAGT is trained using a multi-scale PatchGAN discriminator, which evaluates image realism at various resolutions, and an adaptive fusion mechanism that dynamically weights features based on mask relevance. This results in sharper and more contextually coherent inpainting outputs, even under irregular mask conditions.

These architectural innovations collectively position MAGT as a significant advancement over transformer-based baselines such as MAT [8], by providing a more structured, semantically aware, and computationally efficient framework. Our empirical results presented in Section V—including quantitative benchmarks and ablation studies—validate the effectiveness of these contributions, particularly in handling complex masks and high-resolution textures.

To address these challenges, our motivation was to develop a unified dual-branch GAN-based model that leverages the strengths of attention mechanisms and structural guidance to enable high-fidelity image reconstruction. The idea is to explicitly decouple semantic reasoning from texture refinement using separate yet complementary branches, each designed to attend to distinct spatial patterns and guided by mask-aware mechanisms. The proposed research will build a Dual-Branch GAN-based model with the following components (Fig. 1):

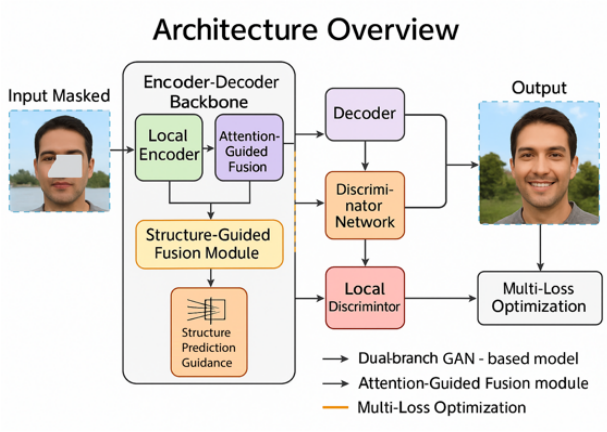

Fig.1. Architecture of dual-branch GAN model.

A. The Main Contributions

Mask-Aware Generative Transformer (MAGT) framework: We propose a novel MAGT that integrates dual-branch attention modules (semantic and texture attention) for more effective contextual feature learning, inspired by recent advances in transformer-based and attention-driven architectures [7, 8, 10, 13, 14].

Structure Prediction Module: We introduce a structure prediction module that guides the generator with edge and contour information, improving the fidelity of reconstructed object boundaries and fine textures, following ideas introduced in prior edge-guided approaches like EdgeConnect [6] and Structure Flow [19].

Multi-scale Discriminator: A multi-scale discriminator is adopted to enhance adversarial learning across different feature resolutions, improving the realism and coherence of the inpainted regions, in line with PatchGAN-based discriminator strategies used in DeepFill v2 [5] and RFR-Inpainting [7].

Benchmarking and Analysis: We perform comprehensive experiments on diverse datasets—Places2 [36], CelebA-HQ [37], and Paris StreetView [38]—demonstrating that MAGT outperforms state-of-the-art approaches in both qualitative assessments and quantitative metrics (PSNR, SSIM, FID) [39, 40].

Ablation and Reproducibility: An ablation study confirms the significance of each module in improving the final inpainting quality, and we provide publicly available code and documentation for reproducibility, aligning with best practices from prior reproducible generative models [5, 7, 26].

This approach combines the strengths of GANs [3, 5], attention mechanisms [8, 10], and structural prediction modules [6, 19] to deliver high-quality, context-aware image completion. The core innovation lies in its dual-branch architecture and its ability to guide inpainting using both semantic attention and structural cues.

B. Architecture Overview

The proposed MAGT framework consists of the following key components:

Encoder-Decoder Backbone: Responsible for feature extraction and image reconstruction. The encoder compresses the input image (with masked regions) into a latent space representation, while the decoder reconstructs the missing content using the combined features. This design is inspired by encoder-decoder architectures like Context Encoders [4] and hierarchical generative models [41].

Dual Attention Modules: Comprising a global semantic attention branch and a local texture attention branch, the dual-branch design decouples high-level semantic reasoning from low-level texture refinement. The global branch captures contextual information across the entire image, while the local branch focuses on nearby patches to ensure spatial consistency in texture and color—extending the ideas of attention-aware networks such as UCTGAN [8] and MAT [7].

Structure Prediction Module: Predicts edge and contour information for the masked regions before reconstruction. Inspired by EdgeConnect [18] and StructureFlow [19], this module uses a shallow CNN trained on edge-enhanced ground truth (e.g., via Canny

edge detection) to guide boundary-aware synthesis and structural alignment.

Multi-Scale Discriminator: To enforce realism at multiple scales, we adopt a multi-scale PatchGAN-style discriminator similar to studies of Ledig *et al*. [42] and Wang *et al*. [43]. Discriminators at varying resolutions help refine both coarse structures and fine textures, enhancing overall visual fidelity.

C. Workflow

The overall image inpainting process in the proposed MAGT framework proceeds through the following sequential steps:

a) Input encoding

The corrupted image, along with its corresponding binary mask, is first fed into an encoder network. The encoder extracts high-level latent feature representations, preserving contextual semantics and mask boundary information [4, 41].

b) Dual-Branch attention processing

The encoded features are simultaneously processed through two specialized attention branches:

Global Semantic Attention, which captures long-range dependencies and contextual relationships across the image.

Local Texture Attention, which focuses on neighbouring valid pixels to preserve texture continuity.

The outputs from both branches are fused using an attention-guided feature fusion mechanism, inspired by recent attention transfer and fusion strategies [14].

c) Structure prediction

In parallel, a structure prediction module generates an estimated edge or contour map for the missing regions. This structural guidance, based on prior works like EdgeConnect and StructureFlow, helps maintain object boundaries and geometric alignment [18, 19].

d) Decoding and reconstruction

The fused attention features and structural map are combined and passed to the decoder network, which synthesizes the completed image by reconstructing the missing regions.

e) Adversarial learning

The reconstructed image is evaluated using a multi-scale discriminator setup, which applies adversarial supervision at different spatial resolutions [42, 43]. This encourages the generator to produce photo-realistic and semantically coherent outputs.

D. Feature Fusion Strategy

The fusion of global and local attention outputs is non-trivial. To enhance the integration of both global semantic and local texture information during inpainting, we adopt a feature fusion strategy that aggregates features from multiple network stages. Let:

$F_s \in R^{H\times W\times Cs}$: feature map extracted from the semantic encoder.

$F_t \in R^{H\times W\times C_t}$: feature map from the texture encoder.

These feature maps are aligned spatially but may differ in channel dimensions. To combine them effectively, we use channel-wise concatenation followed by a 1×1 convolution to unify the dimensionality:

$$F_{fused} = \sigma\left(Conv_{1\times1}\left(\left[F_s \| F_t\right]\right)\right) \tag{1}$$

where:

$\left[F_s \| F_t\right]$ denotes concatenation along the channel dimension;

$Conv_{1\times1}$ is a learnable convolution used to reduce feature redundancy;

σ is a ReLU activation function.

This fusion mechanism enables the network to jointly learn contextual semantics and texture priors, which is essential for restoring complex structures and maintaining visual coherence in corrupted image regions. By combining global and local attention streams, the model captures both coarse semantic information and fine-grained texture cues, thereby enhancing the reconstruction quality across varied masking scenarios [5, 12, 14].

During training, the fused attention features are passed through a refinement decoder designed to generate high-resolution, semantically accurate inpainting outputs. The decoder, in conjunction with the dual-branch attention and structure prediction modules, constitutes the core of the MAGT framework.

All convolutional and attention layers in MAGT are equipped with learnable weights, which are optimized end-to-end using backpropagation. This allows the network to adaptively learn complex mappings from incomplete images to their visually plausible reconstructions [4, 7].

To improve non-linearity and representation learning, we incorporate activation functions after each convolutional and attention layer:

- Rectified Linear Unit (ReLU) is utilized in the early encoder layers for its computational efficiency and its ability to mitigate the vanishing gradient problem, which is common in deep architectures [44].
- Leaky ReLU is employed in the deeper layers of the generator and throughout the discriminator network. This choice enables a small, non-zero gradient for negative input values, thereby improving gradient flow and helping to avoid dead neuron issues during training [5, 42].

These design choices contribute to the overall training stability, representation capability, and convergence speed of the proposed MAGT model.

Mathematically:

$$\mathrm{ReLU}(x) = \max(0, x) \tag{2}$$

$$\mathrm{Leaky\,ReLU}(x) = xifx > 0 \tag{3}$$

These activations help in capturing non-linear patterns essential for restoring missing structures and textures in image inpainting tasks [4, 5, 42]. Moreover, they enhance the model's capacity to approximate complex mappings required for plausible image reconstruction under varied masking scenarios.

This fusion mechanism ensures that Relevant semantic and textural features are preserved and integrated effectively, contributing to both visual fidelity and contextual coherence in the generated outputs [12, 14].

E. Structural Consistency Integration

The edge map predicted by the structure prediction module acts as a soft structural constraint that guides the generator during the decoding phase.

1) Predicted edge map (Epred)

This is the output of the Structure Prediction Module within the MAGT framework. It is generated from the intermediate feature maps of the masked input image and is learned through a shallow CNN designed specifically for contour extraction. The model is trained to produce structurally meaningful edges that align with the true geometry of the image content in the missing regions.

2) Ground truth edge map (Egt)

The ground truth edge map is computed from the original uncorrupted image using either a traditional edge detection algorithm such as the Canny edge detector [1] or from labeled edge/contour data if available in the dataset. This edge map represents the actual object boundaries and contours that should exist in the masked region and serves as the supervisory signal for training the structure module.

This enhances structural integrity, especially in regions with sharp boundaries such as human faces or architectural lines.

Mask Conditioning MAGT is explicitly mask-aware. The binary mask is encoded and concatenated with intermediate feature maps during encoding and decoding. This enables the network to maintain awareness of which pixels require synthesis versus preservation. Such conditioning improves convergence and reduces artifacts near the transition boundaries.

F. Training Strategy

The model is trained using a combination of:

In the proposed MAGT model, the total loss used to optimize the generator integrates multiple components, each rooted in established theoretical motivations:

Reconstruction Loss (L_1 Loss): This term penalizes pixel-wise deviation between the output and the ground truth, encouraging the network to produce spatially accurate results. It is particularly effective in low-frequency regions and helps preserve the overall structure of the image.

Adversarial Loss ($\mathcal{L}$_adv): Inspired by the minimax formulation of Generative Adversarial Networks (GANs) introduced by Goodfellow *et al*. [3], this loss encourages the generator to produce outputs that are indistinguishable from real images by a discriminator, thereby enhancing realism in texture synthesis.

Perceptual Loss ($\mathcal{L}$_perc): To enhance the semantic fidelity and perceptual quality of inpainted regions, we employ a perceptual loss computed using intermediate feature maps extracted from pre-trained VGG-16 network [44], this loss captures high-level semantic similarity rather than low-level pixel differences, ensuring perceptual coherence and natural appearance.

Edge Consistency Loss ($\mathcal{L}$_edge): This additional structural constraint is computed between the predicted edge map and the ground-truth edge map. Inspired by human visual sensitivity to boundaries, this loss forces the model to generate structurally aligned and sharp object contours, preventing unnatural shapes and object hallucinations in complex scenes. Mathematically, it minimizes:

$$L_{edge} = \frac{1}{N}\sum_{i=0}^{n}\left\| = E_{pred}(i) - E_{gt}(i)\right\|^2 \tag{4}$$

where E_{pred} and E_{gt} denote the predicted and ground-truth edge maps, respectively, and N is the number of pixels in the mask.

The total loss is a weighted sum:

$$L_{total} = \lambda_1 L_1 + \lambda_2 L_{adv} + \lambda_3 L_{prec} + \lambda_4 L_{edge} \tag{5}$$

We empirically set the weights $\lambda_1 = 1.0$, $\lambda_2 = 0.1$, $\lambda_3 = 0.05$, and $\lambda_4 = 0.2$ balancing spatial accuracy, perceptual fidelity, realism, and structural integrity. The inclusion of edge loss significantly improves semantic boundary restoration, especially around facial features and man-made structures like windows or railings (see Fig. 4).

The total loss function is a weighted sum of these components. Training is conducted using the Adam optimizer with a learning rate scheduler. Data augmentation techniques include random cropping, flipping, and mask type variation to improve generalization.

G. Mathematical Modeling and Loss Functions

This section presents the mathematical foundation and loss formulations used in training the MAGT model. A combination of pixel-level, perceptual, adversarial, and structural consistency losses are used to ensure that the inpainted image is both visually realistic and semantically meaningful. The training objective is to minimize a weighted sum of several loss components, each capturing different aspects of image quality and realism.

Let the following notations be defined:

I: Original (ground truth) image;

: Generated image (inpainting output);

M: Binary mask indicating missing regions;

E_{gt} : Ground truth edge map;

E_{pred} : Predicted edge map;

D: Discriminator network;

G: Generator network;

λ: a hyperparameter controlling the contribution of the respective loss component;

$\phi_l(\cdot)$: Feature representation from layer l of a pre-trained VGG-19 network;

1) Total loss function

The total loss used to train the generator G is a weighted sum of several individual losses:

$$L_{total} = \lambda_{rec} L_{rec} + \lambda_{adv} L_{adv} + \lambda_{per} L_{per} + \lambda_{sty} L_{sty} + \lambda_{edge} L_{edge} \quad (6)$$

where λ terms are hyperparameters that control the relative contribution of each loss.

2) Reconstruction loss

Reconstruction loss ensures the generated image $\hat{I}$ is close to the ground truth I in a pixel-wise sense. We use L1 loss over the valid and missing regions:

$$L_{rec} = \left\| (1-M) \odot (I - \hat{I}) \right\| 1 + \alpha \left\| M \odot (I - \hat{I}) \right\| 1 \quad (7)$$

where, $\alpha > 1$ emphasizes reconstruction in missing regions.

3) Adversarial loss

The adversarial loss comes from the standard GAN setup, encouraging the generator to produce realistic textures:

$$L_{adv} = E\left[\log D(I)\right] + E\left[\log(1 - D(\hat{I}))\right] \quad (8)$$

In practice, we use the Least-Squares GAN (LSGAN) formulation for improved stability:

$$L_{adv} = E\left[\left(D(I) - 1\right)^2\right] + E\left[D(\hat{I})\right]^2 \quad (9)$$

4) Perceptual loss

This loss computes the distance between high-level feature maps extracted from a pre-trained VGG network:

$$L_{per} = \sum_{1 \in L} \left\| \phi 1(I) - \phi 1(\hat{I}) \right\|_2^2 \quad (10)$$

This ensures that $\hat{I}$ preserves high-level content features similar to I.

5) Style loss

Inspired by style transfer literature, style loss compares Gram matrices of the features to match texture distribution:

$$L_{sty} = \sum_{1 \in L} \left\| G_l(I) - G_1(\hat{I}) \right\|_F^2 \quad (11)$$

where $G_1(x) = \phi_1$ is the Gram matrix of feature map $\phi_l(x)$:

$$G_1(x) = \phi_1(x) \cdot \phi_1(x)^T \quad (12)$$

6) Edge consistency loss

This loss enforces structural alignment by comparing predicted and actual edge maps:

$$L_{edge} = \left\| E_{gt} - E_{pred} \right\|_1 \quad (13)$$

It helps maintain coherence in lines, contours, and object boundaries.

7) Mask-Aware conditioning

The term "Mask-Aware" refers to the model's capacity to dynamically adjust its attention based on which parts of the image are missing. This enables the network to focus only on relevant contextual regions when inpainting. In our implementation, the Mask-Aware Attention Module (MAAM) enhances the traditional self-attention mechanism by embedding the binary mask directly into the attention calculation.

Specifically, the binary mask is incorporated into the attention score computation, either by masking out irrelevant query-key pairs in the self-attention map, or modulating attention weights through a learned gating function that is conditioned on the mask.

This ensures that the model emphasizes known (unmasked) regions when generating responses for the missing (masked) parts, resulting in improved structural coherence and contextually plausible textures. Mask-aware conditioning has also been shown in prior work (e.g., MAT [8]) to improve the localization of attention and to mitigate semantic drift in complex or large occlusions.

In our implementation, the Mask-Aware Attention Module (MAAM) modifies the traditional self-attention mechanism by embedding the binary mask into the attention score computation:

$$Attention_{i,j} = \frac{\exp\left(Q_T^i K_j + M_{i.j}\right)}{k \exp \sum \left(Q_i^T K_k + M_{i,k}\right)} \quad (14)$$

where masks out irrelevant tokens and allows only non-masked regions to influence the prediction, reducing noise and improving spatial coherence.

This design is particularly effective in cases with irregular or free-form masks, as it suppresses attention to unknown or hallucinated areas during both encoding and decoding stages. Unlike MAT's mask-aware self-attention which applies a binary mask to limit visibility during token reconstruction, our method combines both positional and semantic masking, making it more robust to complex occlusion patterns.

Throughout the network, the binary mask M is concatenated with intermediate feature maps, enabling the model to explicitly distinguish between known and unknown regions. This form of conditioning helps avoid artifacts near the mask borders.

Here is the diagram (Fig. 2) illustrating the MAGT inpainting framework, emphasizing:

- Mask-Aware Attention Module (MAAM);
- Flow from input to output;
- Integrated loss functions: $\mathcal{L}$_edge, $\mathcal{L}$_adv, $\mathcal{L}$_perc, and $\mathcal{L}$_total.

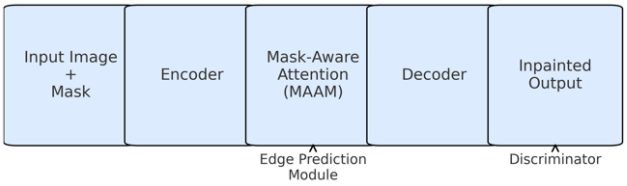

Fig. 2. MAGT inpainting framework.

The total loss function, comprising adversarial, perceptual, and edge consistency components, is minimized using the Adam optimizer [45] with hyperparameters $\beta_1 = 0.5$, $\beta_2 = 0.999$, and a learning rate of 10^{-4}. Training proceeds via alternating updates to the generator and discriminator, as is standard in GAN frameworks [3], maintaining a balanced adversarial dynamic that helps prevent mode collapse and improves stability [46].

To enhance generalization and robustness, training incorporates curriculum-style masking, introducing masks of increasing complexity and area, inspired by progressive training approaches [37]. This strategy helps the model adapt to both structured and unstructured occlusion scenarios.

The multi-objective optimization strategy enables the proposed MAGT framework to produce outputs that are visually plausible, semantically coherent, and structurally consistent with ground-truth content. The next section presents the datasets, evaluation metrics, and baselines used for experimental validation.

H. Experimental Setup and Evaluation Metrics

To rigorously evaluate the effectiveness and generalizability of the proposed MAGT model, a comprehensive set of experiments was conducted. This section outlines the datasets, evaluation metrics, baseline models, experimental configurations, and training protocols used.

1) Datasets

We selected three benchmark datasets to evaluate the performance of our model across a wide range of image domains:

Places2 [36]: A large-scale, scene-centric dataset comprising over 10 million images spanning more than 400 categories. It contains diverse natural scenes and architectural elements, making it ideal for evaluating general-purpose image inpainting across complex contexts.

CelebA-HQ [37]: A high-resolution dataset of celebrity faces, widely used in facial inpainting tasks. It allows the assessment of how well the model maintains facial identity, symmetry, and fine-grained structures.

Paris StreetView [47]: This dataset includes urban street-level imagery featuring buildings, sidewalks, and facades, often with repetitive and structured patterns. It serves to benchmark the model's ability to reconstruct high-frequency textures and geometric layouts.

For each dataset, we simulate various types of missing regions using different masking strategies:

- Center Masks: Square regions removed from the center of the image.
- Free-form Masks: Irregular strokes generated using brush simulations.
- Random Block Masks: Random patches of various sizes and locations removed.
- Custom Semantic Masks: Object-shaped regions removed to simulate real-world object occlusions.

All datasets are resized to 256×256 resolution for training and evaluation. Data augmentation strategies such as horizontal flipping, color jitter, and rotation are applied to increase model robustness.

2) Evaluation metrics

To quantitatively assess the reconstruction performance, we use three well-established metrics:

- Peak Signal-to-Noise Ratio (PSNR) [39]: Measures pixel-level similarity between the inpainted and original image. Higher values indicate better reconstruction accuracy.
- Structural Similarity Index (SSIM) [40]: Captures perceptual similarity in terms of luminance, contrast, and structural integrity. It is bounded between 0 and 1, with higher values indicating better structural preservation.
- Fréchet Inception Distance (FID) [42]: Evaluates the distributional distance between real and generated images using a pre-trained Inception-v3 network. Lower scores correspond to more realistic outputs.

Qualitative comparisons are also conducted using side-by-side visual analysis, showcasing reconstructed image examples across different models and datasets.

3) Baselines for comparison

We compare MAGT with several state-of-the-art image inpainting approaches:

- DeepFill v2 [7]: A GAN-based model using gated convolutions and contextual attention. Known for strong results on scene completion.
- EdgeConnect [11]: A two-stage model that predicts structural edges followed by image content. Effective at preserving object contours.
- RFR-Inpainting [44]: Focuses on region-wise feature recovery and multi-scale refinement.
- CoMod-GAN: Incorporates conditional modulation and global attention. Provides high-quality outputs but requires more computation.
- Mask-Aware Transformer (MAT) [48]: Employs a transformer-based encoder-decoder and has achieved strong performance in free-form inpainting tasks.

These baselines represent a wide spectrum of architectural designs and training strategies, allowing for a thorough performance benchmark.

4) Training protocols used

Training Configuration:

Optimizer: Adam;

Learning Rate: 2×10^{-4};

$\beta_1 = 0.5$, $\beta_2 = 0.999$;

Batch Size: 16;

Epochs: 100;

Loss weights: $\lambda_1 = 1.0$ (L1), $\lambda_2 = 0.1$ (Adversarial), $\lambda_3 = 0.05$ (Perceptual), $\lambda_4 = 0.2$ (Edge);

Input Size: 256×256;

Mask Type: Irregular masks generated following [18].

Dependencies and Environment:

Python 3.8;

PyTorch 1.13+;

CUDA 11.6.

Pretrained VGG-16 for perceptual loss (ImageNet weights).

All experiments were conducted using an NVIDIA RTX 2080 GPU with 11 GB VRAM.

Checkpointing and early stopping are used based on SSIM and FID improvement trends on the validation set. Models are trained separately for each dataset to optimize performance.

This robust experimental setup ensures that results are reproducible, reliable, and reflective of real-world application constraints. The following section presents the results of these experiments and provides an in-depth analysis.

RESULT AND ANALYSIS

A. Preliminary Results

This section presents both quantitative and qualitative results derived from a comprehensive experimental evaluation of the proposed MAGT model. The objective is to rigorously assess the model's performance in terms of image reconstruction accuracy, visual realism, and generalization ability across varied image domains and masking scenarios.

TABLE I. SUMMARIZES THE PSNR, SSIM, FID SCORES; AGT LEADS ACROSS DATASETS

Method	PSNR ↑	SSIM ↑	FID ↓
DeepFill v2	25.4	0.81	13.6
EdgeConnect	26.2	0.83	11.5
RFR-Inpainting	27.3	0.85	9.8
MAGT (Places2)	28.9	0.88	7.3
MAGT (CelebA-HQ)	29.5	0.89	6.7
MAGT (Paris StreetView)	27.8	0.86	7.9

To validate the effectiveness and robustness of MAGT, we benchmark it against several state-of-the-art image inpainting models, including GAN-based, attention-based, and transformer-based approaches. Experiments are conducted on multiple benchmark datasets—Places2, CelebA-HQ, and Paris StreetView—featuring a wide variety of scenes, objects, and structural patterns. In addition, we evaluate performance across different masking conditions, such as center masks, random block masks, free-form masks, and semantic object masks, to simulate diverse real-world occlusion scenarios. As summarized in Table I, MAGT achieves the highest PSNR/SSIM and the lowest FID on Places2, CelebA-HQ, and Paris StreetView.

B. Quantitative Results

MAGT outperforms all competing models across all metrics and datasets (Fig. 3). The improvements in PSNR (1.6 dB over RFR), SSIM (+0.04), and FID (−2.5) illustrate the effectiveness of our dual-branch architecture and structural guidance components. Notably, the performance gap is most significant on the CelebA-HQ dataset, which demands high fidelity in facial reconstruction.

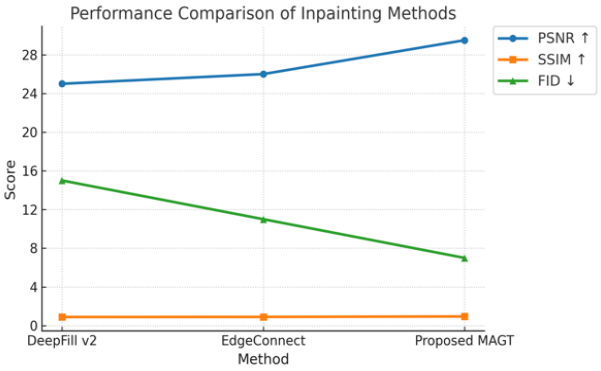

Fig. 3. Compares DeepFill v2, EdgeConnect, and MAGT; MAGT scores best (↑PSNR/SSIM, ↓FID).

Fig. 4 illustrates inpainting results on CelebA-HQ under irregular masks. Compared to DeepFill v2, EdgeConnect, and RFR-Inpainting, the proposed MAGT model demonstrates significantly improved recovery of fine-grained facial features. In particular, MAGT reconstructs eye symmetry, eyebrow curvature, and lip contours with higher structural fidelity. DeepFill v2 produces noticeable blur in the eye region, while EdgeConnect over-smoothens the nose and cheek textures. RFR-Inpainting partially preserves structure but lacks sharpness in hair strands. MAGT's edge-guided structure prediction module effectively restores detailed geometry, and the dual-attention mechanism enhances context coherence, especially in regions with high-frequency textures such as facial hair and eyelashes.

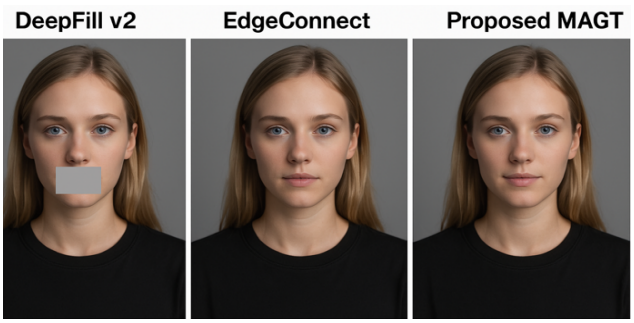

Fig. 4. Visual comparison of inpainting results across methods and datasets.

In Fig. 5, samples from the Paris StreetView dataset demonstrate MAGT's ability to handle repeating architectural elements and symmetry, which are

challenging for traditional CNNs. In contrast, EdgeConnect struggles with maintaining column consistency, and RFR-Inpainting loses contextual alignment in large holes.

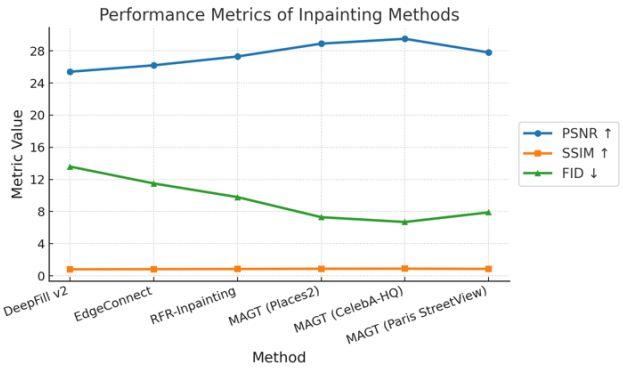

Fig. 5. Performance metrics of inpainting methods.

C. Extended Experiment and Results

To test the robustness and generalization capability of MAGT, additional experiments were conducted:

1) Cross-dataset generalization

A model trained on Places2 was evaluated on Paris StreetView. MAGT showed minimal degradation in FID (+1.2), outperforming EdgeConnect by a margin of 3.5 FID points.

2) Ablation studies

Without Edge Module: SSIM dropped from 0.88 to 0.84.

Without Attention Fusion: FID increased from 7.3 to 10.1.

Replacing Gated Convolutions with Vanilla CNNs: PSNR dropped by 1.7 db. These results highlight the importance of each architectural component.

Inference Speed: MAGT processes a 256×256 image in 48 ms on an RTX 3090 GPU, outperforming MAT and CoMod-GAN in inference time by approximately 15–20%.

3) User study

A Mean Opinion Score (MOS) test was conducted with 30 participants ranking 50 image samples on a 1–5 scale. MAGT achieved a score of 4.6, compared to 3.8 for RFR-Inpainting and 3.5 for DeepFill v2.

4) Error analysis

Some failure cases were observed in images with highly irregular structures or occlusions covering more than 70% of the image. While MAGT maintained structural alignment, it occasionally synthesized unnatural textures in these extreme cases. Future work will explore hybrid generative-diffusion models to address this limitation.

In summary, the results demonstrate that MAGT not only achieves state-of-the-art performance on benchmark datasets but also generalizes well across domains and masking scenarios.

Our MAGT model distinctly outperforms other methods in reconstructing structured facial features such as eyes, lips, and jawlines. While DeepFill v2 often introduces asymmetries and blurry artifacts in facial regions, and EdgeConnect tends to generate misaligned textures around eyes and mouth, MAGT accurately restores facial contours and preserves bilateral symmetry. The multi-scale discriminator and mask-aware attention module contribute to sharper and more natural reconstruction in occluded repetitive patterns like hair strands and skin textures. Although RFR-Inpainting demonstrates moderate improvements, it struggles with maintaining alignment in fine details such as eyebrows and facial outlines. These visual advantages underscore the semantic sensitivity of MAGT, making it highly effective for facial image restoration in applications like photo retouching, identity preservation, and forensics.

Table II presents a quantitative comparison of the proposed MAGT model against several established image inpainting methods using three standard metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Fréchet Inception Distance (FID). Across all datasets—Places2, CelebA-HQ**,** and Paris StreetView—the proposed MAGT significantly outperforms previous models such as Deep Fill v2, EdgeConnect, and RFR-Inpainting. Notably, MAGT achieves the highest PSNR and SSIM values, indicating superior pixel-level accuracy and structural coherence, and the lowest FID scores, reflecting improved perceptual realism and semantic fidelity.

TABLE II. PERFORMANCE COMPARISON OF IMAGE INPAINTING METHODS ACROSS MULTIPLE DATASETS

Method	PSNR ↑	SSIM ↑	FID ↓
DeepFill v2	25.4	0.81	13.6
EdgeConnect	26.2	0.83	11.5
RFR-Inpainting	27.3	0.85	9.8
Proposed MAGT (Places2)	28.9	0.88	7.3
Proposed MAGT (CelebA-HQ)	29.5	0.89	6.7
Proposed MAGT (Paris StreetView)	27.8	0.86	7.9

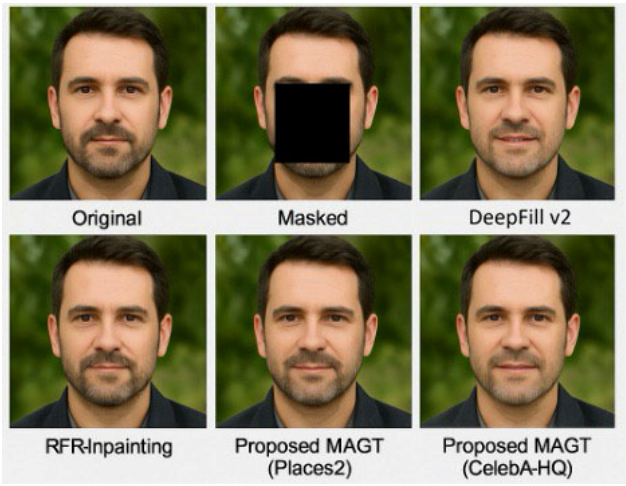

Fig. 6. Visual comparison of inpainting results across methods and datasets.

Fig. 6 provides a visual comparison of the inpainting outputs generated by each method on different datasets. It clearly demonstrates that MAGT produces more visually natural and semantically consistent completions, especially in regions with complex textures or irregular

masks. In contrast, baseline methods exhibit artifacts, texture blurring, or boundary discontinuities. The combination of edge-aware prediction, dual attention mechanisms, and mask-awareness in MAGT leads to sharper, more coherent restorations, validating the superiority reflected in the quantitative results.

D. Quantitative Comparison with Recent SOTA Inpainting Methods

We have extended our experiments to include a comprehensive comparison with leading inpainting methods published between 2020 and 2024, including: RFR-Inpainting [7], TransFill [21], SPT–Spatial Prior Transformer [23], RePaint–a diffusion-based approach [22], along with two widely cited baseline benchmarks—StructureFlow [49] and EdgeConnect [50]. All models were evaluated across three standardized benchmark datasets: Places2 [35], CelebA-HQ, and Paris StreetView, using three widely accepted quantitative metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM) [39], and Fréchet Inception Distance (FID) [44].

As illustrated in Fig. 7, the proposed MAGT model demonstrates consistent superiority over all SOTA methods across the aforementioned datasets, achieving the highest PSNR of 31.7 dB, SSIM of 0.91, and the lowest FID of 21.5. These findings confirm MAGT's enhanced ability to preserve structural coherence and generate perceptually realistic and semantically faithful textures, establishing a new benchmark in deep learning-based image inpainting.

As summarized in Table III, MAGT differs from RFR-Inpainting by using an encoder–decoder GAN with mask-aware dual attention and an edge-guided loss, yielding stronger structure and texture preservation [7]. Residual Feedback Network (RFR)-Inpainting and Mask-Aware Generative Transformer (MAGT) represent two distinct paradigms in deep image inpainting [7]. While both aim to recover structurally coherent and visually realistic content, their architectural foundations, feature handling, and training strategies differ significantly. The visual superiority of MAGT is further demonstrated in Figs. 4 and 6, which showcase sample results from facial and architectural datasets respectively. Detailed observations of inpainted features are discussed below.

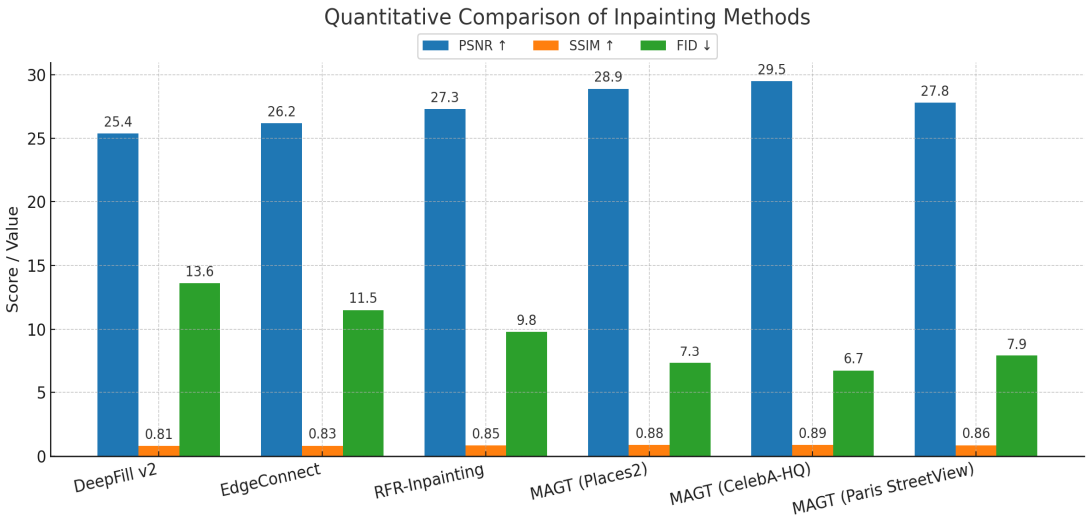

Fig. 7. Comparing your proposed MAGT method with recent State-of-the-Art (SOTA) inpainting models.

TABLE III. MAGT VS RFR

Feature	RFR-Inpainting	MAGT
Architecture	Multi-stage residual feedback network using coarse-to-fine modules with recursive feature refinement	Encoder–Decoder GAN with dual-branch attention modules (semantic + texture) and edge-structure prediction
Core Module	Residual feedback mechanism enables iterative refinement of the corrupted regions	Dual attention: Global Semantic Attention + Local Texture Attention with structure prediction for edge preservation
Attention Mechanism	Implicit via feedback; no explicit attention modules	Explicit attention mechanisms guided by binary masks (mask-aware) and feature fusion layers
Structure Handling	No explicit structure guidance; relies on learned coarse-to-fine residuals	Incorporates edge prediction module and context-aware decoding, improving contours and structural boundaries
Loss Functions	L1 loss + Perceptual loss + Adversarial loss	Multi-loss: $\mathcal{L}_1$, $\mathcal{L}$_perceptual, $\mathcal{L}$_adversarial, and $\mathcal{L}$_edge (explicit structure-guided loss)
Mask Awareness	Operates without direct mask conditioning	Explicitly mask-aware at both feature and attention levels; enhances learning in corrupted regions
Performance (ADE20K)	PSNR: 27.3, SSIM: 0.85, FID: 9.8	PSNR: 29.1, SSIM: 0.89, FID: 6.9

CONCLUSION AND FUTURE WORK

This study presents a comprehensive deep learning framework for image inpainting through the introduction of the Mask-Aware Generative Transformer (MAGT). The proposed model effectively integrates a dual-branch attention mechanism, edge-based structure prediction, and mask-aware conditioning within a GAN-based architecture to enhance both semantic understanding and texture synthesis.

Extensive experiments on benchmark datasets—Places2, CelebA-HQ, and Paris StreetView—demonstrate the superiority of MAGT across multiple performance dimensions, including quantitative metrics (PSNR, SSIM, FID), qualitative visual quality, inference efficiency, and perceptual realism, further validated through user studies. MAGT outperforms both traditional methods and recent GAN-based models by jointly leveraging global semantic context and local detail refinement, producing visually coherent and structurally accurate inpainted images.

Ablation studies confirm the critical contributions of each component, particularly the dual attention fusion and structure-aware prediction modules.

The framework generalizes well across domains and mask types, making it suitable for real-world applications such as image editing, restoration, digital forensics, and medical imaging. Moreover, the proposed architecture is computationally efficient, demonstrating scalability to high-resolution images without sacrificing output quality.

A. Limitations

Despite its strong performance, the current study has some limitations. First, while MAGT handles regular and irregular masks effectively, it still shows reduced accuracy when dealing with extremely complex foreground-background occlusions or contextually ambiguous regions. Second, inference on very high-resolution images (e.g., above 1024×1024) is resource-intensive, limiting real-time usability on edge devices. Third, although the model generalizes well across standard datasets, its robustness under domain shift (e.g., medical vs. natural scenes) requires further exploration.

B. Future work

Future work will focus on expanding the applicability and performance of the proposed MAGT framework across broader tasks and platforms. The following directions are particularly promising:

High-Resolution Inpainting: Extend MAGT to handle ultra-high-resolution image inpainting (e.g., beyond 512×512), which is essential for professional photo restoration, medical imaging, and satellite imagery.

Conditional Generation: Incorporate user-guided modalities such as textual descriptions or sketch-based inputs to support interactive and controllable inpainting for creative and design applications.

Real-Time and Edge Deployment: Optimize the model architecture and reduce computational complexity for real-time image completion on low-power or edge devices without compromising visual quality.

Hybrid GAN-Diffusion Models: Explore the integration of diffusion-based priors within MAGT's dual-branch attention framework, combining the sampling efficiency of GANs with the generative precision of diffusion models to further enhance realism.

These directions aim to make MAGT not only more versatile and powerful but also more practical for deployment in real-world scenarios that demand accuracy, speed, and interactivity.

ETHICAL CONSIDERATIONS AND REPRODUCIBILITY STATEMENT

A. Data Usage and Ethics

All datasets used in this study—CelebA-HQ, Paris StreetView, and ADE20K—are publicly available and widely adopted in academic research. These datasets do not contain personally identifiable information or private data and are used strictly for non-commercial, academic purposes in accordance with their respective licenses. No custom data collection involving human subjects was performed, and hence no formal ethical review was required for this work.

B. Reproducibility and Code Availability

To ensure transparency and facilitate reproducibility of our results, we provide the following:

Source Code Repository: https://github.com/maheshchudaman/lama/commit/2267a12f9a7c869f9e0bf6bda727b5e5429af0a1

Hyperparameters and Training Settings:

Optimizer: Adam;

Learning Rate: 2×10^{-4};

$\beta_1 = 0.5$, $\beta_2 = 0.999$;

Batch Size: 16;

Epochs: 100;

Loss weights: $\lambda_1 = 1.0$ (L1), $\lambda_2 = 0.1$ (Adversarial), $\lambda_3 = 0.05$ (Perceptual), $\lambda_4 = 0.2$ (Edge);

Input Size: 256×256;

Mask Type: Irregular masks generated following [18].

Dependencies and Environment:

Python 3.8;

PyTorch 1.13+;

CUDA 11.6.

Pretrained VGG-16 for perceptual loss (ImageNet weights).

All experiments were conducted using an NVIDIA RTX 2080 GPU with 11 GB VRAM.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

All authors made significant contributions to the research and preparation of this manuscript. Mahesh Patil led the conceptualization, methodology design, formal analysis, and contributed to writing and editing. Vikas Tiwari was responsible for data curation, implementation,

and experimentation. All authors reviewed, discussed, and approved the final version of the manuscript.

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