3D Image Models & Building LLMs with Object Detection

Abstract

This paper presents a novel, integrated framework that addresses key limitations in modern generative AI and 3D vision, specifically the challenge of handling out-of-domain (OOD) concepts and the need for improved geometric understanding. Our system combines a Retrieval-Augmented Generation (RAG) pipeline for text-to-3D synthesis with a geometry-aware 3D object detection model. The RAG component, a variant of the MV-RAG pipeline, dynamically retrieves relevant 2D visual information to ground the generation of novel 3D objects, overcoming the data scarcity and static nature of 3D datasets. The detection component, based on the NeRF-Det framework, leverages a shared Multi-Layer Perceptron (MLP) to explicitly model scene geometry, significantly improving 3D bounding box regression from posed RGB images. Through extensive experimentation on datasets like ScanNet and ARKITScenes, we demonstrate state-of-the-art performance in 3D object detection and show a marked improvement in generative consistency and accuracy for OOD concepts. Our work validates the effectiveness of a hybrid architecture that fuses external, real-world data with robust internal 3D representations, paving the way for more generalizable and scalable AI systems in robotics, AR/VR, and beyond.

1.0 Introduction: Problem Statement and Project Context

1.1 Project Overview and Rationale

The primary objective of this project is to develop a novel framework that bridges the limitations of pre-trained Large Language Models (LLMs) with a robust, real-time understanding of three-dimensional environments. The core challenge in modern generative

AI is its reliance on static, pre-trained knowledge, which often leads to inaccurate or "hallucinated" responses when confronted with concepts that were not part of its original training data.[1] This issue is particularly pronounced in 3D-aware systems, where the scarcity and static nature of 3D datasets make it difficult to adapt to new objects or emerging visual trends.[2]

To address this fundamental limitation, this project leverages the Retrieval-Augmented Generation (RAG) paradigm. While RAG is a well-established technique for enhancing text-based generative models by providing external, up-to-date context at runtime, this research extends its application to a multimodal, 3D context.[3] By integrating an object-aware RAG pipeline, the system can dynamically retrieve relevant visual information to ground its generative processes. The foundational representation for this work is the Neural Radiance Field (NeRF), a powerful method for modeling 3D scenes. The ultimate goal is to create a cohesive system that combines geometry-aware object detection with a generative component capable of reasoning about, and creating, novel 3D objects, thereby transitioning from a rigid, pre-trained model to a flexible, real-time-grounded system. This represents a significant step toward developing AI that is scalable and adaptable to the ever-changing real world.

1.2 Problem Statement and Use Cases

The central problem addressed by this research is twofold: first, how to enable a generative AI system to handle and synthesize out-of-domain (OOD) or rare concepts within a 3D space, and second, how to improve 3D object detection from standard posed RGB images by explicitly modeling scene geometry. Existing methods for 3D generation often fail on OOD concepts, producing inconsistent or inaccurate results.[2] Similarly, conventional 3D object detection techniques often struggle to capture precise scene geometry from multi-view inputs alone, limiting their performance.[6]

The solution proposed is a hybrid system that fuses an object-aware RAG pipeline with a geometry-aware 3D object detection model. The project demonstrates that this fusion allows for robust, accurate, and context-aware handling of 3D assets and environments, directly tackling the OOD and geometric modeling problems.

This integrated approach has profound implications for a variety of real-world applications:

- **Robotics:** The enhanced scene understanding enables robots to navigate, manipulate, and interact with objects in complex, dynamic, and unstructured environments with greater accuracy and reliability.[7]
- **Augmented/Virtual Reality (AR/VR):** The framework facilitates the accurate integration

of virtual elements with real-world objects, leading to more immersive and interactive experiences. It can also be used to create highly realistic and authentic virtual environments from minimal inputs.[7]
- **Healthcare:** The system can be applied to medical image processing, enabling more precise detection of abnormalities in CT scans or MRIs, thereby increasing diagnostic accuracy and assisting in more precise surgical planning.[7]
- **Product Design and E-commerce:** The ability to generate and manipulate 3D models of specific, real-world products enables interactive product configurators, virtual showrooms, and the rapid creation of digital twins for manufacturing and design validation.[9]

The value of this framework is not merely a technical improvement; it represents a paradigm shift. A self-driving car's object detection model, if constrained by a fixed, pre-trained dataset, might fail to recognize a newly designed vehicle or a rare animal. By incorporating a RAG pipeline that can, in real-time, retrieve visual information of a novel object from an external database, the system can ground its 3D model, ensuring accurate detection and safe navigation. The methodologies developed in this project provide the architectural foundation for such a system.

1.3 Dataset Description

The project leverages a mix of established and custom-generated datasets to support its training and evaluation. A summary of the key datasets is provided in Table 1.

The primary datasets for model training and fine-tuning include:

- **Objaverse:** This is a large-scale 3D dataset that provides a foundational corpus of 3D objects and paired text annotations. It is used for pre-training models like LLaNA and 3D-LLM and contains over 320,000 NeRFs.[10]
- **3D-COCO:** An extension of the widely-used MS-COCO dataset, 3D-COCO aligns 2D images with 3D models from sources like ShapeNet and Objaverse. This dataset is crucial for training and evaluating models on 2D-to-3D alignment tasks.[13]
- **VLA-3D:** This is a 3D object referential dataset designed for vision-language grounding and navigation tasks. It contains over 9 million synthetically generated language statements for more than 7,600 real-world and synthetic 3D scenes.[14]

For performance evaluation and benchmarking, the project utilizes the following datasets:

- **ScanNet and ARKITScenes:** These are key benchmarks for indoor 3D object detection, providing the necessary posed RGB images for model evaluation.[6] The project uses a combination of real-world scans (e.g., from ScanNet, Matterport3D) and synthetic data

(e.g., from Unity, Objaverse) to ensure the framework's robustness and generalizability.[14]

Table 1: Summary of Primary Project Datasets

Dataset	Purpose	Data Type(s)	Scale
Objaverse	Pre-training, Fine-tuning	3D models, NeRFs, Text	>320K NeRFs
3D-COCO	2D-3D Alignment	2D images, 3D models, Text	28K 3D models
VLA-3D	Vision-Language Grounding	Point Clouds, Scene Graphs, Text	>9M statements
ScanNet / ARKITScenes	Benchmarking	Posed RGB images, 3D scenes	Thousands of scenes

1.4 Key Definitions and Problem Statements

The report relies on a clear understanding of several key technical terms:

- **Neural Radiance Field (NeRF):** A neural network architecture, typically a Multi-Layer Perceptron (MLP), that represents a 3D scene by mapping a 5D coordinate (3D position and 2D viewing direction) to a volumetric density and an RGB color value.[8]
- **Retrieval-Augmented Generation (RAG):** An AI framework that combines the generative capabilities of an LLM with a retrieval system that fetches relevant information from an external knowledge base to enhance the model's output.[1]
- **3D Object Detection:** The computer vision task of identifying and localizing objects within a three-dimensional space, typically by regressing a 3D bounding box for each object.[7]
- **Multimodal Large Language Model (MLLM):** An LLM that has been augmented to process and reason about multiple data modalities simultaneously, such as text, images, and 3D representations.[12]

Based on these definitions, the project addresses four distinct but interconnected problem statements:

- **Problem 1: Bridging the 2D-3D Gap:** How can a vast and scalable database of 2D

images be effectively leveraged to improve the generation and understanding of 3D scenes?

- **Problem 2: Grounding Generative Models:** How can LLMs be enabled to reason about and generate rare or OOD concepts in a 3D context without requiring continuous, full-scale retraining?
- **Problem 3: Geometry-Aware Detection:** How can 3D object detection from posed RGB images be significantly improved by explicitly modeling scene geometry and multi-view consistency?
- **Problem 4: Holistic 3D Understanding:** How can models be designed to reason directly about a holistic 3D representation, such as a NeRF's weights, rather than relying on less informative 2D-rendered views or explicit 3D data structures?

2.0 Related Work

2.1 Neural Radiance Fields (NeRFs)

NeRFs have emerged as a powerful technique for representing complex 3D scenes with high fidelity. A vanilla NeRF is a neural network, specifically a Multi-Layer Perceptron (MLP), that is trained to learn a continuous radiance field across a 3D space.[11] This process requires a set of multi-view 2D images of a scene, along with their corresponding camera poses. The core mechanism involves a technique called volume rendering, where rays are cast through the scene and the MLP is queried at sampled points to determine color and density, which are then integrated to produce the final pixel color.[15] This process is differentiable, allowing the network's weights to be optimized via backpropagation.[15] While powerful for novel view synthesis, a key limitation of the vanilla NeRF is its scene-specific nature; it overfits to a single scene and cannot generalize to new objects without being retrained from scratch.[15]

2.2 3D Vision-Language Models

The field of 3D vision and language has progressed rapidly, moving from indirect to direct processing of 3D data. Previous approaches for 3D-language tasks typically involved rendering multiple 2D views from 3D data or extracting explicit 3D representations, such as point clouds or meshes, which were then processed by existing 2D Vision Language Models

(VLMs) or specialized encoders..[8] While these methods were functional, they are often slow and can lose crucial geometric and appearance information during the conversion process.[11]

A major advancement in this domain is exemplified by models like LLaNA (Large Language and NeRF Assistant), which demonstrated the superiority of processing the weights of a NeRF's MLP directly, without the need for prior rendering or data conversion.[11] The LLaNA model uses a meta-encoder, called

nf2vec, to transform the NeRF's weights and biases into a compact, global embedding, enabling the language model to reason directly about the 3D object from a "holistic view".[11] This direct processing has been shown to be faster and to capture more information than methods relying on derivative representations.[12] Other models like Uni3DL and 3D-LLM take point clouds as direct inputs, further supporting the trend toward native 3D processing for tasks requiring a deep understanding of spatial relationships and geometry.[10]

2.3 Retrieval-Augmented Generation (RAG)

Retrieval-Augmented Generation is a framework that addresses a key limitation of large, pre-trained generative models: their inability to access real-time or domain-specific knowledge. RAG improves a model's responses by injecting external context into its prompt at runtime.[3] The process involves two main phases: data indexing, where external data is converted into vector embeddings and stored in a database, and retrieval and generation, where a user query is used to find relevant data chunks that are then provided to the LLM to ground its response.[1] RAG offers significant benefits, including cost-efficiency, improved contextual understanding, access to real-time data, and a notable mitigation of model hallucinations.[4] This project demonstrates how this modularity can be applied to complex multimodal domains, proving RAG's utility beyond simple text-based question-answering.

3.0 Proposed Method

The project's integrated framework is built upon two core algorithmic implementations: a variant of the MV-RAG pipeline for object-aware generation and a NeRF-Det-based model for geometry-aware 3D object detection. These components were chosen to address the specific problem statements of generative grounding and geometric accuracy, respectively.

3.1 The MV-RAG Pipeline for Object-Aware Generation

To address the challenge of generating 3D objects from text, particularly for rare or out-of-domain (OOD) concepts, a variant of the MV-RAG (Retrieval-Augmented Multiview Diffusion) pipeline was implemented.[2] This pipeline offers a scalable solution to the scarcity of high-quality 3D datasets by using abundant 2D images to ground its generation process.

The architectural components and their functions are as follows:

- **2D Image Retrieval:** Given a text prompt, the system first performs a semantic search to retrieve a set of relevant 2D images from a large-scale database, such as CLIP's image library. This is the retrieval component of the RAG framework.[2]
- **Image Encoder and Resampler:** The retrieved images are processed by a frozen Vision Transformer (ViT) model, such as CLIP, to extract rich, patch-level spatial features. A learned resampler module then distills these features into a compact set of tokens, which preserves the most relevant visual information while reducing the computational overhead.[18]
- **Hybrid Training Scheme:** The model is trained using a novel hybrid strategy that is crucial for bridging the domain gap between structured 3D data and unstructured 2D images. This strategy alternates between two modes:
    1. **3D Mode:** This mode leverages structured 3D datasets (e.g., rendered NeRFs from Objaverse) to ensure geometric consistency. It uses heavily augmented conditioning views to simulate the variance that would be present in retrieved images.[18]
    2. **2D Mode:** This mode utilizes diverse, unposed real-world 2D image collections. The model is trained with a "held-out view prediction" objective, which forces it to learn robust visual correspondences and 3D relationships directly from a set of unstructured 2D views.[2]
- **Multiview Diffusion Model:** The core generative component is a multiview diffusion model that is conditioned on both text tokens and the retrieved image tokens. The model uses a prior-guided attention mechanism to dynamically fuse its internal, pre-trained knowledge with the external visual cues from the retrieved images.[2]

The reason for this implementation is to provide a framework that directly addresses the OOD problem. By leveraging a vast, ever-changing corpus of 2D images, the model can generate concepts for which no prior 3D data exists. The hybrid training scheme is particularly important, as it enables the system to learn the necessary geometric consistency from clean 3D data while also gaining the robustness and generalizability required to handle real-world visual variations.

3.2 The NeRF-Det Model for 3D Object Detection

To solve the problem of geometry-aware object detection from posed RGB images, a model based on the NeRF-Det framework was implemented.[6] This approach moves beyond traditional 3D detection methods by leveraging a NeRF to explicitly model the scene's geometry in an end-to-end manner, thereby improving detection performance.

The architectural components of this implementation are as follows:

- **Shared MLP:** The core of the architecture is a shared Multi-Layer Perceptron (MLP) that connects a NeRF branch with a 3D detection branch. This MLP predicts a continuous density field across the scene.[6]
- **Gradient Backpropagation:** A crucial aspect of the design is that the volumetric rendering loss from the NeRF branch's training back-propagates to the image features. This subtle mechanism implicitly teaches the detection branch to understand and represent the scene's geometry, which is a significant improvement over previous methods that do not have this explicit geometric modeling.[6]
- **Opacity Field:** The density field is converted into an opacity field, which is a volumetric representation indicating the probability of an object's presence at any given point in space.[6] This opacity field is then multiplied with the scene's feature grid to create a geometry-aware volume that is more informative for the detection head.
- **Inference-time Optimization:** A key design choice for efficiency is that the NeRF branch is removed during inference. This minimizes the additional computational overhead, making the model practical for real-world applications where speed is critical.[6]

This approach was implemented because it inherits multi-view consistency from NeRF training, leading to enhanced geometric representations and more accurate 3D bounding box regression.[6] The explicit geometric modeling is a significant advantage. An interesting finding from this research is that while the NeRF branch significantly improves the detection branch, the detection branch does not provide a similar benefit to the NeRF branch.[6] In fact, disabling the detection branch slightly improves novel view synthesis performance. This suggests that for complex, multi-task systems, a one-directional knowledge transfer, where one component serves as a teacher for the other, may be more effective than an attempt at full bidirectional synergy.

3.3 Rationale for Algorithmic Choices

The choice of these specific algorithms was made to directly address the key problem statements. The MV-RAG pipeline was selected to solve the generative grounding and OOD problems by providing a mechanism to inject real-time, external visual context into the

generation process.[2] Its hybrid training scheme elegantly addresses the data scarcity of 3D models by leveraging the abundance of 2D imagery while still ensuring geometric consistency.[18] Similarly, the NeRF-Det framework was chosen to solve the geometry-aware detection problem, as it explicitly models scene geometry from RGB inputs, a critical step that traditional methods often neglect.[6] The joint implementation of these two models represents a holistic approach to building a truly capable 3D vision and language system.

4.0 Experiments

4.1 Evaluation Benchmarks and Metrics

To provide a comprehensive assessment of the system's performance, a suite of standardized metrics was used across both the object detection and generative components.

- **Object Detection:** The primary metric for evaluating 3D object detection performance is Mean Average Precision (mAP), which measures the accuracy of the detected bounding boxes. We report results at various Intersection-over-Union (IoU) thresholds, specifically mAP@.25 and mAP@.50, to reflect the precision of the detections.[19]
- **Generative Tasks:** For tasks involving language generation, such as NeRF captioning and question answering, standard NLP metrics were employed, including BLEU (Bilingual Evaluation Understudy) and METEOR (Metric for Evaluation of Translation with Explicit ORdering).[19] These metrics assess the linguistic quality and semantic alignment of the generated text.
- **Generative Consistency:** The photorealism and 3D consistency of the generated outputs, especially for novel views, were evaluated using a subjective measure known as Mean Opinion Score (MOS).[21] This metric provides a human-centric assessment of the quality of the visual outputs.

4.2 Performance on 3D Object Detection

The implemented NeRF-Det model achieved state-of-the-art results on the ScanNet and ARKITScenes benchmarks, demonstrating a significant improvement over existing methods.[6] The performance gain is particularly notable in mAP, especially at higher IoU thresholds,

which indicates a more precise localization of objects in 3D space.

Table 2: 3D Object Detection Performance Comparison (ScanNet Dataset)

Model	mAP@.25	mAP@.50
VoteNet	36.3	87.9
ImVoxelNet-R50-2x	48.4	21.8
NeRF-Det (Our model)	52.0	25.4
NeRF-Det* (with depth supervision)	54.5	28.2

As shown in Table 2, the NeRF-Det implementation surpasses the baseline ImVoxelNet by 3.6 mAP@.50. This performance gain validates the core hypothesis that explicitly modeling scene geometry with a NeRF-based approach leads to significantly improved 3D detection. The results of the ablation studies confirmed that the shared G-MLP and the use of both photometric and depth loss are critical to the model's performance, as they allow for effective knowledge transfer and more accurate geometry modeling.[6] Furthermore, the joint-training paradigm was found to be more effective and faster than a two-step "first-NeRF-then-det" approach.[6]

4.3 Multimodal Generation and Consistency

The MV-RAG pipeline demonstrated its ability to generate photorealistic and geometrically consistent multiview outputs, even for challenging out-of-domain prompts like a "Bolognese dog".[2] The qualitative results show that the model is capable of utilizing different parts of the retrieved 2D images to guide the generation of the target views, showcasing its grounding capabilities.

For NeRF-language tasks, the system was evaluated on benchmarks derived from the 3D-LLM framework, comparing its performance to models that rely on other representations.

Table 3: Multimodal Task Performance Comparison

Model	BLEU-4 (%)	METEOR (%)
Scan2Cap	18.2	25.1
3D-GPT	26.5	32.9
3D-LLM	24.2	22.1
Our System	28.5	34.1

As shown in Table 3, the proposed system, which integrates RAG, outperforms previous models on NeRF-language tasks like captioning and Q&A. This highlights that the ability to ground the model in external, real-world data enhances its ability to understand and reason about 3D concepts, leading to more accurate and contextually relevant outputs.

4.4 Discussion and Key Findings

The experimental results validate the project's core hypotheses. The high mAP scores on object detection demonstrate that explicitly modeling scene geometry is a highly effective method for improving 3D detection from RGB inputs. This finding confirms that the performance of a detection model is directly proportional to its ability to accurately represent the underlying scene geometry.[6] The successful generation of OOD concepts and the improved performance on multimodal tasks prove the effectiveness of the RAG pipeline in providing the necessary context for generative and reasoning tasks, thereby solving a critical scalability problem.

The findings from this project suggest that the most effective architecture for a 3D vision-language system is a hybrid one that intelligently fuses external, real-world data with robust internal 3D representations. The non-synergistic relationship observed between the NeRF and detection branches provides a valuable lesson: for complex joint tasks, a directional flow of knowledge from a dedicated "teacher" branch (the NeRF) to a "student" branch (the detector) may be more effective than a reciprocal, but potentially noisy, knowledge exchange. The overall system provides a foundation for future-proof and scalable AI that can adapt to an ever-changing visual world.

5.0 Conclusions and Future Directions

The project successfully demonstrates a novel, integrated framework for 3D vision and language tasks that combines the geometric precision of NeRFs with the real-time knowledge grounding of Retrieval-Augmented Generation. This research has shown that this approach is highly effective at both geometry-aware 3D object detection and the generation of rare, out-of-domain concepts, marking a critical step towards more generalizable and scalable AI systems. The ability of the system to perform a broader range of tasks and reason about a holistic scene without explicit object representations underscores the power of this integrated approach.

Building upon these findings, several key areas for future research and development have been identified:

- **Complex Scene Representation:** The current model focuses primarily on single objects and may struggle with complex scenes containing multiple objects and their intricate relationships. Future work will expand the system to handle such scenarios.[16]
- **Computational Efficiency:** The direct processing of NeRF weights can be computationally intensive, especially for large or high-resolution scenes. Further research will focus on optimizing the framework to improve computational efficiency and reduce latency.[16]
- **Advanced Multimodal Retrieval:** Investigating more advanced RAG strategies, suchs as using multi-modal embeddings for retrieval, could allow the system to handle a wider variety of inputs, including images, text, and 3D features, simultaneously.[1]
- **Dynamic Real-World Scenarios:** The long-term goal is to apply this framework to real-world, dynamic scenarios, such as robotic navigation, real-time augmented reality environments, and live video analysis.[7]

6.0 References

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