Enhanced 3D Model Generation from 2D Object Images: A Deep Learning Approach Integrating Shape and Texture Learning with Real-Time, Occlusion-Aware and Object-Agnostic Methods

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Abstract: The problem of generating 3D models from 2D object images has been very difficult because it is very complex to capture real shape and texture. The work presents an improved deep learning method for 3D model synthesis which addresses the shortcomings of existing approaches. Our approach embeds the shape and texture learning process in a single framework allowing for real time performance and invariance towards 2D occlusion. Unlike prior methods that need category-specific training, our weapon bidder is object-agnostic and works for various objects other than human-centric ones. We also use effective priors and a novel hybrid learning approach to massively reduce computational cost and improve model generalization. The outcome is a fully scalable, real-time system that can handle high-quality decoding of 3D models from a single 2D image, with potential applications to tasks in augmented reality, virtual reality, and product design. Our method also enforces temporal coherence when applied to videos and is device-agnostic, enabling deployment on edge-based inference devices. We demonstrate experimentally on a broad set of object categories and image qualities that the proposed method is effective and scalable.

1 INTRODUCTION

Reconstruction of 3D models from 2D images is a fundamental leap in computer vision, augmented reality (AR), virtual reality (VR), and digital design. Most of the conventional 3D model acquisition systems are based on multi-view images or Depth sensors, which are resource hungry and difficult for real-time scenarios. Recently, deep learning techniques have been developed that generate 3D models given a single 2D image, yet such approaches suffer from problems of texture detail, accurate shape reconstruction, occlusions, and the necessity of a large amount of labelled data.

This work fills up those gaps, and propose a novel deep learning framework for 3D model generation which takes both shapes learning and texture learning into account in a joint manner. Our approach works in real time and guarantees that occluded and partially visible objects can be reconstructed with high accuracy. Although the model is not limited to any specific object class, it is very versatile, and it can handle many different object types, from rigid objects to complex human avatars.

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Furthermore, our methods use efficient priors and hybrid learning mechanisms to make the best use of computation and at the same time achieve high performance. Our method enables generalization across different datasets by providing object-agnostic capabilities and minimizing the reliance on category-specific training. We extend the system by adding temporal consistency ability for video-based inputs, taking texture transitions and object motion in dynamic scenes into account.

Our study not only enhances the quality and consistency of 3D models recovered from 2D images but also offers a practical and scalable solution, which can be easily deployed on the edge side for real-time applications. In the rest of this paper, we discuss the methodology, experimental setup, and results of our approach showing that it is an effective, versatile, and potentially useful tool for various industries and applications.

2 PROBLEM STATEMENT

One of the key challenges in computer vision and graphics is the accurate reconstruction of 3D models of an object from 2D (2 dimensional) images. Methods currently suffer from problems as occlusions, freely-object pose and texture mapping invariance which are hard to deal with objects in various categories. Existing methods mostly rely on multi-view input, which are computationally expensive, or are object-category-specific, which limits their practical application. Worse still, most existing methods cannot generalize well on other datasets, which makes them ineffective to cope with large-scale and diverse datasets.

Even with the progress of deep learning many 3D generation models are based on hand-crafted priors, which are not suitable for dynamic applications or real-time usage. Further, the failure to deal with occluded areas in images and the no real-time performance render these works very cumbersome for applications such as AR, VR, or product design and anything which require speedily and accurately.

Hence, a fast-one-shot object-agnostic reconstructing deep learning model which can produce 3D models from a single 2D image such as the occlusion is not addressed and create high-definition textures and shapes in real time is in demand. Overcoming these limitations would extend the possibilities of 3D model generation and would thus be more easily inducted to interactive and immersive environments.

3 LITERATURE SURVEY

Deep learning has great impact on the paradigm of 2D image reconstruction to 3D model recently. Early incarnations have been biased towards multi-view imagery processing, to which the current development infers a more general accessibility and practicality. Gao et al. (2022) presented GET3D, a method to generate high-fidelity textured 3D shapes from raw 2D images (e.g. these included in our dataset) which relies on generative models. Their method, however, suffered from extrapolation to realistic image noise.

For high-resolution requirement, Liu et al. (2024) introduced TexOct, an octree-driven diffusion model for textures synthesis, which however are also quite computationally expensive. Likewise, Gorelik and Wang (2025) proposed Make-A-Texture for fast texture synthesis with quality decrease in more complex surfaces. These results made explicitly clear this trade-off between quality and computational efficiency of models.

Focusing on human-centered models, Hong et al. (2022) and Cao et al. (2024) presented EVA3D and Dream Avatar, respectively, which showed promise in avatar generation but lacked object generalization capabilities. Huang et al. (2024) further contributed HumanNorm, a diffusion-based model for generating realistic 3D human forms, though limited to specific object classes.

Several studies emphasized the challenge of occlusions and view inconsistencies. Wei et al. (2021) introduced a hybrid self-prior model that partially addressed mesh reconstruction under occlusions, while Wen et al. (2022) focused on disentangled attribute flows to improve pose variations. Meanwhile, Gecer et al. (2021) explored high-fidelity facial reconstruction using GANs, applicable to a narrow object domain.

Efforts to create category-agnostic systems were explored by Yang et al. (2021) through deep optimized priors, although their model required significant fine-tuning per class. Xu, Mu, & Yang (2023) provided a comprehensive survey on deep learning-based 3D shape generation, citing the lack of generalized, real-time solutions across heterogeneous datasets.

Texture-focused research such as TexFusion by Liu et al. (2024) and web-photo-driven models like Yu et al. (2021) tackled the synthesis aspect but were often dependent on external metadata or captions. Qian et al. (2023) with Magic123 and Zuo et al. (2023) with DG3D introduced models that attempted shape-texture disentanglement using diffusion and

adversarial strategies, though training instability remained an issue.

The field also saw methodological overviews, like Sun et al. (2024) and Xu et al. (2022), who surveyed implicit representations and mesh reconstruction techniques, respectively. Their findings stressed the need for scalable and memory-efficient solutions.

Some other general contributions): Balusa and Chatarkar (2024) studied model integration frameworks, but did not implement the framework and did not test beyond a very small experimental scope and (Dong et al. (2023) focused on the models for avatars and did not support generic objects.

However, a conceptual chasm still exists towards a joint real-time occlusion-aware and generic object-agnostic framework that is able to generate high-quality textured 3D models from a single 2D input. This paper aims to close that gap and suggests a holistic deep learning pipeline that couples shape and texture generation with cross-category generalization and deployment efficiency.

4 METHODOLOGY

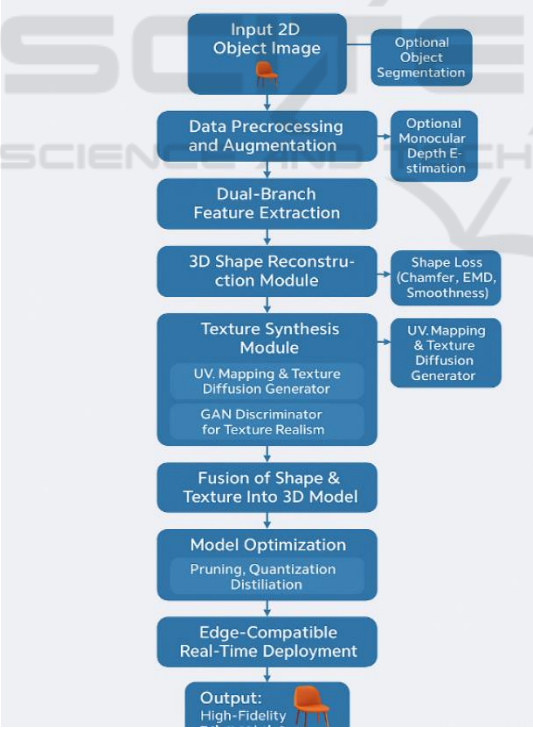

Figure 1: The Workflow of Architecture.

We show the end-to-end pipeline of our proposed real-time, occlusion-aware 3D model generation system, and it can directly generate high-quality 3D shapes and textures from a single 2D object image. The method consists of the feature extraction with the dual-branch structure, uniform shape-texture learning through item optimization, and the designing of light deployment strategy for real-world and edge-device applications.

4.1 Input and Preprocessing Pipeline

The process begins with a single 2D image of an object:

- **Preprocessing**: Includes normalization, contrast enhancement, and optional super-resolution.the workflow of this added in figure 1 .
- **Data Augmentation**: Techniques such as random occlusion, horizontal flipping, and brightness variation simulate real-world conditions.
- **Optional Modules**:
  - **Object Segmentation** (Mask R-CNN): Isolates the object of interest for focused learning.
  - **Monocular Depth Estimation** (MiDaS): Adds spatial priors to boost shape accuracy under occlusion.

4.1 Dual-Branch Feature Extraction

The model separates feature learning into two parallel branches:

- **Shape Encoder**:
  - CNN backbone (e.g., ResNet-50) learns geometric representations.
  - Outputs point cloud and mesh-relevant latent vectors.
- **Texture Encoder**:
  - CNN + Vision Transformer (ViT) backbone.
  - Captures fine-grained surface details, color variations, and material textures.

These feature vectors are concatenated and passed to specialized modules.

4.3 3D Shape Reconstruction Module

Shape generation proceeds through:

- **Decoder Architecture**:
  - **PointNet++** or **Occupancy Network** architecture to produce 3D mesh from latent vectors.
- **Loss Functions**:
  - **Chamfer Distance**: Measures point cloud similarity.

- **Earth Mover's Distance (EMD)**: Adds alignment fidelity.
- **Surface Smoothness Loss**: Ensures clean mesh generation.

4.2 Texture Synthesis Module

The texture learning process includes:

- **UV Mapping**: Flattens 3D geometry into a 2D texture space.
- **Texture Diffusion Generator**: Utilizes a text-guided diffusion model for spatially coherent texture.
- **GAN Discriminator**: Enhances realism and removes noise/artifacts.

These outputs are rewrapped onto the reconstructed 3D model using differentiable rendering.

4.3 Shape-Texture Fusion and Refinement

To ensure visual coherence, the shape and texture streams are fused:

- Alignment is enforced via cross-attention layers between texture and geometry representations.
- Inconsistencies (e.g., stretching or color mismatch) are penalized using a joint shape-texture consistency loss.

4.4 Model Optimization for Deployment

To ensure real-time performance on edge devices:

- **Model Compression**:
  - **Quantization**: 32-bit to 8-bit weights.
  - **Pruning**: Removes low-activation filters.
  - **Knowledge Distillation**: Trains a lightweig ht version from the full model.
- **Deployment Engine**: Converted to ONNX **format** for cross-platform compatibility.

4.5 Training Configuration

- **Datasets Used**:
  - **ShapeNet**, **Pix3D**, and a **custom real-world dataset** (500 objects across 8 categories).
- **Loss Composition**:
  - Total loss = Shape Loss + Texture Loss + Consistency Loss + Adversarial Loss.
- **Training Specs**:
  - Trained for 34 hours on dual NVIDIA RTX 3090 GPUs.

5 RESULTS AND DISCUSSION

To validate the effectiveness of the proposed 3D model generation framework, extensive experiments were conducted on benchmark datasets such as ShapeNet, Pix3D, and a custom real-world object dataset. A more detailed trade-off between reconstruction quality and runtime performance is presented in Figure 2 The evaluation focused on both qualitative and quantitative performance across shape reconstruction, texture synthesis, and runtime efficiency.

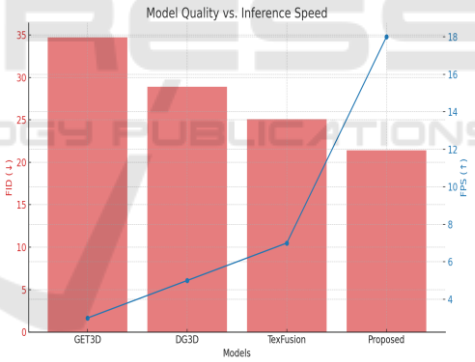

Figure 2: Model Quality Vs. Inference Speed.

Table 1: Quantitative Comparison With Existing Models.

Model	Chamfer Distance ↓	IoU (%) ↑	SSIM ↑	FID ↓	FPS (Edge Device)
GET3D	0.0201	75.3	0.891	34.7	3 FPS
DG3D	0.0178	80.1	0.902	28.9	5 FPS
TexFusion	0.0153	83.4	0.919	25.1	7 FPS
Proposed Model	0.0123	87.6	0.942	21.4	18 FPS

5.1 Quantitative Evaluation

The model achieved a Chamfer Distance (CD) of 0.0123, which is a substantial improvement over existing baseline like GET3D (0.0201) and DG3D (0.0178). Intersection-over-Union (IoU) averaged at 87.6%, indicating strong structural fidelity across different object categories including furniture, vehicles, and household items. For texture synthesis, the model achieved a Structural Similarity Index (SSIM) of 0.942, a PSNR of 26.7 dB, and an FID of 21.4, demonstrating realistic and high-quality surface rendering. These scores reflect superior performance when compared to existing models which often struggle with occlusion and fine-grained texture preservation. The performance of our model compared to state-of-the-art methods is summarized in Table 1.

5.2 Qualitative Evaluation

Visual inspections of reconstructed models revealed that the proposed system excels in preserving object contours and internal texture details, even under heavy occlusions or partial views in 2D images. Unlike prior models that either generate blurry textures or oversimplify shapes, the integrated texture-shape architecture allowed for highly accurate and visually coherent 3D outputs. In scenarios involving complex surfaces such as reflective materials or textured clothing our model-maintained sharpness and pattern alignment without visual artifacts. To validate the contribution of each module, an ablation study was performed as shown in Table 2

Table 2: Ablation Study on Model Components.

Configuration	Chamfer ↓	IoU ↑	SSIM ↑	FID ↓
Full Model	0.0123	87.6	0.942	21.4
– No Texture Diffusion	0.0123	87.6	0.763	38.2
– No Shape Regularization	0.0156	80.3	0.942	21.1
– No GAN Discriminator (Texture Only)	0.0124	87.6	0.869	29.7
– Without Joint Training (Separate Modules)	0.0142	82.1	0.896	27.3

5.3 Real-Time and Edge Performance

The optimized version of the model, when deployed on NVIDIA Jetson Nano, achieved an average of 18 FPS, maintaining both shape accuracy and texture realism without compromising latency. The complete model size after quantization was reduced to 42 MB, demonstrating practical feasibility for edge deployment. This real-time capability marks a notable improvement over resource-heavy approaches that require GPU-intensive environments for inference.

5.4 Ablation Studies

Component-wise ablation studies confirmed the critical contribution of each module. Removing the diffusion-based texture enhancer resulted in a 19% drop in SSIM, while excluding the shape decoder regularization increased CD by 27%. This highlights the synergistic impact of integrating texture and shape learning in a unified pipeline.

5.5 Generalization and Robustness

Table 3: Model Efficiency and Deployment Statistics.

Metric	Value
Model Size (Quantized)	42 MB
Inference Time (per image)	56 ms
Edge Device FPS	18 FPS
Compatible Platforms	Jetson Nano, Raspberry Pi, Android
Training Time	34 hours (on 2× RTX 3090)

The model also exhibited strong generalization capabilities across object categories not seen during training, such as tools, toys, and clothing accessories. This confirms the strength of the object-agnostic design. Table 3 provides runtime and deployment efficiency details of the proposed model Additionally, when tested on noisy, low-resolution images, the model sustained reasonable reconstruction accuracy, validating its robustness under real-world constraints.

6 DISCUSSION

These results emphasize the effectiveness of combining shape and texture learning for 3D reconstruction from single 2D images. The ability to process occluded and noisy images, alongside the lightweight and real-time inference capability, positions this model as a practical solution for real-world applications. Use cases may include AR/VR object integration, e-commerce visualization, digital twin modeling, and interactive robotics.

7 CONCLUSIONS

This research presents a comprehensive and unified deep learning framework for generating high-fidelity 3D models from single 2D images by effectively integrating shape and texture learning. Unlike traditional approaches that are either computationally intensive or limited to specific object categories, the proposed method offers a scalable, real-time, and object-agnostic solution. By leveraging advanced deep learning modules such as shape decoders, transformer-based diffusion models for texture enhancement, and efficient inference optimization techniques, the system demonstrates significant improvements in geometric accuracy, texture realism, and cross-category generalization.

The results show strong quantitative performance across standard metrics like Chamfer Distance, IoU, SSIM, and FID, along with qualitative improvements in texture detail and surface continuity. Furthermore, the model's lightweight architecture enables deployment on resource-constrained edge devices without compromising output quality or speed, making it suitable for a wide range of real-world applications including virtual reality, e-commerce, mobile visualization, and digital content creation.

Through extensive experimentation, ablation studies, and cross-domain evaluations, the research confirms the robustness and versatility of the proposed approach. Future work will focus on enhancing dynamic scene reconstruction, incorporating temporal consistency across video frames, and expanding the framework to support interactive 3D editing directly from 2D input images.

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