I still see Bad Shadows in my Room: Analyzing and Detecting Lighting Inconsistencies in AI-Generated Images

CS 543 Progress Update

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1 Current Project description and goals

Generative models have made extraordinary strides in producing photorealistic images, particularly in rendering complex textures and objects. However, subtle inconsistencies, especially in illumination and shadow rendering, often expose the synthetic nature of these images. This proposal outlines a research project focused on analyzing and detecting shadow and illumination inconsistencies in AI-generated images. Our goal is to create a comprehensive framework that identifies both significant and nuanced discrepancies in lighting, including misaligned shadows, inconsistent penumbra effects, and unrealistic inter-object lighting interactions. By leveraging geometric and photometric analyses, we aim to enhance detection accuracy across multiple SOTA generative models. The outcomes of this research are expected to contribute significantly to image forensics and the development of robust detection mechanisms for AI-generated content.

2 Methodology & Experiments

Whereas our original proposal described a number of potential avenues for shadow and lighting analysis, we have since refined our approach to on two key experiments, described as follows:

2.1 Shadows

To perform shadow detection and assess consistency, we employed the Single Instance Shadow Detection (SSIS) method [14]. This approach uses a single-stage, fully convolutional network to directly learn relationships between shadow instances and the objects casting those shadows through a bidirectional relation learning module. Unlike traditional two-stage methods, SSIS efficiently predicts shadow-object pairs by learning offset vectors in both directions—from shadow to object and object to shadow—making it particularly robust for irregular or occluded shadows. With this technique, we get the shadow mask and object mask that we plan to use to compare the shadow and object relationship. We also plan to build a framework on top of this method to compare the shadows in the original and AI-generated images, with the goal of identifying any notable inconsistencies. Additionally, we will use a combination of manual and automated methods to detect and analyze such inconsistencies.

2.2 Lighting

In computer vision, lighting detection lacks a standardized approach, making it challenging to identify and apply a quick, effective method. For our analysis, we selected DiffusionLight [11], a technique that captures light characteristics by rendering a reflective chrome sphere within the image. In our case, the raw light data gathered to form the chrome spheres will be compared between the original and AI-generated images for notable discrepancies. We also plan to use the lighting condition obtained in association with the shadow detection method to check the direction of shadow with respect to lighting (more detail in section 2.6).

2.3 Control Net based generation

To evaluate our methods on similar pairs of real and synthetic images, we generate synthetic images using ControlNet model [17] with Stable Diffusion 3 [5]. Specifically, we use the real images from SOBA dataset [15] and apply ControlNet using guidance information to get the synthetic counterparts of the images. To get the input prompt guidance, we use BLIP-2 model [8] and caption the real

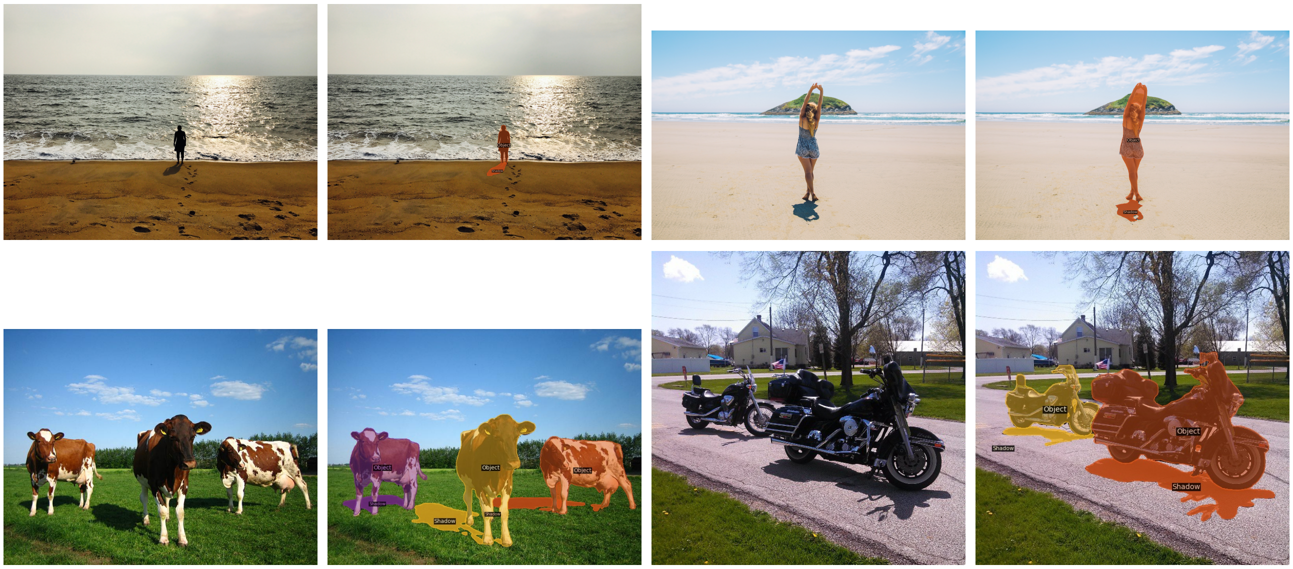


Figure 1: Samples and resulting shadow generation from SSIS

images use the generated caption as the input prompt for synthetic image generation. For the layout guidance, we use canny edge detection [3] and use the edge detection output as the layout guidance for ControlNet. This particular setup allows us to generate similar synthetic images for better comparison with the real images while also enabling us to evaluate the generation capabilities of the underlying stable diffusion 3 model.

2.4 Rendering

To obtain ground-truth images for testing unique scenarios, we explored rendering using both PyRender and PyBullet, as detailed in Appendix A. The PyRender implementation allowed us to create detailed scenes by loading various 3D meshes such as fuse, drill, and water bottle objects. We set up multiple light sources—including directional, spot, and point lights with specific intensities and angles—to simulate different lighting conditions. By configuring a perspective camera with a defined field of view and pose, and combining these elements with ambient lighting, we rendered the scenes offscreen using OpenGL's EGL backend. This approach produced high-quality images with proper lighting and shadows, providing precise control over lighting conditions essential for our analysis.

In contrast, the PyBullet implementation took a physics-based approach by loading URDF models and rendering them using either GPU-accelerated EGL rendering or the CPU-based TinyRenderer. While both methods were implemented, we ultimately chose PyRender due to its fine-grained control over lighting conditions and support for multiple light types. PyBullet's rendering capabilities are more focused on real-time physics simulation visualization, which was outside the scope of our work. By utilizing PyRender, we generated synthetic images with meticulously controlled lighting and shadow properties, ensuring that any observed discrepancies could be attributed to specific factors. This strengthened the validity of our analysis and supported the testing of our conjectures.

2.5 Real Shadows vs. Synthetic Shadows

To analyze the realism of shadows, we propose several conjectures as potential indicators of synthetic images. Shadows created by specific light sources adhere to physical principles that influence

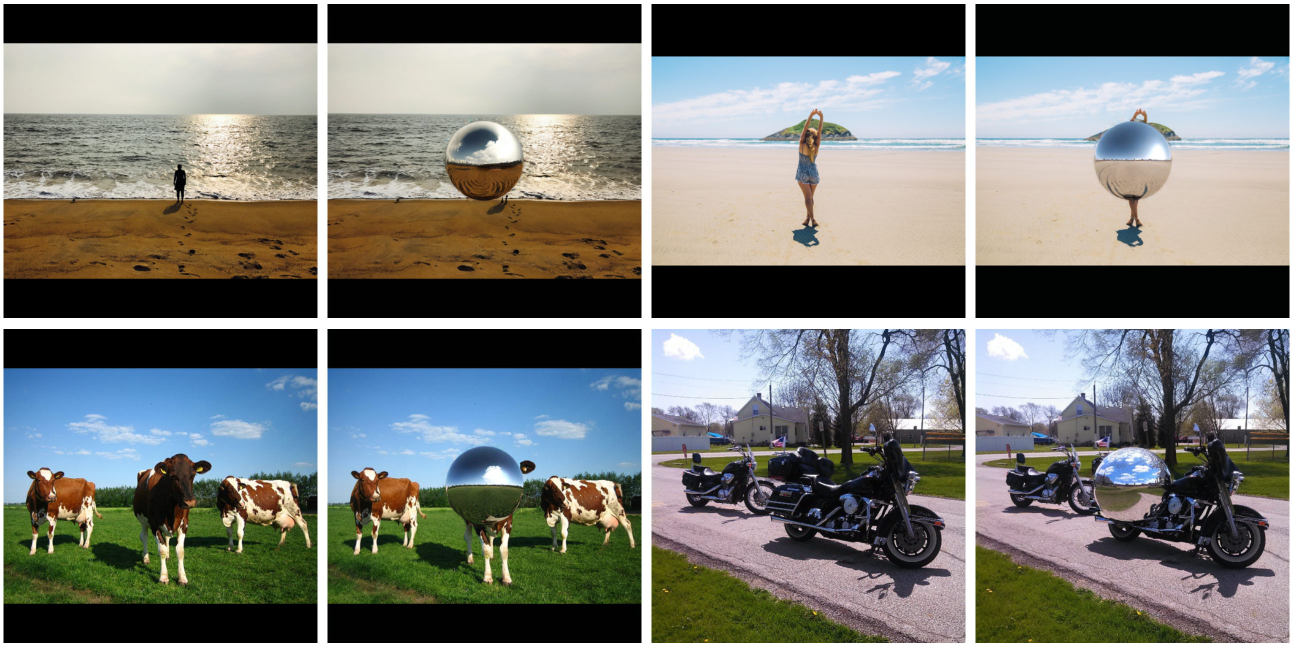


Figure 2: Samples and resulting Light Detection (chrome ball) via DiffusionLight

their appearance. Our conjectures draw on these principles to identify inconsistencies and check for synthetic images.

Conjecture 1: Consistency with Object and Light source

Shadows have two properties; firstly, shadows are always associated with the object that casts and the behavior of that object. Secondly, both the position and strength of the light source are known from shadows [7]. So, we conjecture that a synthetic image will show a discrepancy in the lighting source detected by the lighting source detection model and the lighting source location expected by shadow. And similarly, we expect a discrepancy in the object-shadow relationship.

Conjecture 2: Shadow Geometry Coherence

The spatial geometry of shadow regions—including their size, shape, and relative orientation—depends on the object's distance from the light source and the surface it casts a shadow. Shadow shape is the projection of the object shape on the background. For an extended light source (not a point light source), the projection is unlikely to be perspective. [7] We conjecture that synthetic images will not demonstrate coherence in shadow geometry with respect to the physical layout of objects and the direction of light. For instance, shadows should exhibit lengths proportional to the object sizes and distances and orientation with respect to the light source. In synthetic images, shadows may appear stretched or shortened in ways that are incongruent with the scene's spatial setup.

Conjecture 3: Consistency in Shadow Smoothness and gradient

In single-source lit scenes, shadows transition uniformly from umbra to penumbra, maintaining consistent softness and color gradients influenced by ambient light and object properties [2]. Real light sources produce shadows with uniform sharpness or softness based on their distance and the positioning of objects alongside well-defined color transitions. We hypothesize that synthetic images often exhibit irregular and unnatural color consistency—such as blurred or monotone shadows—that lack the natural gradation and consistent tone of genuine shadows. These atypical sharpness and color transitions may identify synthetic images.

Conjecture 4: Feature Consistency in Shadowed Regions

The features within shadowed regions, such as textures, edges, and gradients, should maintain consistency in genuine images. [7]. We conjecture that synthetic images may reveal mismatches in

Figure 3: Samples and resulting synthetic images via ControlNet

texture or intensity within shadowed areas due to inconsistent blending or shadow generation. This change in texture thus will potentially indicate the synthetic image.

2.6 System Integration

We plan to verify shadow consistency in images with a single lighting source. Drawing on insights from digital forensics literature, we have developed conjectures around shadow properties and authenticity, which we will test using a suite of algorithms and models.

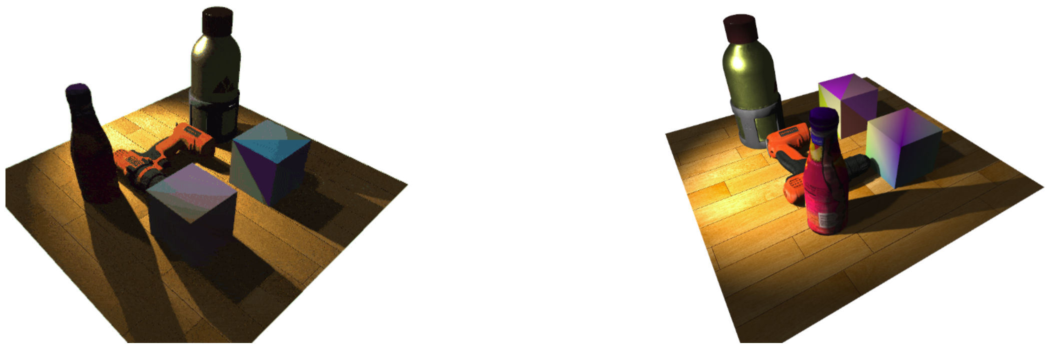
Our current model suite includes an object-shadow detection model, a lighting source detection model, a ControlNet-based image generator, and a rendering pipeline capable of producing synthetic datasets with controlled lighting and camera conditions. These resources will enable us to conduct controlled experiments, comparing real and synthetic images to identify characteristic differences in shadow properties.

To integrate these components, we will use the rendering pipeline to simulate conditions in synthetic datasets. For instance, we'll extract lighting direction with respect to the object from a synthetic image to generate a corresponding shadow in the rendered image and then compare this generated shadow from the render to the one in the synthetic image. We'll also perform the same comparison with real images to validate our approach.

ControlNet will assist in generating images that closely resemble real-world conditions, enabling more accurate cross-comparisons between real and synthetic images. Section 5 outlines the algorithms we will apply to both synthetic images and real images, ensuring alignment in lighting and object conditions.

3 Resources

Two particular datasets are used to train and test our models: RdSOBA and DESOBAv2 [9, 13]. These datasets are designed using ground truth lighting to predict shadow generation. Additionally, we are using a combination of the PyBullet physics engine and PyRender to generate synthetic images for manual analysis and testing. Through a combination of existing datasets and synthetic images, we aim to train a comprehensive model to detect shadow and lighting inconsistencies while giving ourselves the ability to manually review individual cases. These images will be used to retrieve captions using BLIP-2 [8] and layout using canny edge detection [3] to generate images through a ControlNet [17]. Similar to our proposal, the comparison process will employ straightforward metrics [6, 12, 16] and classifiers [4] to assess the realism of generated images.



(a) (b)

Figure 4: Sample images from PyRender

4 Initial Results

Currently, we have implemented a number of elements related to setting up comparisons between our ground-truth image datasets and synthetic images. In particular, we have successfully generated simple scenes through PyBullet and PyRender, as well as the tools necessary for lighting and shadow comparison, DiffusionLight and SSIS respectively [11, 14]. Using this foundation, we can begin the process of batch-generating synthetic images with a captioning-based ControlNet [17], then perform all necessary comparisons.

5 Next set of tasks

We propose to utilize our current available and experimented tools to test each of conjectures:

Consistency with Object and Light source We will test this conjecture by comparing the light source positions inferred from shadows using our instance shadow detection model with those detected by the DiffusionLight chrome ball light detection model. By assessing discrepancies between these two light source positions in both real and synthetic images, we aim to identify inconsistencies that are more prevalent in synthetic images.

Shadow Geometry Coherence To evaluate this conjecture, we will analyze the geometric coherence of shadows relative to object sizes, positions, and light source direction. By detecting objects and their corresponding shadows, we will compare the expected shadow shapes and sizes—predicted based on geometric principles—with the actual detected shadows. We anticipate that synthetic images will exhibit significant geometric inconsistencies compared to real images.

Consistency in Shadow Smoothness and Gradient We will assess this conjecture by measuring the gradient transitions across shadow edges in both real and synthetic images. Using edge detection algorithms like the Canny edge detector, we will quantify the softness of shadow boundaries by analyzing the width of the transition from the umbra to the penumbra. Additionally, we will perform color profiling along lines perpendicular to shadow edges to evaluate color gradients influenced by ambient light. We expect synthetic images to display irregularities such as unnatural sharpness or blurriness in shadow edges and inconsistent color transitions, unlike the uniform gradients observed in real images.

Feature Consistency in Shadowed Regions To test this conjecture, we will analyze the consistency of textures and edges within shadowed regions compared to illuminated areas. By extracting texture features using methods like Local Binary Patterns and detecting edges within shadowed regions, we will compare the preservation of surface details across shadow boundaries. Any abrupt changes or loss of detail in synthetic images may indicate inconsistent blending or artificial rendering. We hypothesize that real images will maintain feature consistency despite reduced illumination, while synthetic images may reveal mismatches in textures and edges within shadows.

6 Current Member Roles

Group discussion and collaboration is key to the success of our project. We regularly meet to discuss our progress once or twice a week, typically in person, to ensure that any rising issues are addressed. A shared GitHub repository is used to store project-related code, data, and report drafts. Additional writing is achieved through a combination of real-time Overleaf collaboration and pushes to the GitHub repository. Finally, all asynchronous communication is conducted through Slack, including the sharing of necessary resources that other members may find useful. Each of the member will also be assisting with building different tools to test different conjectures using the method mentioned above. Our individual backgrounds and current project roles are as follows:

- **Dwip Dalal** is a PhD ECE student advised by Prof. Narendra Ahuja at UIUC. He has been working in the domain of computer vision for four years now. He's working in Visual-Language grounding-related areas. Currently, Dwip is focused on implementing the necessary algorithms for shadow detection and light appearance. He has also significantly contributed to the project propsal through personal literature review.

- **Adheesh Juvekar** is a CS PhD student in PLAN Lab at UIUC, advised by Prof. Ismini Lourentzou. His primary research interests are in multimodal learning and generative AI. He also has experience working on the compositionality problem of image generation models through his internship experience at Amazon Science. Currently, Adheesh is focused on creating a comprehensive dataset for the project and generating synthetic images for analysis.

- **Evan Matthews** is a second-year Masters student in the Audio Lab under the direction of Prof. Paris Smaragdis and Minje Kim. His experience is primarily in machine learning and audio computation, but he also has a strong interest in computer vision and generative models. Currently, he is focusing on building auxiliary tools necessary for analyzing and detecting lighting and shadow inconsistencies. He is also a primary contributer to all project reports and assists Adheesh in the generation of synthetic images.

- **Jiachen Tu** is a PhD ECE student. While he is not actively enrolled in the course, Jiachen has continued to actively contribute to the project through occasional code assistance and discussions. He will be joining as a coauthor once we get the project into a more publishable state.

7 Reservations

Compared to our initial proposal, we find that reservations have remained exactly the same, with one additional exception. That is:

- Generated images of complex scenes or lighting may introduce a number of challenges, so we are beginning with relatively simple scenes first (one angle of light or reflection).
- Scalability of scenes to arbitrary numbers of rays and reflections is still a question of interest.
- (*new*) Hallucination during the image generation process may affect the quality of any remotely successful images with respect to lighting and shadows.

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Appendix A Pseudo-code

A.1 Using PyBullet to Generate Rendering Images

```
# Initialize PyBullet in GUI or DIRECT mode
connect_to_pybullet()

# Set search path for additional assets
set_asset_path()

# Enable GPU rendering if available
enable_gpu_rendering_if_possible()

# Load environment objects (e.g., plane, table, robots)
load_environment_objects()

# Configure camera properties (distance, angle, target position)
set_camera_properties()

# Optionally, configure lighting for shadows and visibility
configure_lighting_and_shadows()

# Capture multiple frames from different angles for animation or analysis
for each angle in camera_angles:
    adjust_camera_angle(angle)
    capture_image_frame()

# Save or display the rendered images
save_or_display_images()
```

A.2 Using PyRender to Generate Rendering Images

```
# Set up environment for OpenGL rendering (use EGL if available)
setup_opengl_environment()

# Load 3D models using trimesh and create PyRender meshes
load_3d_models()

# Create and configure light sources (directional, spot, or point lights)
create_and_configure_lights()

# Define a perspective camera and set its position
initialize_camera_with_position()

# Initialize a scene and add objects, lights, and camera
create_scene()
add_objects_to_scene()
add_lights_to_scene()
add_camera_to_scene()

# Render the scene offscreen with specified resolution
offscreen_rendering_with_camera()

# Display or save the rendered image
display_or_save_image()
```

Appendix B Project Proposal (10/14/2024)

B.1 Project description and goals

Generative models have made extraordinary strides in producing photorealistic images, particularly in rendering complex textures and objects. However, subtle inconsistencies, especially in illumination and shadow rendering, often expose the synthetic nature of these images. This proposal outlines a research project focused on analyzing and detecting shadow and illumination inconsistencies in AI-generated images. Our goal is to create a comprehensive framework that identifies both significant and nuanced discrepancies in lighting, including misaligned shadows, inconsistent penumbra effects, and unrealistic inter-object lighting interactions. By leveraging geometric and photometric analyses, we aim to enhance detection accuracy across multiple SOTA generative models. The outcomes of this research are expected to contribute significantly to image forensics and the development of robust detection mechanisms for AI-generated content.

B.2 Methodology & Experiments

B.2.1 Shadow Detection Algorithms

Detecting shadows accurately is crucial to this research. We plan to utilize some of advanced shadow detection algorithms that leverage various techniques:

- Color Space Analysis: Using color spaces like `HSV` and `YCbCr` to distinguish shadow regions.
- Edge Detection: Identifying edges where shadows form to analyze the sharpness or softness of shadow boundaries.
- Instance Shadow Detection: Applying instance shadow detection techniques, such as those explored in Wang et al.'s work [15], which focus on detecting shadow regions associated with specific objects.

By comparing results from different detection techniques, we will identify the most effective methods for highlighting inconsistencies in AI-generated images.

B.2.2 Penumbra and Umbra Analysis

We plan to analyze the Penumbra (soft shadows) and Umbra (hard shadows) of the shadows (with a conjecture that these regions will not be consistent in the synthetic images). These shadows vary in softness depending on light source size, distance, and object placement.

- **Edge Gradient Analysis:** Measure the gradient of shadow edges to determine softness, an essential feature for detecting inconsistencies.
- **Consistency Checks:** Compare the softness of shadows across a scene. Consistent lighting should produce shadows with similar properties, while generative models may inadvertently produce discrepancies.

B.2.3 Inter-Object Light Interactions

Another check for discrepancies - Global illumination effects. Effects such as color bleeding and ambient occlusion contribute to the overall realism of a scene:

Color Bleeding Detection: Analyze subtle color transfers between adjacent surfaces caused by indirect lighting, indicative of accurate global illumination modeling.

Ambient Occlusion Assessment: Evaluate shading in occluded areas where ambient light is minimal, ensuring consistency with the scene's geometry and light distribution.

B.2.4 Illumination Estimation

Dominant Light Source Estimation: Implement algorithms to determine the number, direction, and intensity of light sources in a scene. Methods include Principal Component Analysis (PCA), Training CNNs to estimate lighting parameters from images, or adapting a pre-trained classifier.

Joint Shadow and Multi-Object consistency check - Illumination check

We plan to implement a Joint Shadow and Multi-Object Consistency Check to ensure illumination coherence within a scene. This approach begins by analyzing the surface normals of multiple objects to accurately estimate the primary light source's direction and intensity. Concurrently, we will examine the shadows cast by these objects to identify potential additional light sources. By cross-referencing the estimated positions and orientations of all inferred light sources with the scene's geometry and shading characteristics, we will verify their consistency. This dual verification process ensures that multiple light sources align with physical lighting principles, effectively detecting discrepancies that may indicate AI-generated artifacts. Incorporating this joint consistency check will enhance the robustness of our illumination analysis, thereby improving the overall reliability of our shadow-based forensic framework.

B.2.5 Physically-Based Rendering Simulations

To validate the detected inconsistencies, we will simulate the lighting conditions of the scene using physics-based rendering techniques:

- **Scene Reconstruction:** Build simplified 3D models of the scene using depth maps and object segmentation data. This allows us to estimate how the scene should appear under realistic lighting conditions.
- **Rendering Comparisons:** Compare the reconstructed scenes with the original image, identifying quantifiable differences in illumination or shadow placement.

B.2.6 Data Curation

A comprehensive dataset is crucial to ensuring the robust evaluation of different methods. We aim to apply these methods to a comprehensive dataset comprising real-world images from diverse scenes and objects sourced from diverse datasets ensuring relevance and robustness. Additionally, we incorporate realistic synthetic images that are intentionally challenging to distinguish from real ones, thereby evaluating the methods under more rigorous conditions. We will also curate a diverse prompt set for image generation, encompassing a variety of scenes and objects, and employ straightforward metrics [6, 12, 16] and classifiers [4] to assess the realism of generated images.

B.2.7 Application of the work:

Enhance Image Forensics: Provide more reliable tools for distinguishing real images from AI-generated ones, contributing to digital media authenticity verification.

Inform Generative Model Development: Highlight areas where generative models need improvement, particularly in accurately modeling complex lighting phenomena, thereby guiding future advancements.

Promote Trust in Digital Content: Strengthen the ability to detect synthetic images, mitigating potential misuse of generative technologies in creating deceptive or misleading visual content.

B.3 Member roles

The project is designed in a way to play into each member's research strengths and experience. **Each of the members** will primarily work on one method each for the detection and analysis of inconsistencies in generated images.

Adheesh Juvekar, will take lead on dataset curation to decide a comprehensive data curation process of real images and generation of image prompt set, along with Dwip Dalal. Dwip will take the lead on the methods, while each member will also individually work on the implementation and evaluation with at least one method each. Evan Matthews, will primarily take lead on writing with assistance from each member. Evan will also take lead on the generation of synthetic images from our curated prompt set along with Adheesh.

B.4 Resources

Perplexity.ai will be used to access state-of-the-art models such as Playground v3, DALL-E 3, Stable Diffusion XL, and FLUX.1 [1]. We also have access to more recent Stable Diffusion 3 [5] for image generation. These models will serve as our primary sources of generated images, and comparisons will be made against real-world and physically-rendered images to be manually developed. Physical rendering will consist of some combination of PyRender and Blender, with respective rendering depending on scene complexity [10].

(a) Playground FLUX.1 and v3. These examples show us that the model generates a reflected part of the image without reflection consistency.

(b) Images with inconsistencies circled. In the left image, the shadow of the table is not consistent; the direction of the shadow of the table and the sofas is not parallel, and there is no shadow of the object placed on the table. In the right image, there are multiple light sources, as a result of which there should be multiple shadows, but there is only one shadow of the table, which again is inconsistent.

Shadow and Illumination analysis algorithms necessary for the project will be either hand-written from state-of-the-art references or forked from respective GitHub repositories. While we expect these algorithms to provide quantitative metrics, we ultimately want our analysis to come from manual conclusions backed up by these algorithmic results. We additionally expect outside code to not necessarily be designed for our specific use, so we expect to rewrite functionality or build frameworks from scratch to fit our needs.

Finally, heavy computational resources are not necessarily required but are readily available should the more complex scenes require more time to render. These computational resources are primarily clusters of the Siebel School for Computing and Data Science and Department of Electrical and Computer Engineering.

B.5 Reservations

Given the scalable nature of our dataset and process of analyzing images, we are confident in our ability to complete the project within the given time frame. However, we acknowledge that the complexity of the generated images and the need for manual verification may introduce challenges. We plan to start with simple scenes, particularly those with single reflections or light rays for easy detection. Once these analyses are successful, we'll work to implement more complex scenes by incrementing the number of rays and/or reflections. The biggest hurdle to our work- and an additional hypothesis in the back of our minds- is whether or not our analysis method can generalize to any number of rays and reflections.

B.6 Relationship to your background

Dwip Dalal is PhD ECE student advised by Prof. Narendra Ahuja at UIUC. He has been working in the domain of computer vision for four years now. He's working in Visual-Language grounding-related areas.
Adheesh Juvekar is a CS PhD student in PLAN Lab at UIUC, advised by Prof. Ismini Lourentzou. His primary research interests are in multimodal learning and generative AI. He also has experience working on the compositionality problem of image generation models through his internship experience at Amazon Science.
Evan Matthews is a Masters's student in the Audio Lab under the direction of Prof. Paris Smaragdis and Minje Kim. His experience is primarily in machine learning and audio computation, but he also has a strong interest in computer vision and generative models.
Jiachen Tu Ph.D ECE; he dropped the course but is interested in collaboration.