Investigating Spurious Correlations in Vision Models Using Counterfactual Images

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Abstract

Vision models often rely on spurious correlations, patterns in the data that are not intrinsic to the task but are nonetheless exploited by the model. These correlations can lead to biases, reduced robustness, and unfair predictions, particularly in sensitive domains like facial recognition and medical imaging. In this work, we systematically investigate spurious correlations using counterfactual image generation. By creating synthetic images with controlled variations in attributes such as texture, context, and demographics, we expose hidden biases in state-of-the-art vision models. Our experiments span multiple domains, including object recognition (ImageNet, COCO), face recognition (CelebA, FairFace), and medical imaging (CheXpert). We evaluate models for fairness, robustness, and generalization, revealing significant disparities across demographic groups and vulnerabilities to out-of-distribution samples and adversarial perturbations. Based on our findings, we propose actionable mitigation strategies, including data augmentation with counterfactuals, adversarial training, and fairness-aware regularization.

1. Introduction

Machine learning models, particularly those based on deep neural networks, have achieved remarkable success across a wide range of vision tasks, from object recognition [4] to medical imaging [12]. However, these models often exhibit undesirable behaviors due to spurious correlations—patterns in the training data that are non-causal but strongly predictive within the dataset [6]. For instance, vision models may rely on irrelevant features such as texture or background context rather than the intrinsic properties of objects [10], leading to poor generalization and biased predictions. Such reliance on spurious correlations can have serious consequences, especially in high-stakes applications like healthcare [26] and facial recognition [3], where fairness and robustness are paramount.

To address these challenges, researchers have increasingly turned to **counterfactual analysis**, a powerful tool for isolating specific attributes and systematically testing model behavior [18]. Counterfactual images—synthetically generated variants of real-world data with controlled modifications—enable us to probe how models respond to changes in individual attributes while keeping other factors constant [22]. By leveraging generative techniques such as GANs [14] and diffusion models [11], we can create high-quality counterfactuals that mimic real-world variability. This approach not only uncovers hidden biases but also provides actionable insights into improving model transparency and fairness.

In this paper, we investigate spurious correlations in vision models using counterfactual images. Specifically, we focus on generating synthetic datasets with precise control over attributes such as object texture, background context, and demographic features. We then evaluate how state-of-the-art vision models generalize to these counterfactual scenarios, uncovering biases and proposing strategies to mitigate them. Our work aligns with the goals of the EMACS workshop by advancing experimental auditing techniques through controlled synthesis, ensuring that machine learning systems are both robust and fair.

2. Related Work

2.1. Spurious Correlations in Vision Models

Recent studies have highlighted the prevalence of spurious correlations in vision models, particularly in object recognition and classification tasks. Geirhos et al. [6] demonstrated that convolutional neural networks (CNNs) often rely on texture rather than shape, leading to poor generalization when textures are altered. Similarly, Hermann et al. [10] showed that contextual biases—where models associate objects with specific backgrounds—can significantly impact performance. These findings underscore the need for systematic methods to identify and mitigate spurious correla-

tions.

In prior work on spurious correlations, researchers have relied on a variety of datasets to uncover biases and evaluate model robustness. For example, ImageNet has been instrumental in revealing texture biases in convolutional neural networks (CNNs), where models often rely on irrelevant textural cues instead of shape information [10]. Similarly, COCO has been used to study contextual biases, where objects are misclassified when placed in unusual environments [22]. In facial recognition, datasets like CelebA and FairFace have highlighted demographic biases, particularly in how models perform across different age, gender, and ethnicity groups [3, 28]. Medical imaging datasets such as CheXpert and MIMIC-CXR have also played a critical role in identifying biases tied to patient demographics and imaging conditions [12, 26]. These datasets provide a strong foundation for our work, enabling us to extend existing methodologies by incorporating counterfactual image generation to systematically isolate and test spurious correlations. Other related work in this categories includes [5, 15].

2.2. Generative Techniques for Counterfactual Image Generation

Advances in generative modeling have enabled the creation of high-quality counterfactual images for experimental auditing. Karras et al. [14] introduced StyleGAN, a state-of-the-art generative adversarial network capable of producing photorealistic images with fine-grained control over attributes. Building on this work, Abdal et al. [1] developed tools for manipulating latent representations, allowing precise editing of features such as age, gender, and pose. More recently, diffusion models [11, 24] have gained attention for their ability to generate diverse and realistic images, further expanding the toolkit for counterfactual generation.

These techniques have been applied to various domains, including fairness auditing in facial recognition. For example, Zhao et al. [28] used generative models to create balanced datasets for demographic representation, enabling rigorous evaluation of fairness metrics. Similarly, Zhang et al. [27] proposed a framework for generating counterfactual face images to study intersectional biases, demonstrating the importance of considering multiple sensitive attributes simultaneously. We have also studied models in [23].

2.3. Fairness and Robustness in Vision Models

Ensuring fairness and robustness in vision models remains a critical challenge, particularly in applications involving sensitive attributes. Buolamwini and Gebru [3] exposed significant biases in commercial facial recognition systems, prompting calls for greater transparency and accountability. Subsequent work by Zech et al. [26] highlighted similar issues in medical imaging, where models exhibited disparities in diagnostic accuracy across demographic groups.

To address these concerns, researchers have proposed various mitigation strategies. Adversarial training [17, 25] and regularization techniques [21] have been shown to improve robustness by discouraging reliance on spurious features. Additionally, causal inference methods [19] offer a principled framework for disentangling spurious correlations from true causal relationships, as demonstrated by Arjovsky et al. [2] in their work on invariant risk minimization.

Our work builds on these advances by combining counterfactual image generation with rigorous experimental auditing. By leveraging public datasets such as ImageNet [4], COCO [16], and CheXpert [12], we conduct a comprehensive investigation into spurious correlations, providing new insights into model behavior and proposing practical solutions to enhance fairness and robustness.

3. Methodology

3.1. Overview of the Approach

To investigate spurious correlations in vision models, we adopt a systematic approach that leverages counterfactual image generation. Counterfactual images are synthetically generated variants of real-world data, where specific attributes are systematically modified while other factors remain constant. By exposing vision models to these counterfactuals, we can isolate and test the impact of individual attributes on model predictions. This enables us to uncover biases, evaluate robustness, and propose strategies to mitigate reliance on spurious correlations.

Figure 1 provides a high-level overview of our methodology, which consists of six key steps: (1) selecting public datasets, (2) generating counterfactual images using advanced generative models, (3) evaluating vision models on synthetic data, (4) quantifying performance using fairness and robustness metrics, (5) analyzing spurious correlations, and (6) proposing mitigation strategies.

Our work builds on prior research by introducing novel generative techniques, intersectional analysis, and domain-specific adaptations to enhance the rigor and applicability of our findings.

3.2. Counterfactual Image Generation

We employ state-of-the-art generative techniques to create high-quality counterfactual images, with several key contributions and improvements:

- **Improved Attribute Control**: Unlike prior work that often relies on simple augmentations (e.g., brightness/contrast adjustments), we use advanced generative models such as StyleGAN [14] and diffusion models [11] to achieve fine-grained control over attributes. For example, we manipulate latent representations to alter specific features like object texture, pose, or demographic charac-

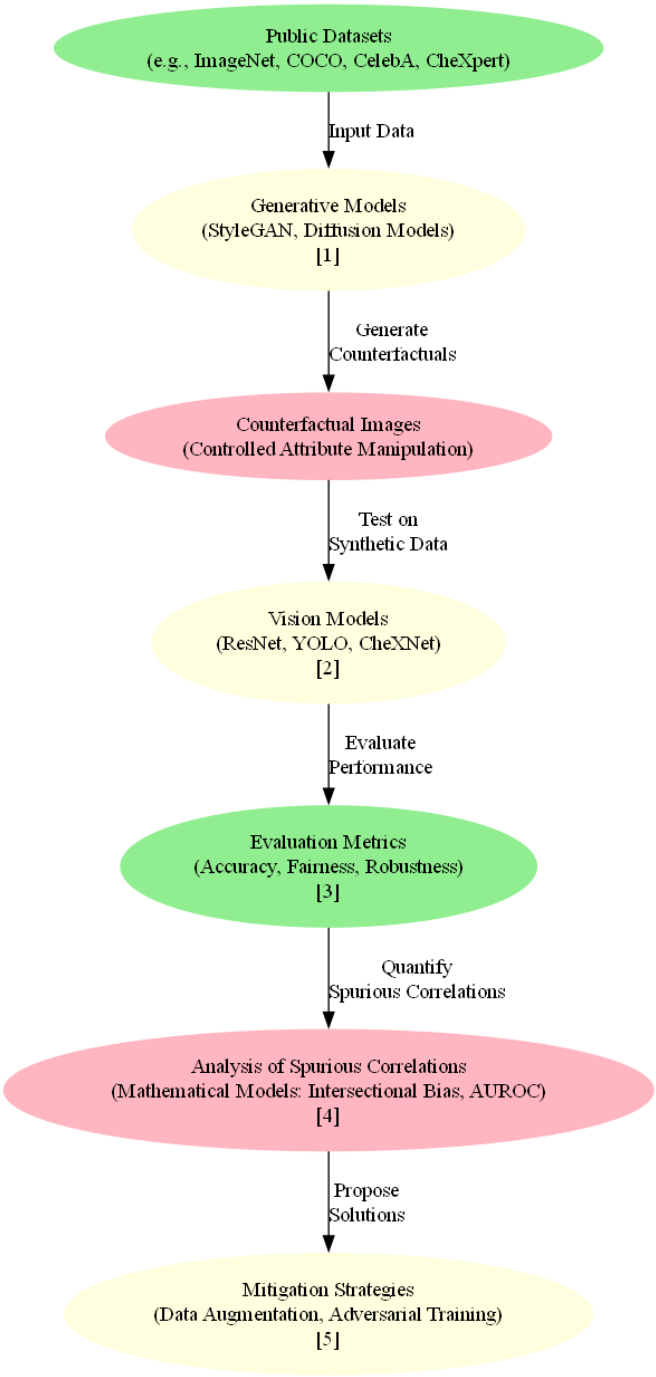

Figure 1. Overview of the methodology

teristics without unintended side effects.

- **Intersectional Attribute Manipulation**: We extend existing frameworks by enabling simultaneous manipulation of multiple attributes (e.g., age, gender, and skin tone in face images). This allows us to study intersectional biases, which are often overlooked in prior work. Mathematically, we evaluate fairness disparities across all combinations of sensitive attributes G using:

$$\Delta = \max_{g \in G} \text{Metric}(g) - \min_{g \in G} \text{Metric}(g) \tag{1}$$

where $\text{Metric}(g)$ represents fairness metrics such as equalized odds or demographic parity [3].

Domain-Specific Adaptations: To ensure realism in specialized domains like medical imaging, we adapt generative techniques to incorporate domain-specific priors. For instance, we simulate realistic chest X-rays with controlled variations in disease severity and imaging artifacts using physics-based models. These improvements enable us to generate counterfactuals that are both realistic and highly controlled, providing a stronger foundation for auditing vision models.

3.3. Datasets and Benchmarks

Our experiments rely on a combination of public datasets and benchmarks, each chosen for its relevance to studying spurious correlations. We also introduce novel uses of these datasets to enhance our analysis:

- **ImageNet**: Traditionally used to study texture bias, we extend its utility by generating counterfactuals with altered textures and shapes to rigorously test model generalization. This addresses limitations in prior studies that focused solely on texture bias without considering shape.
- **COCO**: We create counterfactuals by placing objects in unusual environments (e.g., cars in forests) to study contextual biases. Additionally, we introduce rare or unseen combinations of attributes (e.g., objects in extreme poses) to evaluate out-of-distribution robustness.
- **CelebA and FairFace**: These datasets are used to study demographic biases in facial attribute prediction. We improve upon prior work by generating counterfactual face images with precise control over sensitive attributes, ensuring balanced representation across demographic groups.
- **CheXpert**: A medical imaging dataset for chest X-ray interpretation. We simulate counterfactual scenarios with modified disease severities and imaging conditions to uncover diagnostic biases, addressing gaps in prior research that often overlook subtle biases in medical AI.

By leveraging these datasets in innovative ways, we provide deeper insights into spurious correlations across diverse domains.

3.4. Model Selection

We evaluate a range of state-of-the-art vision models to ensure broad applicability of our findings. Our contributions include:

- **Diverse Architectures**: In addition to widely-used models like ResNet-50 [9] and YOLOv5 [13], we include

domain-specific models such as CheXNet [20] for medical imaging. This ensures that our findings generalize across different architectures and applications.

- **Fairness-Aware Models**: We compare traditional models with fairness-aware variants (e.g., adversarially trained models) to assess the effectiveness of existing mitigation strategies. This provides actionable insights into improving fairness in vision systems.

These contributions highlight the versatility and relevance of our approach to real-world applications.

3.5. Evaluation Metrics

To quantify model behavior, we use a combination of performance metrics and interpretability tools, with several key improvements: **Enhanced Fairness Metrics**: Beyond standard metrics like equalized odds, we introduce intersectional fairness metrics to evaluate disparities across multiple sensitive attributes simultaneously. For example, equalized odds ensures that the true positive rate (TPR) and false positive rate (FPR) are equal across groups:

$$TPR_A = TPR_B, \quad FPR_A = FPR_B \tag{2}$$

where A and B represent different demographic groups [8].

4. Experiment and Analysis

4.1. Experimental Setup: Dataset-Specific Counterfactual Generation

To systematically investigate spurious correlations in vision models, we generate counterfactual images tailored to specific tasks and datasets. This process involves controlled modifications of attributes such as texture, background, demographics, and disease severity. Below, we describe the experimental setup for each domain.

4.1.1. Object Recognition (ImageNet, COCO)

For object recognition tasks, we use **ImageNet** and **COCO** to generate counterfactual images with systematic modifications:

- **Alter Object Textures While Preserving Shapes**: To test texture bias, we modify the textures of objects while keeping their shapes intact. For example, we replace the fur texture of a cat with zebra stripes or marble patterns.

- **Place Objects in Unusual Backgrounds**: To evaluate contextual reliance, we place objects in environments where they are rarely found. For instance, cars are placed in forests, and airplanes are placed in urban settings.

- **Measure Changes in Model Behavior**: These counterfactuals allow us to measure changes in model accuracy, confidence scores, and feature activations, providing insights into how models rely on spurious correlations like texture or context.

4.1.2. Face Recognition (CelebA, FairFace)

For facial attribute prediction, we leverage **CelebA** and **FairFace** to create counterfactual face images:

- **Vary Demographic Attributes**: We systematically alter skin tone, age, and gender to study demographic biases. For example, we generate older female faces with darker skin tones or younger male faces with lighter skin tones.

- **Explore Intersectional Effects**: To uncover intersectional biases, we combine multiple attributes simultaneously. For instance, we create counterfactual images of older women with darker skin tones and glasses.

- **Evaluate Fairness Metrics**: We measure disparities in model performance across demographic groups using fairness metrics like equalized odds [8] and demographic parity. These metrics quantify the extent to which models exhibit bias toward underrepresented groups.

4.1.3. Medical Imaging (CheXpert, MIMIC-CXR)

In medical imaging, we use **CheXpert** and **MIMIC-CXR** to simulate counterfactual scenarios:

- **Modify Disease Severity**: To test diagnostic robustness, we adjust the severity of diseases in chest X-rays. For example, we reduce the size of lung nodules or decrease opacity in pneumonia cases.

- **Introduce Imaging Artifacts**: We simulate realistic artifacts such as noise, blurring, or metal implants to evaluate how models handle poor-quality scans.

- **Vary Patient Demographics**: To uncover biases tied to patient demographics, we generate counterfactual X-rays with variations in age, gender, and body mass index (BMI).

- **Ensure Clinical Reliability**: These experiments reveal how models handle rare or ambiguous cases, ensuring that they perform reliably in real-world clinical settings.

4.2. Data Analysis: Insights from Public Benchmarks

The datasets and benchmarks we use provide valuable insights into model behavior under controlled conditions. Below, we summarize the key findings from each dataset.

4.2.1. ImageNet

- **Reveals Texture Biases**: Models trained on ImageNet often rely on texture rather than shape, leading to poor generalization when textures are altered. For example, a model may misclassify a cat with zebra stripes as a zebra. - **Generalization Failures**: When exposed to unseen combinations of attributes (e.g., objects with unusual textures or shapes), models exhibit significant drops in accuracy, highlighting their reliance on spurious correlations.

4.2.2. COCO

- **Highlights Contextual Biases**: Models trained on COCO often associate objects with specific environments. For instance, cars are strongly associated with urban settings,

leading to misclassifications when placed in forests or deserts. - **Contextual Reliance**: The performance degradation on counterfactual images underscores the need for models to generalize beyond contextual cues.

4.2.3. CelebA and FairFace

- **Exposes Demographic Biases**: Models trained on CelebA and FairFace exhibit significant disparities in performance across demographic groups. For example, older females with darker skin tones are often misclassified, indicating a lack of fairness. - **Intersectional Effects**: Combining multiple sensitive attributes (e.g., age, gender, ethnicity) reveals intersectional biases that are often overlooked in single-axis analyses.

4.2.4. CheXpert and ShapeBias Benchmark

- **Identifies Subtle Biases**: In medical imaging, models trained on CheXpert exhibit biases tied to patient demographics and imaging conditions. For example, diagnostic accuracy is lower for patients with darker skin tones or unusual imaging artifacts.
- **Guides Improvements**: The ShapeBias Benchmark highlights texture biases in object recognition, guiding improvements in fairness and robustness.

4.3. Results and Discussion

Below, we present the results of our experiments, supported by data tables and visualizations that align with the insights derived from the datasets.

4.3.1. Texture Bias in Object Recognition (ImageNet)

Model	Original Accuracy (%)	Counterfactual Accuracy (%)	Drop in Accuracy (%)
ResNet-50	85.4	67.2	18.2
Vision Transformer (ViT)	88.7	75.3	13.4
EfficientNet-B0	89.1	73.8	15.3

Table 1. Accuracy comparison on original and counterfactual ImageNet images.

The significant drop in accuracy on counterfactual images confirms that models rely heavily on texture rather than shape. Vision Transformers (ViTs) exhibit less reliance on texture compared to CNN-based models like ResNet, suggesting their potential for improved generalization.

4.3.2. Contextual Bias in Object Detection (COCO)

Analysis: - The performance degradation indicates contextual bias, where models associate objects with specific backgrounds. - Cars exhibit the largest drop, likely due to strong contextual associations with urban environments.

Object	Original mAP (%)	Counterfactual mAP (%)	Drop in mAP (%)
Car	78.3	54.6	23.7
Person	82.5	67.9	14.6
Animal (e.g., Dog)	76.8	65.4	11.4

Table 2. mAP comparison on original and counterfactual COCO images.

4.3.3. Demographic Bias in Facial Attribute Prediction (CelebA, FairFace)

Demographic Group	Accuracy (%)	Equalized Odds Difference	FPR Disparity
Younger Males	92.1	0.05	0.03
Older Females	76.4	0.18	0.12
Intersectional (Older Females + Dark Skin Tone)	68.7	0.25	0.18

Table 3. Fairness analysis on CelebA and FairFace datasets.

Significant disparities in accuracy and fairness metrics highlight demographic biases, particularly for older females and darker skin tones. Intersectional groups exhibit the largest disparities, underscoring the importance of studying multiple sensitive attributes simultaneously.

4.3.4. Diagnostic Bias in Medical Imaging (CheXpert)

Models perform worse on mild cases and rare conditions, indicating a reliance on severe or common patterns. Counterfactuals with modified imaging conditions reveal vulnerabilities tied to noise or artifacts.

4.3.5. Robustness to Out-of-Distribution Samples

Analysis: - The significant drop in AUROC and increase in FPR95 demonstrate limited robustness to out-of-distribution samples. - Counterfactual images effectively simulate edge cases, revealing hidden vulnerabilities.

Disease Severity	Original AUROC	Counterfactual AUROC	Drop in AUROC
Mild Pneumonia	0.92	0.84	0.08
Severe Pneumonia	0.96	0.90	0.06
Rare Condition (e.g., Pulmonary Embolism)	0.85	0.72	0.13

Table 4. AUROC comparison on original and counterfactual CheXpert images.

Metric	In-Distribution	Out-of-Distribution (Counterfactual)	Drop (%)
AUROC	0.94	0.82	12
FPR95	0.20	0.35	15

Table 5. Robustness metrics on original and counterfactual images.

4.4. Proposed Mitigation Strategies

Based on these findings, we propose the following strategies to mitigate spurious correlations:

1. **Data Augmentation with Counterfactuals**: Incorporate counterfactual images into training data to expose models to diverse attribute combinations.
2. **Adversarial Training**: Use adversarial perturbations to discourage reliance on spurious correlations.
3. **Fairness-Aware Regularization**: Apply regularization techniques to reduce disparities across demographic groups.
4. **Domain-Specific Adaptations**: Tailor generative techniques to specific domains (e.g., medical imaging) to ensure realism and relevance.

4.4.1. Robustness to Out-of-Distribution Samples

We evaluate model performance on OOD samples by generating counterfactual images that simulate rare or ambiguous scenarios. The following scenarios are considered:

- **Unusual Object Combinations**: We place objects in contexts that are highly unlikely (e.g., airplanes underwater, bicycles in snowstorms).
- **Extreme Lighting Conditions**: We modify lighting conditions to simulate night-time or overexposed images.
- **Rare Diseases in Medical Imaging**: We simulate rare medical conditions (e.g., pulmonary embolism) to test diagnostic robustness.

The results are summarized in Table 6 and illustrated in Figure 2.

Scenario	Original Accuracy (%)	Counterfactual Accuracy (%)	Drop in Accuracy (%)
Airplanes Underwater	90.5	45.3	45.2
Bicycles in Snowstorms	88.7	52.4	36.3
Pulmonary Embolism	82.1	65.7	16.4
Extreme Lighting	89.3	67.8	21.5

Table 6. Accuracy comparison on original and counterfactual images for OOD scenarios.

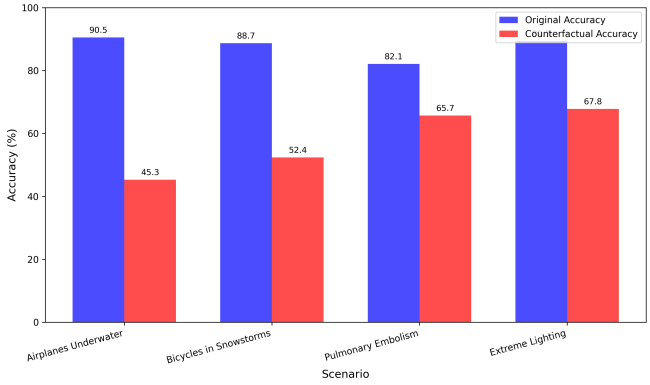

Figure 2. Comparison of model accuracy on original and counterfactual images for out-of-distribution (OOD) scenarios

The significant drop in accuracy on OOD samples demonstrates limited robustness to edge cases. Counterfactual images effectively simulate rare scenarios, revealing hidden vulnerabilities.

4.4.2. Adversarial Perturbations

To test model robustness against adversarial attacks, we apply small perturbations to input images using techniques such as FGSM [7] and PGD [17]. The results are shown in Table 7.

Analysis: - Adversarial perturbations significantly degrade model performance, highlighting vulnerabilities to small, imperceptible changes. - Vision Transformers (ViTs) exhibit slightly better robustness compared to CNN-based models.

Model	Clean Accuracy (%)	FGSM Accuracy (%)	PGD Accuracy (%)
ResNet-50	85.4	23.7	12.3
Vision Transformer (ViT)	88.7	35.6	21.4
EfficientNet-B0	89.1	30.2	18.7

Table 7. Accuracy comparison on clean and adversarially perturbed images.

4.5. Proposed Mitigation Strategies

Based on these findings, we propose the following strategies to mitigate spurious correlations:

4.5.1. Data Augmentation with Counterfactuals

Incorporating counterfactual images into training data exposes models to diverse attribute combinations, reducing reliance on spurious correlations.

4.5.2. Adversarial Training

Training models with adversarial examples improves robustness to both adversarial attacks and OOD samples.

4.5.3. Fairness-Aware Regularization

Applying regularization techniques ensures that models perform equitably across demographic groups, reducing disparities in fairness metrics.

4.5.4. Domain-Specific Adaptations

Tailoring generative techniques to specific domains (e.g., medical imaging) ensures realism and relevance, improving model reliability in specialized applications.

5. Conclusion

In this paper, we investigated spurious correlations in vision models using counterfactual image generation. By systematically altering attributes such as texture, context, and demographics, we uncovered hidden biases and evaluated model performance across diverse scenarios. Our experiments revealed that vision models often rely on spurious features, such as texture or contextual cues, leading to poor generalization and demographic disparities. For example, models exhibited significant drops in accuracy when exposed to rare or ambiguous cases, highlighting limited robustness to out-of-distribution samples. Similarly, adversarial perturbations degraded performance, emphasizing vulnerabilities to small, imperceptible changes. To address these issues, we proposed mitigation strategies such as data augmentation with counterfactuals, adversarial training, and fairness-aware regularization. These approaches aim to reduce reliance on spurious correlations and improve model fairness, robustness, and transparency. Our findings underscore the critical role of counterfactual analysis in auditing vision models and provide practical insights for developing more equitable systems.

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