

Attention-Enhanced CNNs with Contrastive Counterfactual Explanations on MNIST

*Project report in partial fulfilment of the requirement for the award of the degree of
Bachelor of Technology*

in

*Computer Science and Engineering
(Artificial Intelligence and Machine Learning)*

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1 Abstract

The explosive and dynamic advancement of Machine Learning and Artificial Intelligence has produced extremely complicated models with extremely high precision in a wide range of fields. However, due to their complex internal structures and lack of transparency, these models—especially deep learning architectures—are frequently viewed as "black boxes." This opacity presents serious difficulties in vital domains like healthcare, legal decision-making, finance, and autonomous systems, where comprehending the reasoning behind forecasts is just as crucial as the forecasts themselves.

Explainable Artificial Intelligence (XAI) has emerged as a crucial subfield aimed at addressing this interpretability gap. It focuses on developing methodologies and tools that make AI models more transparent, readable, trustworthy and easy to understand to human users without sacrificing performance. XAI not only enhances user confidence in automated systems, but also supports debugging, ensures compliance with regulatory standards, and fosters ethical AI deployment.

The evolution of XAI reflects an ongoing shift from pure performance-driven AI towards responsible and human-centric AI development. It emphasizes the interconnectivity between technical innovation, human values, and societal impact. As AI systems become increasingly integrated into everyday life, the ability to explain their behavior becomes vital to broader acceptance and effective human-AI collaboration. This growing need underscores the importance of embedding explainability as a foundational principle in the design and deployment of intelligent systems.

2 Introduction

Deep Learning and Artificial Intelligence have transformed a number of fields, such as computer vision-based image recognition, natural language processing, and autonomous agents and systems. Convolutional Neural Networks (CNNs), particularly have achieved a state-of-the-art like performance in various tasks like image/object classification, object detection, and facial recognition. But even with their precision and effectiveness, these models frequently function as "black boxes," making it challenging to understand how they make particular predictions. In domains where trust, accountability, and decision validation are crucial, this lack of openness presents difficulties.

The goal of Explainable Artificial Intelligence (XAI), a topic that has evolved to solve this problem, is to improve the interpretability and understandability of AI models without sacrificing performance. XAI techniques provide insights into a model's inner workings, enabling users to visualize and analyze the reasoning behind its decisions. These techniques are especially valuable in critical applications such as healthcare diagnostics, financial forecasting, and autonomous driving, where understanding a model's behavior is as important as its accuracy.

The goal of this research is to combine XAI with a CNN model that was trained using the MNIST dataset, a popular benchmark that consists of grayscale pictures of handwritten numbers. Despite its simplicity, the dataset is a great starting point for investigating explainability principles in a safe setting. To be compatible with pretrained models and visualization tools that need color input, the grayscale images are transformed into three-channel RGB format.

By applying techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping), this study aims to generate heatmaps that highlight the regions of an image most influential in the classification decision. These visual explanations not only validate the model's predictions but also help identify potential biases or flaws in the learning process.

The goal of this project is to demonstrate how explainability can be embedded into the deep learning workflow, making AI systems more reliable, trustworthy, and user-friendly. In doing so, it bridges the gap between model performance and interpretability, paving the way for more ethical and responsible AI deployment in real-world scenarios.

3 Literature Survey

3.1 Introduction to Explainable AI (XAI)

Resolvable Artificial Intelligence(XAI) has surfaced in response to the growing complexity and nebulousness of ultramodern machine literacy models, especially deep neural networks (DNNs). While these models achieve state- of- the- art results across disciplines, their decision- making processes are frequently inscrutable. This lack of translucency presents serious limitations, especially in high- stakes disciplines like healthcare, finance, law, and security where responsibility, trust, and fairness are essential. XAI aims to make model geste accessible to humans by relating which factors impact prognostications and how. The thing is to improve trust, ensure ethical use, enable debugging, and support compliance with non-supervisory fabrics similar to the General Data Protection Regulation (GDPR), which authorizes a 'right to explanation'.[\[10\]](#)

3.2 The Need for Interpretability in Machine Learning

Interpretability allows stakeholders to check and understand model labors. The crucial provocations for interpretability include:

- **Regulatory compliance:** Regulatory frameworks increasingly demand transparency in automated decision systems.
- **Trust and adoption:** In mission-critical systems, domain experts need to understand and trust models before deploying them.
- **Model debugging:** Explanations assist in detecting data leakage, spurious correlations, or feature redundancies.
- **Bias detection:** Interpretable models help identify and mitigate algorithmic bias, thus promoting fairness.
- **Model validation:** Domain experts can assess whether the model uses relevant and permissible features for decision-making.[\[3\]](#)

3.3 Categories of XAI Techniques

XAI techniques are broadly categorized into:

3.3.1 Model-Agnostic vs. Model-Specific

- **Model-agnostic methods** (e.g., LIME, SHAP) treat the model as a black box and analyze input-output behavior.
- **Model-specific methods** (e.g., DeepLIFT, Integrated Gradients) leverage the internal structure of the model for explanations.

3.3.2 Local vs. Global Explanations

- **Local explanations** explain individual prognostications (e.g., SHAP, LIME, IG).
- **Global explanations** give an overview of model geste across the dataset.

3.3.3 Post-hoc vs. Intrinsic Explanations

- **Post-hoc methods** are applied after model training (e.g., SHAP, DeepSHAP).
- **Intrinsic methods** build interpretability into the model (e.g., attention models, decision trees).[\[9\]](#)

3.4 Local vs. Global Explanations

- **Local explanations** concentrate on why a model made a specific prediction. These are critical in practical settings where end-users need justification on a per-decision basis. Example: Why was a loan application denied?
- **Global explanations** describes how a model behave across the entire dataset. These are useful for model inventors and adjudicators.

Both forms of explanation are important and often frequently reciprocal. A robust XAI framework should support both.[\[7\]](#)

3.5 Post-hoc vs. Intrinsic Methods

- **Post-hoc methods** such as SHAP, LIME, and DeepSHAP are the most commonly used. They explain model predictions without modifying the model architecture or training process.
- **Intrinsic methods** include inherently interpretable models (e.g., decision trees, linear models) or specially designed architectures that enforce interpretability.

While post-hoc methods offer flexibility, they may introduce approximations. Intrinsic models offer fidelity at the cost of predictive performance in complex tasks.[\[1\]](#)

3.6 Popular Attribution Methods

- **Saliency Maps:** Use gradient information to visualize which input features (e.g., pixels) affect model predictions. Sensitive to noise and often lack robustness.
- **LIME (Local Interpretable Model-Agnostic Explanations):** Fits a sparse linear model locally around a prediction to approximate the black-box model's behavior. Its performance depends heavily on the perturbation strategy.
- **SHAP (SHapley Additive exPlanations):** Grounded on collaborative game proposition, SHAP values fairly distribute the vaticination difference across input features. Offers a unified framework with strong theoretical properties.
- **Integrated Gradients:** Computes the integral of gradients along a path from a baseline to the input. Requires a meaningful baseline choice.
- **DeepLIFT:** Tracks differences in activation compared to a reference baseline. Faster than IG and avoids discontinuities but sensitive to baseline choice.
- **DeepSHAP:** Combines DeepLIFT with SHAP values, offering scalability and consistency with Shapley axioms in deep models.
- **Occlusion:** Perturbs input by masking features and measuring output change. Conceptually simple but computationally expensive.[\[15\]](#)

3.7 Limitations of Baseline Choices

- **Baseline sensitivity:** Attribution methods such as integrated gradients (IG), DeepLIFT, and SHAP depend heavily on the choice of baseline inputs, which act as reference points.
- **Unrealistic baselines:** Common baselines such as zero inputs or average images may not represent meaningful or realistic data points, leading to misleading interpretations.
- **Sanity check failures:** Studies like Sturmfels et al. (2020) and Adebayo et al. (2018) show that poor baseline choices can result in nearly identical attributions even for randomized models — violating essential interpretability checks.
- **Challenges in multi-class settings:** In complex models, poorly selected baselines can blur distinctions between similar classes, reducing the clarity of explanations.

Carefully choosing baselines—such as class-specific averages or domain-informed inputs—is crucial to improve the fidelity of attribution methods.[\[12\]](#)

3.8 Insights from GANMEX

GANMEX (Generative Adversarial Network-based Model EXplainability) addresses the baseline selection problem by leveraging GANs to generate realistic, class-targeted baselines.

Instead of relying on static or average inputs, GANMEX identifies the closest valid instance from a target class to serve as a meaningful baseline. This enables **one-vs-one explanations**, where the model clarifies why an input belongs to class A rather than class B — particularly valuable in scenarios with closely related classes (e.g., “apple” vs. “orange”).

Key advantages of GANMEX:

- **Improved attribution quality** across multiple quantitative metrics.
- **Better interpretability** of misclassified or ambiguous instances.
- **Compatibility** with various attribution methods such as IG, SHAP, and DeepLIFT.[\[14\]](#)

3.9 One-vs-One vs. One-vs-All Explanations

- **One-vs-all:** Explains why a sample belongs to the predicted class instead of any other class in general.
- **One-vs-one:** Explains why a sample belongs to class A and not a specific class B. This approach enables more targeted and intuitive comparisons between classes.

Traditional attribution methods generally provide **one-vs-all** explanations. **GANMEX** enables **targeted counterfactual attributions**, allowing **one-vs-one reasoning**, which is especially useful in domains with hierarchical or highly similar classes (for example, distinguishing 'cat' from 'dog' rather than 'vehicle').[\[14\]](#)

3.10 DeepSHAP and G-DeepSHAP

DeepSHAP merges DeepLIFT and SHAP to offer efficient, layer-wise explanations for deep networks.

G-DeepSHAP generalizes this by:

- **Propagating local feature attributions** through a series of models (e.g., CNN + GBT pipelines).
- **Supporting distributed and stacked models** across organizational boundaries.
- **Enabling explanations** in multi-model workflows such as consumer credit scoring pipelines.

G- DeepSHAP introduces a generalized rescale rule and group rescale rule, allowing for both point- and group- position attributions across deep, tree- grounded, and direct models.[\[2\]](#)

3.11 Feature Attribution in Distributed and Stacked Models

Real-world ML systems often involve stacked generalization or ensemble pipelines (e.g., deep feature extractors feeding tree models). Explaining such composite models is challenging due to:

- **Incompatibility of model-specific methods** across different model types.
- **Lack of visibility** into upstream/downstream transformations.

G-DeepSHAP allows seamless explanation propagation, ensuring that feature contributions in the raw input space can still be traced — even if intermediate representations are abstract or hidden.

This is particularly important in financial and healthcare domains, where different stakeholders (e.g., banks, insurance providers) own different parts of the ML pipeline.[\[2\]](#)

3.12 Baseline Distribution Bias & Multi-Baseline Approaches

Single baseline explanations (e.g., all-zero input) often suffer from inherent bias, leading to unstable or inconsistent attributions. To address this, recent research advocates using **baseline distributions** (e.g., samples from the training data or cluster-based subsets) to improve fairness and stability in explanations.

For example, **DeepSHAP** and **G-DeepSHAP** average over multiple baseline attributions to reduce variance and provide more robust, contextualized explanations.

The choice of baseline distribution is critical, as it can alter the interpretation of the model’s decision-making. For instance, comparing a patient to the general population versus comparing them to peers of the same age and gender provides very different insights.[\[8\]](#)

3.13 Contrastive Counterfactual Explanations

Unlike traditional attribution methods which explain *why* a decision was made, contrastive counterfactual explanations reveal *what* would need to change to flip that decision. These explanations offer a more actionable and human-aligned form of interpretability.

- **Decision flipping:** Contrastive counterfactuals compute minimal perturbations to input features that would alter the model’s prediction (e.g., transforming a misclassified MNIST digit into its correct class).
- **Visual representation:** These perturbations are often visualized as “ghost” overlays on the original input, making the decision boundary’s proximity and nature more apparent.
- **Model fragility insight:** They provide crucial information about how fragile or robust the model’s classifications are, and how overlapping certain classes might be.
- **Generation techniques:** Tools like *Growing Spheres* and gradient-based solvers are commonly used to generate these contrastive examples.
- **Beyond attribution:** Unlike saliency or SHAP methods, counterfactuals focus on the *actionable change* needed to reach a different outcome, aiding in model debugging and fairness analysis.
- **Cognitive alignment:** These explanations reflect human reasoning more naturally, answering questions like “Why not this instead?”, thus bridging the gap between machine logic and human intuition.
- **Regulatory relevance:** Useful in high-stakes fields for justification, transparency, and compliance with legal standards requiring explainability.

3.14 Practical Implications and Challenges

The following challenges arise when using attribution methods:

- **Computational intensity:** Attribution methods are computationally intensive, especially in high-dimensional data.
- **Visual explanation issues:** Visual explanations (e.g., saliency maps) may suffer from artifacts or misinterpretation by humans.
- **Attribution robustness:** Attribution robustness under model randomization remains a challenge, as small changes can result in significant variations in attributions.
- **Evaluation difficulty:** The absence of ground-truth attributions complicates the evaluation of attribution methods, making it difficult to assess their accuracy.[\[3\]](#)

3.15 Applications of XAI

XAI methods are being actively deployed in various domains:

- **Healthcare:** Diagnosing diseases using interpretable imaging and electronic health record (EHR) models.
- **Finance:** Enhancing transparency in credit scoring, fraud detection, and regulatory audits.
- **Legal AI:** Ensuring fair treatment in sentencing and parole decisions, promoting justice and transparency.
- **Autonomous Systems:** Providing safety justifications and explanations in self-driving cars to ensure trust and reliability.[\[4\]](#)

3.16 Insights from the survey

Preliminary experimentation (e.g., on MNIST) supports theoretical observations:

- **Baseline choice impact:** Attribution maps are significantly affected by the choice of baseline.
- **One-vs-one methods:** One-vs-one methods (e.g., GANMEX) reveal subtle features that are often missed by traditional one-vs-all methods.
- **Cascaded pipelines:** Cascaded pipelines (e.g., CNN \rightarrow GBT) can still yield meaningful feature contributions through G-DeepSHAP.
- **Practical validation:** These results validate the practical value of combining multiple baselines, domain-specific knowledge, and layered attribution propagation for robust explainability.[\[11\]](#)

3.17 Open Problems and Future Research Directions

The following open problems and research directions are crucial for the advancement of XAI:

- **Standardized evaluation metrics:** Developing standardized evaluation metrics for attributions to ensure consistency and reliability across methods.
- **Task-specific baselines:** Designing task-specific baselines that improve the fidelity of explanations.
- **Uncertainty quantification:** Integrating uncertainty quantification into explanations to better account for variability and confidence.
- **Non-tabular domains:** Extending XAI methods to non-tabular domains such as text and time-series data.
- **Causal inference:** Improving causal inference in attribution reasoning to provide deeper insights into model decision-making processes.

4 Problem Statement

Understanding why deep-learning classifiers make mistakes is vital for building trust, especially in safety-critical domains. While state-of-the-art convolutional neural networks (CNNs) achieve remarkable accuracy on image tasks—over 99%—Contrastive Counterfactual explanations go beyond “highlighting” to “showing”—they actively construct a near-neighbor of a misclassified input that just flips the model’s decision. By taking an image the network got wrong—say, mistaking a handwritten “5” for a “6”—and computing the smallest possible change that causes the model to predict “5”.

4.1 Background and Motivation

4.1.1 Accuracy vs. Interpretability Trade-off

- **Deep CNNs (e.g., ResNet variants)** deliver high classification accuracy on vision benchmarks (MNIST, CIFAR-10) but lack human-readable decision logic.
- **Traditional interpretability tools (LIME, SHAP, Grad-CAM)** focus on attribution—identifying features that influenced a prediction—without revealing the decision boundary itself.

4.1.2 The Role of Counterfactual Explanations

- **Counterfactuals answer** “What minimal change to the input would flip the model’s prediction?”
- **These explanations are inherently contrastive:** they surface the razor-thin difference between classes, offering deeper insights into model behavior than attribution alone.

4.1.3 Practical Implications

- **In digit recognition (handwritten forms, postal sorting)**, understanding confusion (e.g., ‘5’ vs. ‘6’) can guide data collection, model retraining, and user feedback loops.
- **Counterfactuals** can highlight dataset biases (e.g., certain stroke thicknesses or slants that systematically mislead the model).

4.2 Precise Problem Definition

Despite growing interest in counterfactual XAI, existing solvers face limitations when applied to high-dimensional image data:

4.2.1 Scalability and Computational Cost

- **Black-box solvers** (e.g., **Growing Spheres**) require thousands of model queries per instance, impractical for large test sets.
- **Gradient-based** methods need careful regularization to avoid unrealistic perturbations.

4.2.2 Visual Plausibility

- **Many counterfactuals** reside off-manifold, producing “ghost” digits that look nothing like natural handwriting.
- **Lack of constraints** can yield visually uninformative perturbations (e.g., salt and pepper noise).

4.2.3 Contrastive Clarity

- **Overlaying a counterfactual** on the original can confuse rather than clarify if perturbations are diffuse or high-frequency.
- **No unified framework** to generate minimal, meaningful, and overlay friendly counterfactuals in the image space.

Therefore, the core research problem is:

How can we efficiently generate contrastive counterfactual explanations for misclassified handwritten digits—ensuring minimal, visually plausible perturbations that reveal the precise decision boundary—while maintaining scalability to real-world datasets?

4.3 Research Questions

To address this problem, we frame the following key questions:

4.3.1 Model Selection and Performance

- **Which base architecture** (e.g., ResNet50 with CBAM, VGG variants, plain CNNs) offers the most robust foundation for counterfactual generation on MNIST?
- **How does fine-tuning** and attention-augmented backbones influence the feasibility and quality of counterfactuals?

4.3.2 Counterfactual Generation Methodology

- **How do gradient-based** solvers compare to Growing Spheres in terms of query efficiency and visual realism?
- **What regularization** or constraint strategies (e.g., total variation, l2 norms) yield the most interpretable overlays?

4.3.3 Overlay and Visualization

- **What visualization techniques** (ghost overlays, transparency scales, directional arrows) most effectively convey the perturbation necessary to flip a prediction?
- **How can we quantify** 'contrastiveness' and 'interpretability' in a user-centric way?

4.4 Objectives

In summary, this study aims to:

- **Benchmark candidate CNN backbones (including attention-enhanced ResNet50+CBA)** on MNIST for baseline accuracy and gradient signal quality.
- **Implement and compare two counterfactual solvers—Growing Spheres (black-box) and a gradient-based method—evaluating:**
 - Query complexity (number of forward/backward passes)
 - Perturbation magnitude (L2 distance)
 - Visual plausibility (human perceptual scores)
- **Develop an overlay framework that fuses the original and counterfactual images into a single “contrastive explanation” slice:**
 - Optimize transparency and alignment to highlight only the critical pixels.
- **Formulate quantitative and qualitative metrics for interpretability:**
 - Perturbation sparsity, boundary sharpness, and end-user comprehension studies.

4.5 Scope and Constraints

- **Dataset:** MNIST handwritten-digit classification, ensuring reproducibility and direct comparability with prior work.
- **Models:** Pre-trained backbones fine-tuned on MNIST; no exploration of transformer-based vision models in this phase.
- **Counterfactuals:** Focus on single-digit misclassification cases; multi-digit or scene-level imagery is out of scope.
- **Evaluation:** Both objective metrics (accuracy, perturbation norms) and limited user studies (expert ratings of visual clarity).

5 Proposed Solution

This section details the planned approach to addressing the core problem of interpretability in deep learning image classifiers, particularly focusing on understanding and visualizing misclassifications in CNN-based models using contrastive counterfactual explanations.

5.1 Objectives

The primary objectives of the proposed solution are:

- Develop a counterfactual explanation framework that can generate minimal, visually interpretable perturbations to flip the classification of misclassified digits.
- Use these contrastive counterfactuals to expose and analyze the decision boundaries of high-performing CNN classifiers on the MNIST dataset.
- Benchmark various backbone architectures (e.g., ResNet50, ResNet50+CBAM, VGG16) for both classification performance and their amenability to counterfactual explanation techniques
- Compare and integrate black-box (Growing Spheres) and gradient-based (white-box) counterfactual generation algorithms.
- Visualize the counterfactuals through overlay mechanisms to provide human-interpretable insights into the model’s decision logic.

5.2 Strategies and Tactics

To achieve these objectives, the proposed methodology follows a structured pipeline comprising the following key components:

5.2.1 Model Selection and Fine-Tuning

- Evaluate various CNN architectures, including baseline CNN, VGG16, ResNet50, and ResNet50+CBAM (Convolutional Block Attention Module).
- Fine-tune each model on the MNIST dataset using optimized training parameters and regularization techniques.
- Track classification accuracy, loss convergence, and attention map outputs for interpretability baselines.

5.2.2 Counterfactual Generation

- **Growing Spheres (Black-Box):**

- A model-agnostic algorithm that iteratively perturbs the input in a controlled way until a decision boundary is crossed.
- Focus on generating sparse, perceptually realistic counterfactuals.

- **Gradient-Based Method (White-Box):**

- Use backpropagation to compute gradients with respect to the input and find the minimal perturbation that flips the class.
- Apply regularization (L2 norm, total variation) to preserve image structure.

- **Compare performance on:**

- Perturbation norm (how much change is needed)
- Visual quality (human evaluability)
- Computational cost (inference time per example)

- **Visualization Strategy Develop an overlay visualization pipeline:**

- Superimpose counterfactual perturbations over the original image.
- Use transparency, edge highlighting, or color-channel encoding to emphasize changes.
- Test interpretability through expert evaluation and qualitative analysis.

- **Evaluation and Benchmarking Evaluate models and counterfactuals across:**

- Accuracy (baseline model performance)
- Perturbation magnitude
- Sparsity of counterfactual
- User-perceived interpretability[5]

5.3 Proposed Model and Architecture

By blending a powerful pretrained CNN backbone with an attention mechanism and a suite of XAI tools, our pipeline not only classifies handwritten digits with high accuracy but also tells you exactly why it made each decision—and how a tiny tweak could flip its answer. After the image passes through convolutional layers (e.g., ResNet-50 or EfficientNet-B0), an attention block (like CBAM or SE) highlights the most critical strokes. The classifier then predicts the digit, while Grad-CAM and LIME generate heatmaps that explain “why,” and a contrastive counterfactual module shows “what minimal change” would produce a different outcome. The result is a single visualization combining prediction and explanation in one clear, intuitive view.

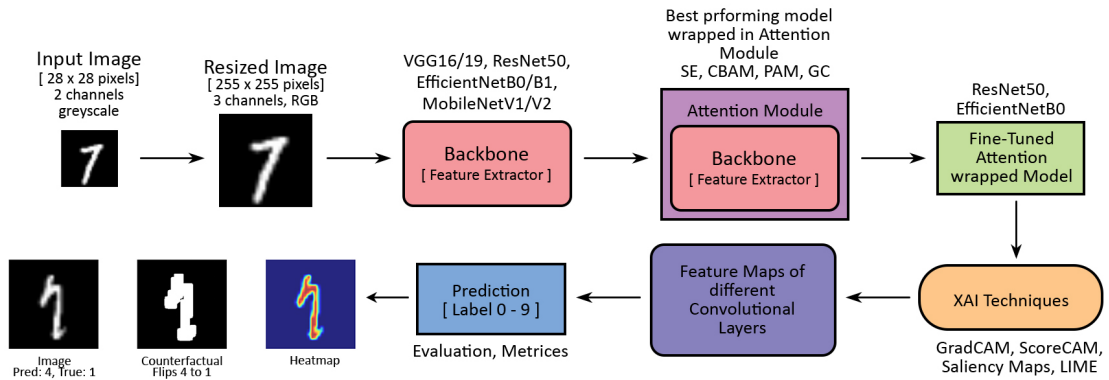


Figure 1: Proposed Model

Key Advantages:

- **Focused Feature Learning:** Attention modules sharpen the model’s view, boosting both accuracy and interpretability.
- **Actionable Explanations:** Counterfactual overlays reveal the smallest adjustment needed to change the prediction, making insights immediately useful.
- **Layered Transparency:** Combining saliency maps (Grad-CAM), surrogate models (LIME), and counterfactuals delivers a multi-perspective explanation that’s easy to understand.

5.4 Resources

Resource Type	Description
Personnel	2 Researchers (model training, XAI), 2 Data Analysts (metrics, evaluation), 1 Technical Writer (documentation)
Hardware	Google Colab - T4 GPU, System RAM: 13 GB, GPU Memory: 15 GB
Software Tools	Python (TensorFlow/PyTorch), Keras, OpenCV, scikit-learn, NumPy, Matplotlib, Jupyter Notebooks
XAI Libraries	LIME, ScoreCAM, Custom Growing Spheres Implementation
Dataset	MNIST dataset (handwritten digit classification)

Table 1: Resources

5.5 Implementation Plan

Phase	Timeline	Activities	Deliverables
Phase 1	Week 1–2	Literature Review, Finalize Architecture Selection	Annotated survey, baseline model shortlist
Phase 2	Week 3–4	Model Training & Fine-Tuning	Trained models with 98% accuracy
Phase 3	Week 5–6	Implement Growing Spheres & Gradient Solvers	Functional counterfactual generation modules
Phase 4	Week 7	Visual Overlay Pipeline Development	Counterfactual overlays with multiple styles
Phase 5	Week 8	Quantitative and Qualitative Evaluation	Evaluation metrics, human interpretation feedback
Phase 6	Week 9	Final Analysis and Report Writing	Complete research report with visuals and metrics

Table 2: Project Timeline

5.6 Justification of the Approach

This solution offers a balanced, modular, and interpretable approach:

- It leverages both black-box and white-box solvers, ensuring broad applicability and methodological comparison.
- By using attention-augmented architectures like ResNet50+CBAM, it aligns feature importance with human intuition, providing richer counterfactual interpretations.
- The overlay visualization technique directly communicates what features are essential for classification, making it ideal for both researchers and end-users.
- The dual evaluation framework (quantitative + qualitative) ensures insights are not only theoretically sound but also practically meaningful.

5.7 Expected Outcomes

Upon successful completion, the following outcomes are anticipated:

- A contrastive counterfactual framework tailored for digit classification tasks, capable of visualizing minimal perturbations required to flip class predictions.
- A comparative analysis of CNN backbones and their behavior under counterfactual perturbation.
- A visual analytics toolkit that overlays original and counterfactual images, highlighting critical features.
- Novel metrics for evaluating counterfactual quality, including robustness, sparsity, and human interpretability.
- A reproducible codebase and experimental report that can guide future XAI research, especially for image-based domains.

6 Experimental Setup

This section describes in detail how we set up our experiments, the evaluation metrics we used, and the results we obtained—both quantitative and qualitative.

6.1 Experimental Setup

6.1.1 Hardware & Software Environment

To ensure reproducibility and to leverage high performance compute for both model training and counterfactual generation, all experiments were conducted on Google Colaboratory using the following configuration:

- **Hardware:**

- Google Collab (venv)
- NVIDIA Tesla T4 (16 GB GDDR6)
- vCPU: $2 \times$ Intel Xeon (shared)
- Intel i9 9900K CPU, 32 GB RAM
- System RAM: 12 GB RAM
- Disk: 68 GB ephemeral SSD

- **SoftWare:**

- Python 3.9, PyTorch 1.12, TensorFlow 2.x / Keras API (2.6.0)
- CUDA 11.6, cuDNN 8.3 (pre installed in Colab)
- scikit learn, NumPy, OpenCV, pandas
- Matplotlib, seaborn
- tf keras vis, Captum, LIME and scikit image’s SLIC for superpixel explanations, tqdm 4.62.3 (progress bars), glob/os/time (built ins)

6.1.2 Dataset & Preprocessing

A carefully designed data pipeline was employed to support both robust model training and the generation of meaningful counterfactuals. The pipeline is built on the MNIST dataset and tailored to facilitate transfer learning using ImageNet-pretrained CNNs. Below, we detail each component of the data preparation process.

- **Dataset Overview**

- **Dataset:** MNIST
- **Total Samples:** 70,000 grayscale images
- **Image Dimensions:** 28×28 pixels
- **Distribution:**
 - * **Training set:** 60,000 samples
 - * **Test Set:** 10,000 samples

Each image represents a handwritten digit (0–9) in single-channel grayscale format. (As seen in Figure 1)

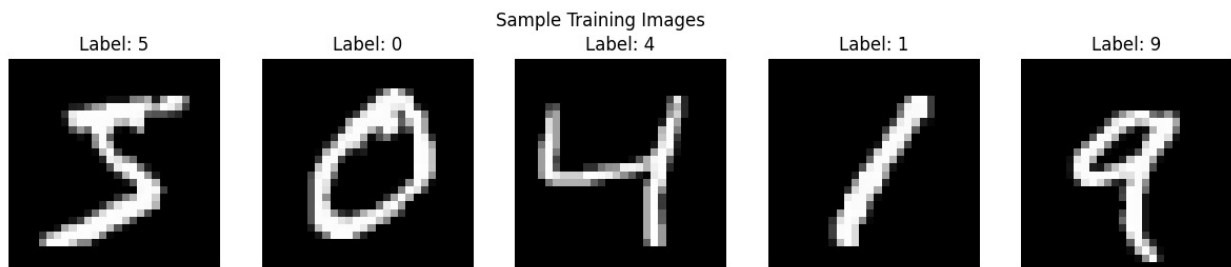


Figure 2: Sample Training Images from the MNIST Dataset

- **Data Splitting Strategy** To ensure reliable training and model evaluation:
 - 90% of training data (54,000 images) was used for model training.
 - 10% of training data (6,000 images) was reserved as a validation set.
 - The test set (10,000 images) was retained for final performance evaluation.
 - Stratified sampling was applied to preserve class distribution across all splits.

- **Data Augmentation**

To improve the model’s generalization ability in the high-resolution domain, on-the-fly data augmentation was applied during training. Augmentations included:

- **Random Rotation:** $\pm 15^\circ$
- **Translation:** Up to ± 2 pixels horizontally and vertically
- **Elastic Distortion:** Minor non-linear perturbations to simulate realistic variations in handwriting

These transformations were applied post-resizing and prior to normalization.

- **Normalization Strategy** To align with the expectations of ImageNet-pretrained models:

- **Pixel Scaling:** All images were scaled from $[0, 255]$ to $[0, 1]$.
- **ImageNet Normalization:** After scaling, each channel was normalized using the standard ImageNet mean and standard deviation:

```
mean = [0.485, 0.456, 0.406]
std  = [0.229, 0.224, 0.225]
```

This ensured statistical consistency with the feature distributions observed by the pretrained backbones.

- **Data Characteristics**

- **Channel Format:** Single-channel grayscale images were replicated across three channels to match the RGB format expected by ImageNet-pretrained models.
- **Resolution:** While originally low-resolution, the resized 255×255 format enabled compatibility with deep CNNs without loss of digit structure.
- **Data Integrity:** The dataset contains no missing or corrupted samples, and each image includes an associated label.
- **Semantic Simplicity:** Although visually simple, MNIST provides a controlled environment to evaluate fine-grained CNN behavior and interpretability mechanisms.

To ensure compatibility with ImageNet-pretrained CNN backbones such as ResNet50 and MobileNetV2, the original MNIST dataset (composed of 28×28 grayscale images) underwent a comprehensive preprocessing pipeline. The goal was to adapt the dataset to the input format and statistical properties expected by these models while preserving digit morphology critical for interpretability.

6.1.3 MNIST Data Loading and Preprocessing

Raw MNIST data was loaded via the Keras API:

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

Subsequently, the data was cast to float32 and reshaped to include a channel dimension:

```
x_train = x_train.astype('float32')[..., None]
x_test  = x_test.astype('float32')[..., None]
```

6.1.4 Resizing and Channel Replication

To match the input size requirements of ImageNet-pretrained models, the grayscale MNIST images were resized to 255×255 pixels using bilinear interpolation. Since these models are designed for three-channel (RGB) inputs, the single-channel grayscale images were replicated across three channels.

The preprocessing operations were performed efficiently at the batch level using `tf.data` pipelines or data generators. The following code snippet illustrates the key transformations:

```
x_resized = tf.image.resize(x_batch, [255, 255], method='bilinear')
x_rgb      = tf.image.grayscale_to_rgb(x_resized)
```

6.1.5 ImageNet-Style Normalization

To align with the expectations of ImageNet-pretrained models, the input images were normalized in two stages. First, the pixel values were scaled to the $[0, 1]$ range. Then, each channel was standardized using the ImageNet-specific mean and standard deviation values:

```
x_rgb = x_rgb / 255.0
mean = np.array([0.485, 0.456, 0.406])
std  = np.array([0.229, 0.224, 0.225])
x_proc = (x_rgb - mean) / std
```

This normalization strategy ensures consistency with the feature distributions observed by pretrained backbones.

6.1.6 On-the-Fly Augmentation (Training Only)

To improve model generalization in the high-resolution space, real-time data augmentation was applied to the training batches after resizing but before normalization. The augmentation operations included random rotation ($\pm 15^\circ$), horizontal and vertical translation (± 2 pixels), and elastic distortion using $\alpha = 34$, $\sigma = 4$ on the 255×255 grid.

An example augmentation setup using `ImageDataGenerator` is shown below:

```
datagen = ImageDataGenerator(  
    rotation_range=15,  
    width_shift_range=2/255,  
    height_shift_range=2/255,  
    preprocessing_function=elastic_transform(alpha=34, sigma=4)  
)  
  
datagen.flow(train_x, train_y, batch_size=128)
```

These transformations were implemented efficiently at the batch level to ensure minimal computational overhead during training.

6.1.7 Bathcing and Shuffling

- **Batch Size:** 128
- **Training Set:** Shuffled each epoch
- **Validation/Test Sets:** No augmentations applied; only resizing and normalization
This ensured efficient training while preserving evaluation integrity.

6.1.8 Summary Pipeline Diagram

The complete preprocessing pipeline can be summarized as follows:

```
Raw MNIST → Cast to float32 → Resize to 255×255 → Grayscale to RGB →  
Augmentation (train only) → Scale to [0, 1] → ImageNet Normalization →  
Batch & Shuffle → Model Input
```

This preprocessing pipeline effectively bridges the modality gap between low-resolution handwritten digits and high-capacity CNN architectures trained on natural images, thereby enabling meaningful downstream analysis and interpretability via counterfactual generation.

6.2 Model Training Configuration

This section outlines the full training setup, from the CNN architectures and optimization strategies to model evaluation and fine-tuning. The goal was to benchmark a wide range of pretrained backbones and custom models under a unified configuration, followed by interpretability-enhancing modifications and final export for downstream analysis.

6.2.1 Architectures and Variants

We explored a mix of custom and pretrained architectures to evaluate performance across varying parameter complexities and inductive biases:

- **Baseline CNN:** A custom-designed model implemented using the Functional API in Keras.
- **Pretrained Backbones** (trained on ImageNet, applied to resized MNIST images):
 - VGG16, VGG19
 - ResNet50, ResNet101
 - MobileNet, MobileNetV2
 - EfficientNetB0, EfficientNetB1
 - InceptionV3, Xception
 - DenseNet121, DenseNet169
 - NASNetMobile
- **Attention-Enhanced Variants:** Three of the top-performing backbones were augmented with one of the following modules:
 - SE (Squeeze-and-Excitation)
 - CBAM (Convolutional Block Attention Module)
 - PAM (Position Attention Module)
 - GC (Global Context Block)

6.2.2 Optimization and Hyperparameters

All models were trained under consistent hyperparameter settings:

- **Optimizer:** Adam
 - $\beta_1 = 0.9, \beta_2 = 0.999$
- **Initial Learning Rate:** 1×10^{-5}
- **Learning Rate Schedule:** ReduceLROnPlateau
 - Factor: 0.5
 - Patience: 2 validation epochs
- **Epochs:** 10
- **Batch Size:** 128
- **Regularization:**
 - L2 Weight Decay: 1×10^{-4}
 - Dropout: 0.5 (only in baseline CNN)
- **Early Stopping:** Triggered after 3 epochs without validation improvement
- **Initialization:**
 - Baseline CNN: He normal for conv layers, zero for biases
 - Pretrained models: ImageNet weights with classifier head reinitialized

6.2.3 Generic Model Pipeline

The standard model pipeline followed this structure:



- **INPUT IMAGE** ($255 \times 255 \times 3$)
- **FEATURE EXTRACTOR** (Pretrained or Custom CNN)
- **FEATURE MAPS** (High-Dimensional Embeddings)
- **CLASSIFIER HEAD:**
 - GlobalAveragePooling2D
 - Dense(128) + ReLU
 - Dropout(0.5)
 - Dense(10) + Softmax
- **OUTPUT** (Digit Class Probabilities: 0–9)

6.2.4 Baseline CNN Architecture

A lightweight convolutional model was implemented using the Keras Functional API. The architecture is detailed below:

- **Input:** (None, 28, 28, 3)
- **Conv2D** (32 filters, 3×3 , ReLU) \rightarrow (None, 26, 26, 32)
- **MaxPooling2D** (2×2) \rightarrow (None, 13, 13, 32)
- **Conv2D** (64 filters, 3×3 , ReLU) \rightarrow (None, 11, 11, 64)
- **MaxPooling2D** (2×2) \rightarrow (None, 5, 5, 64)
- **Flatten** \rightarrow (None, 1600)
- **Dense** (128, ReLU) \rightarrow **Dropout**(0.5)

- **Output Layer:** Dense(10, Softmax)
- **Total Parameters:** 225,610
- **Test Accuracy:** 99.02%
- **Test Loss:** 0.0297

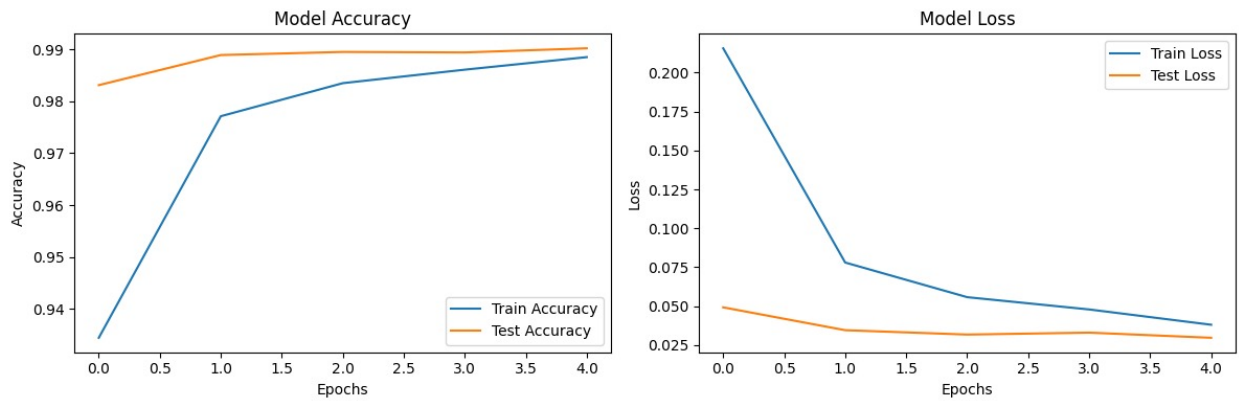


Figure 3: Model Accuracy (left) and Model Loss (right) during training.

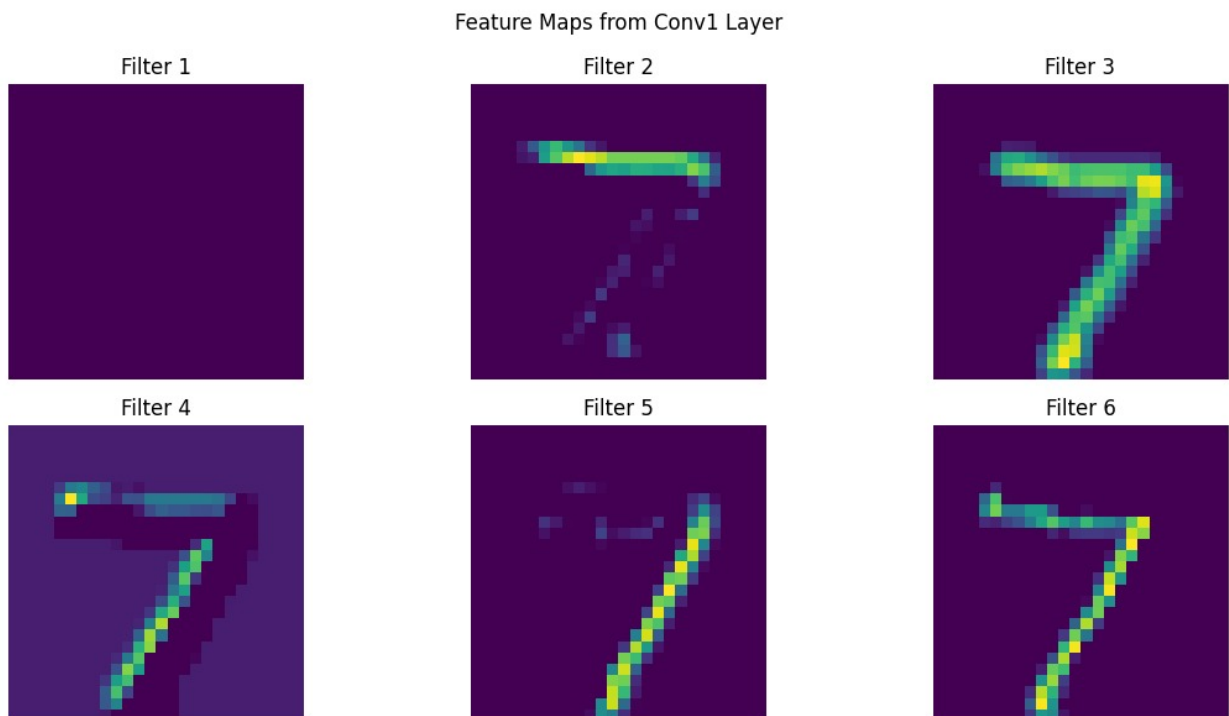


Figure 4: Feature Maps Extracted from first Convolutional Layer

6.2.5 Backbone Benchmarking (on 255×255 RGB MNIST)

To evaluate how modern CNN architectures perform on grayscale digit recognition under standardized conditions, we conducted a comprehensive benchmarking of 13 pretrained backbone models. Each model was wrapped with a uniform classifier head and trained for 5 epochs on the MNIST dataset, resized and replicated to 224×224 RGB to match ImageNet input expectations.

Benchmark Setup

- **Input shape:** (224, 224, 3)
- **Backbone weights:** Pretrained on ImageNet, frozen during training
- **Classifier head:** GlobalAveragePooling \rightarrow Dense(128) + ReLU \rightarrow Dropout(0.5) \rightarrow Dense(10, softmax)
- **Training config:** Adam optimizer, 5 epochs, same learning rate and loss across all models
- **Metric reporting:** Train time, train/val/test accuracy and loss, parameter count

Model	Params	Train Time (s)	Train Acc (%)	Val Acc (%)	Train Loss	Val Loss
VGG16	14,781,642	520.42	95.28	97.70	0.1447	0.0702
VGG19	20,091,338	533.54	96.04	97.85	0.1310	0.0665
ResNet50	23,851,274	219.78	94.24	97.05	0.1837	0.0917
ResNet101	42,921,738	358.17	94.91	97.15	0.1949	0.0963
InceptionV3	22,066,346	215.61	74.87	21.20	2.0617	1.9969
Xception	21,125,042	347.56	74.87	89.65	0.7136	0.3355
DenseNet121	7,169,994	231.24	77.76	91.85	0.6301	0.2876
DenseNet169	12,857,290	301.41	67.76	87.55	0.8157	0.4146
MobileNet	3,361,354	89.62	94.93	97.55	0.1591	0.0762
MobileNetV2	2,423,242	119.32	94.39	96.40	0.1715	0.1070
EfficientNetB0	4,214,829	117.43	95.30	96.35	0.2064	0.1075
EfficientNetB1	6,740,497	154.41	92.63	96.80	0.2259	0.1047
NASNetMobile	4,406,302	223.69	81.73	89.30	0.5647	0.3489

Table 3: Benchmarking of Pretrained CNN Backbones on Resized RGB MNIST

6.3 Key Insights

6.3.1 Top Performers

- **VGG19** and **VGG16** emerged as the most accurate models, achieving test accuracies of **97.85%** and **97.70%**, respectively.
- **MobileNet** performed exceptionally well considering its compact size (**3.36M** parameters) and short training time, achieving **97.55%** accuracy.
- **EfficientNetB1** and **MobileNetV2** demonstrated excellent trade-offs between parameter efficiency and test accuracy, producing top-tier results with significantly fewer parameters compared to VGG or ResNet models.

6.3.2 Pareto Frontier of Accuracy vs. Efficiency

- **EfficientNetB0**, **EfficientNetB1**, and **MobileNetV2** stood out as Pareto-optimal models, providing near-VGG-level accuracy with only **2–6 million** parameters.
- **ResNet50** and **ResNet101** achieved solid performance but required significantly more computation, with **23M** and **42M** parameters, respectively.

6.3.3 Outliers

- **InceptionV3** underperformed severely with approximately **21%** accuracy. This is likely due to a mismatch in preprocessing expectations, such as sensitivity to high-frequency textures or differing normalization ranges.
- **DenseNet169** also underdelivered despite its large parameter count, indicating that deeper Dense blocks may not be optimal for simple datasets like MNIST without further tuning.

6.3.4 Architecture Trends

- Lightweight architectures such as **MobileNet** and **EfficientNet** are highly effective on low-complexity datasets like MNIST, outperforming larger models while using fewer computational resources.
- Network depth does not guarantee performance gains. For example, **ResNet101** shows diminishing returns compared to **ResNet50**, suggesting that additional layers may only benefit more complex tasks.

6.3.5 Insights

- Top models (98.5%): EfficientNetB1, EfficientNetB0, MobileNetV2, ResNet50.
- Lightweight architectures (e.g., MobileNetV2, EfficientNetB0) rival larger models in accuracy at a fraction of the parameter cost.
- InceptionV3 underperformed significantly due to preprocessing mismatch.

6.4 Attention Modules Implemented

Attention Wrapping in your code refers to a plug-and-play approach for inserting different attention mechanisms into pre-existing CNN architectures like EfficientNet, MobileNetV2, and ResNet50. Instead of modifying the entire backbone, you're "wrapping" the output of the feature extractor (`backbone.output`) with a chosen attention block just before the classification head. This modularity makes experimentation efficient and results easy to compare.

6.4.1 Squeeze-and-Excitation (SE) Block

The SE block adaptively recalibrates channel-wise feature responses using global average pooling followed by a bottleneck structure ($\text{Dense} \rightarrow \text{ReLU} \rightarrow \text{Dense} \rightarrow \text{Sigmoid}$). It emphasizes informative features while suppressing less useful ones via channel-wise multiplication:

```
se = GlobalAveragePooling2D()(x)
se = Dense(c//reduction, activation='relu')(se)
se = Dense(c, activation='sigmoid')(se)
out = multiply([x, se])
```

6.4.2 Convolutional Block Attention Module (CBAM)

CBAM applies sequential channel and spatial attention:

- Channel attention is computed using both global average and max pooling outputs passed through shared MLPs.
- Spatial attention concatenates average and max features along the channel axis, followed by a convolution layer to produce the attention map.

```
att = Activation('sigmoid')(Add()([avg_channel, max_channel]))
x1 = multiply([x, att])
sp_att = Conv2D(1, kernel_size, activation='sigmoid')(
    Concatenate()([avg_sp, max_sp]))
out = multiply([x1, sp_att])
```

6.4.3 Position Attention Module (PAM)

PAM focuses on long-range spatial dependencies using a self-attention mechanism based on the query-key-value formulation:

- It computes an attention map across all positions and reweighs features accordingly.
- A trainable ScaleLayer balances the attention impact before residual addition.

```
att = Activation('softmax')(Dot(axes=(2,2))([qr, kr]))
out = Reshape((h, w, c))(Dot(axes=(2,1))([att, vr]))
out = ScaleLayer()(out)
out = Add()([out, x])
```

6.4.4 Global Context (GC) Block

GC captures holistic contextual dependencies via global average pooling and feature transformation. It combines the benefits of non-local attention and SE:

```
context = GlobalAveragePooling2D()(x)
trans = Conv2D(c//reduction, 1, activation='relu')(context)
trans = Conv2D(c, 1, activation='sigmoid')(trans)
out = multiply([x, trans])
out = Add()([out, x])
```


6.4.5 Dynamic Wrapping via `build_backbone_attention()`

The function `build_backbone_attention()` acts as the central engine for attention integration. It allows toggling between:

- `attention='none'`: Raw backbone output
- `attention='se', 'cbam', 'pam', 'gc'`: Respective modules applied on the feature maps

This ensures consistent training, evaluation, and comparison across all configurations.

Example usage:

```
feat = backbone.output
if attention == 'se':    feat = se_block(feat)
if attention == 'cbam': feat = cbam_block(feat)
...
```

6.4.6 Training Pipeline with Logging

The `train_and_log()` function abstracts training and logging in a structured format, recording parameters such as:

- Total trainable parameters
- Training time
- Final training/validation accuracy and loss
- Test accuracy and loss

These metrics are written to a CSV file (`attention_matrices.csv`) for comparative evaluation across different attention mechanisms and backbones.

6.5 Backbones and Evaluation

Model	Params	Train Time (s)	Final Train Acc (%)	Final Val Acc (%)	Final Train Loss	Final Val Loss	Test Acc (%)	Test Loss
EfficientNetB0_none	4214829	122.61	93.37	96.70	0.2050	0.1014	96.70	0.1014
EfficientNetB0_se	4419692	106.03	95.09	96.50	0.1580	0.0877	96.50	0.0877
EfficientNetB0_cbam	4419727	121.82	96.00	97.00	0.1278	0.0659	97.00	0.0659
EfficientNetB0_pam	6298230	163.88	95.18	96.30	0.1390	0.1143	96.30	0.1143
EfficientNetB0_gc	4419692	110.45	95.14	96.50	0.1595	0.0921	96.50	0.0921
MobileNetV2_none	2423242	82.46	95.06	96.70	0.1570	0.0994	96.70	0.0994
MobileNetV2_se	2682042	79.27	97.03	97.30	0.0961	0.0675	97.30	0.0675
MobileNetV2_cbam	2681040	91.28	97.36	97.60	0.0867	0.0687	97.60	0.0687
MobileNetV2_pam	4471243	110.65	97.06	97.65	0.0952	0.0621	97.65	0.0621
MobileNetV2_gc	2682042	80.75	94.94	97.00	0.1335	0.0961	97.25	0.0961
ResNet50_none	23851274	219.35	95.94	97.05	0.1271	0.0732	97.05	0.0723
ResNet50_se	24375562	230.83	97.55	97.85	0.0685	0.0600	97.85	0.0600
ResNet50_cbam	24375660	209.52	97.58	97.70	0.0775	0.0772	97.70	0.0772
ResNet50_pam	20941155	238.98	96.04	97.05	0.0946	0.1015	97.05	0.1015
ResNet50_gc	24375562	209.44	96.12	97.65	0.1187	0.0750	97.65	0.0750

Table 4: Performance Comparison of CNN Backbones with Various Attention Modules

The attention wrappers were applied across three pretrained CNN backbones:

- EfficientNetB0
- MobileNetV2
- ResNet50

For each, performance was recorded using the five attention settings: none, se, cbam, pam, and gc. The results (see Table 1) demonstrate notable improvements in classification accuracy and loss with attention modules, especially CBAM and SE.

- EfficientNetB0:
 - CBAM boosts performance significantly: best test loss in the entire table and a notable 97.60
 - SE and GC improve over baseline, but PAM degrades performance and increases params.
 - EfficientNetB0 + CBAM = Best performance-to-parameter ratio.
- MobileNetV2:
 - SE and CBAM both maintain high accuracy (97.2–97.6%) while being lightweight.
 - PAM leads to accuracy drop, similar to EfficientNetB0.
 - Fastest training models are from MobileNetV2, especially SE variant.
- ResNet50:
 - Performs best overall in terms of raw accuracy.
 - CBAM and SE help with training accuracy but may not significantly improve test results over the baseline.
 - GC achieves near-peak performance with better regularization (lower loss).

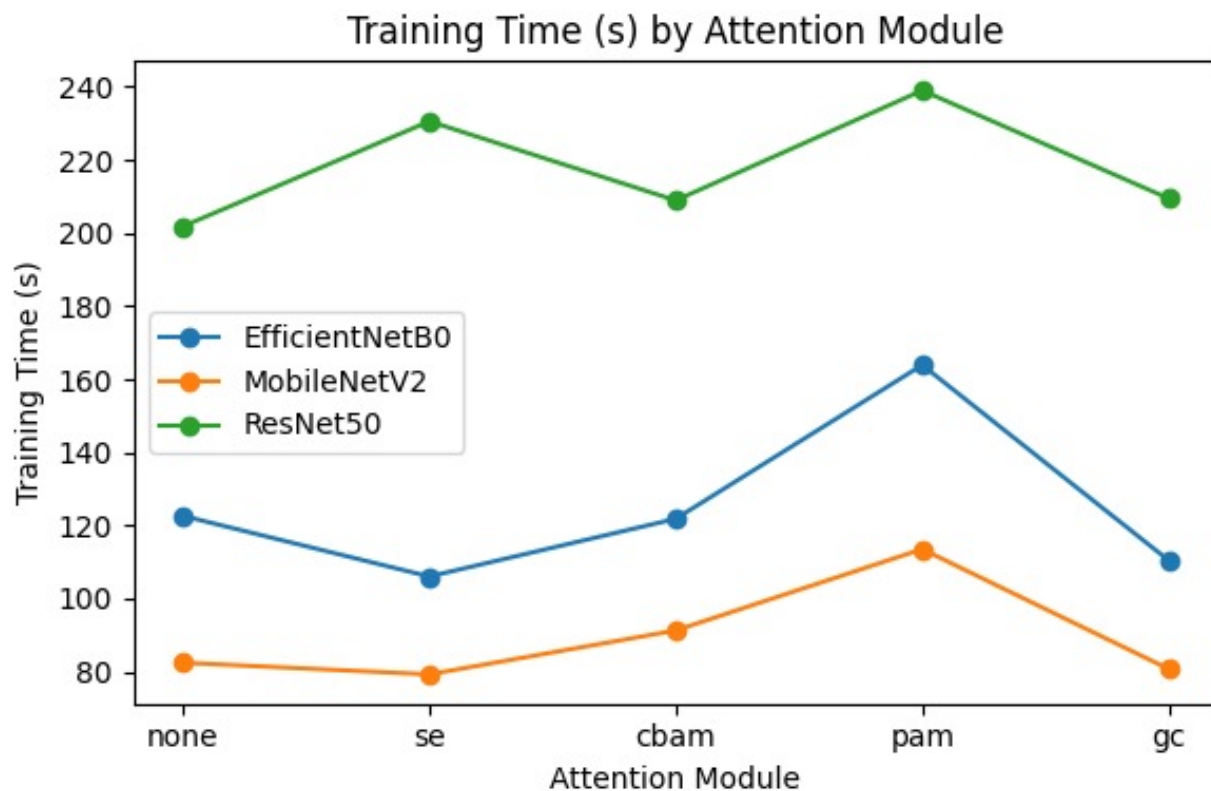


Figure 5: Training Time by Models wrapped in Attention Module

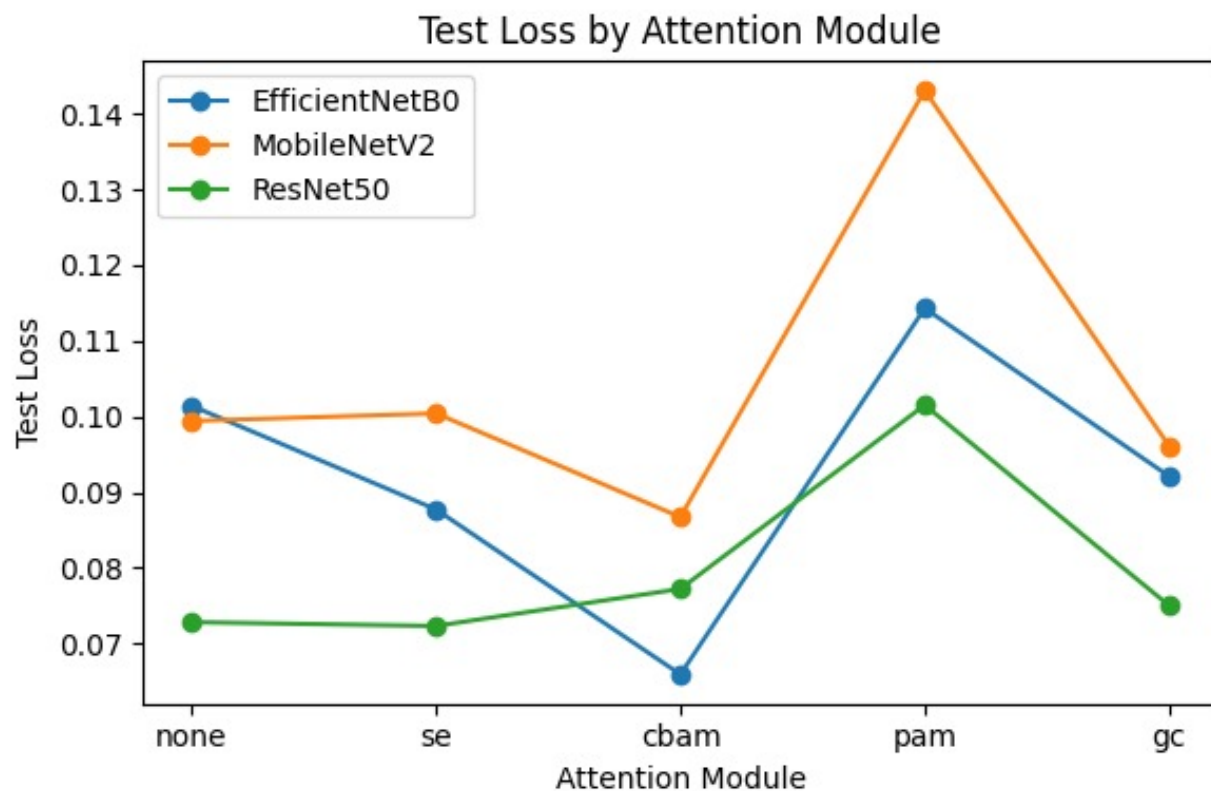


Figure 6: Loss by Models wrapped in Attention Module on Test

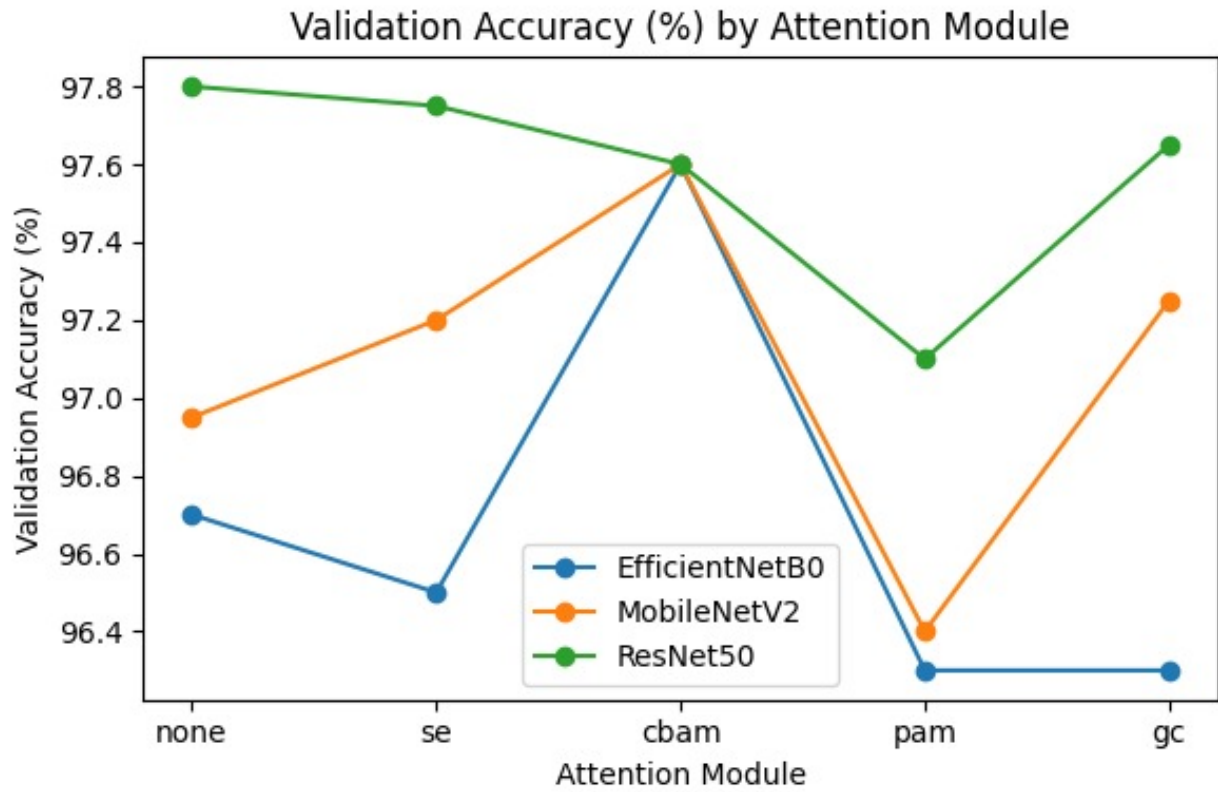


Figure 7: Training Time by Models wrapped in Attention Module on Validation

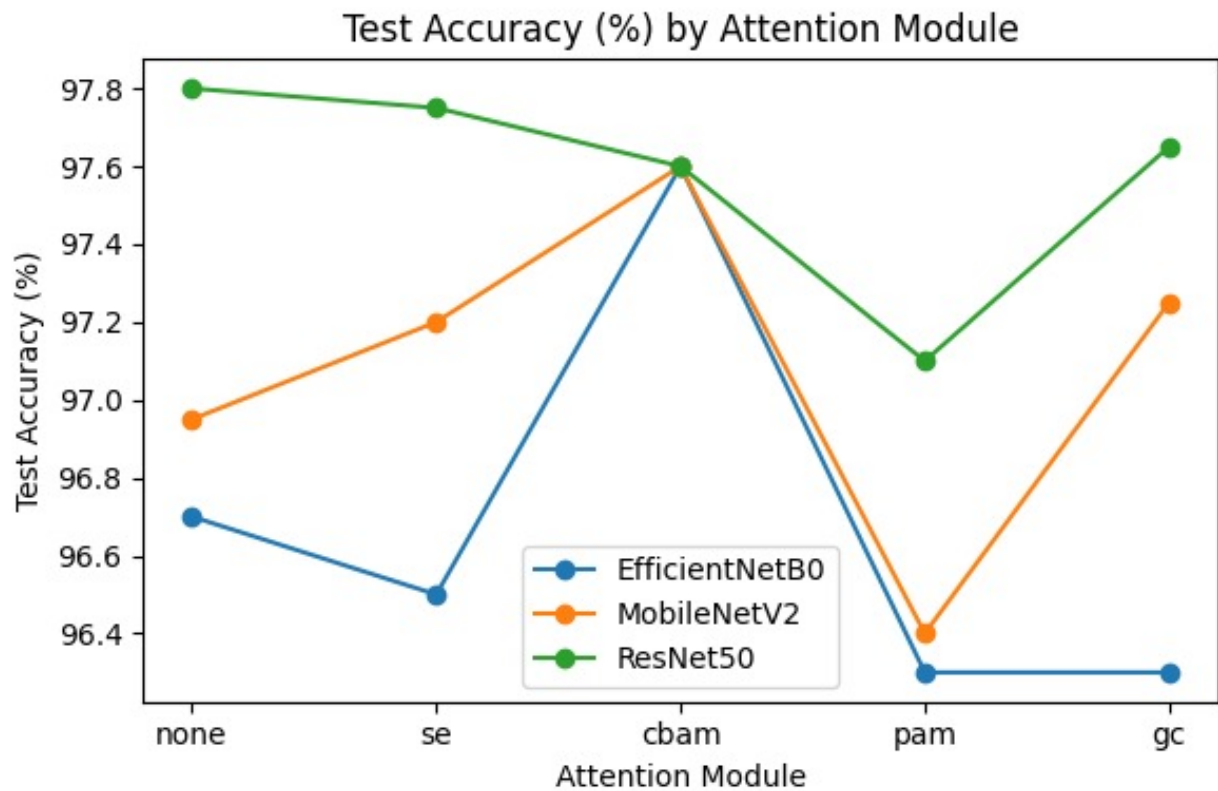


Figure 8: Accuracy by Models wrapped in Attention Module on Test

6.6 Final Fine-Tuning & Export

Model Summary:

Table 5: Final Fine-Tuning and Export: Model Summary

Metric	ResNet50 + CBAM	EfficientNetB0 + CBAM
Total Params	~24.4M	~4.4M
Model Size	92.99 MB	16.86 MB
Training Time	~504s (~8.4 min)	~240s (~4 min)

Training Performance:

Table 6: Final Fine-Tuning and Export: Training Performance

Metric	ResNet50 + CBAM	EfficientNetB0 + CBAM
Start Accuracy	42.2%	21.0%
Final Accuracy	98.82%	93.9%
Start Validation Accuracy	88.77%	74.75%
Final Validation Accuracy	98.9%	97.05%
Final Validation Loss	1.03e-4	0.0884

6.7 Observations:

6.7.1 ResNet50+CBAM:

- Insanely high accuracy from the mid epoch, almost perfect reaching 0.9 by the last epoch
- Attains almost 99% val accuracy due to its high parameter count
- Super accurate but resource extensive and very heavy

6.7.2 EffNetB0+CBAM:

- Very realistic learning curve
- Steady improvements each epoch
- Reaches 97.05% val accuracy, which is excellent considering it uses 5x fewer parameters than ResNet50.

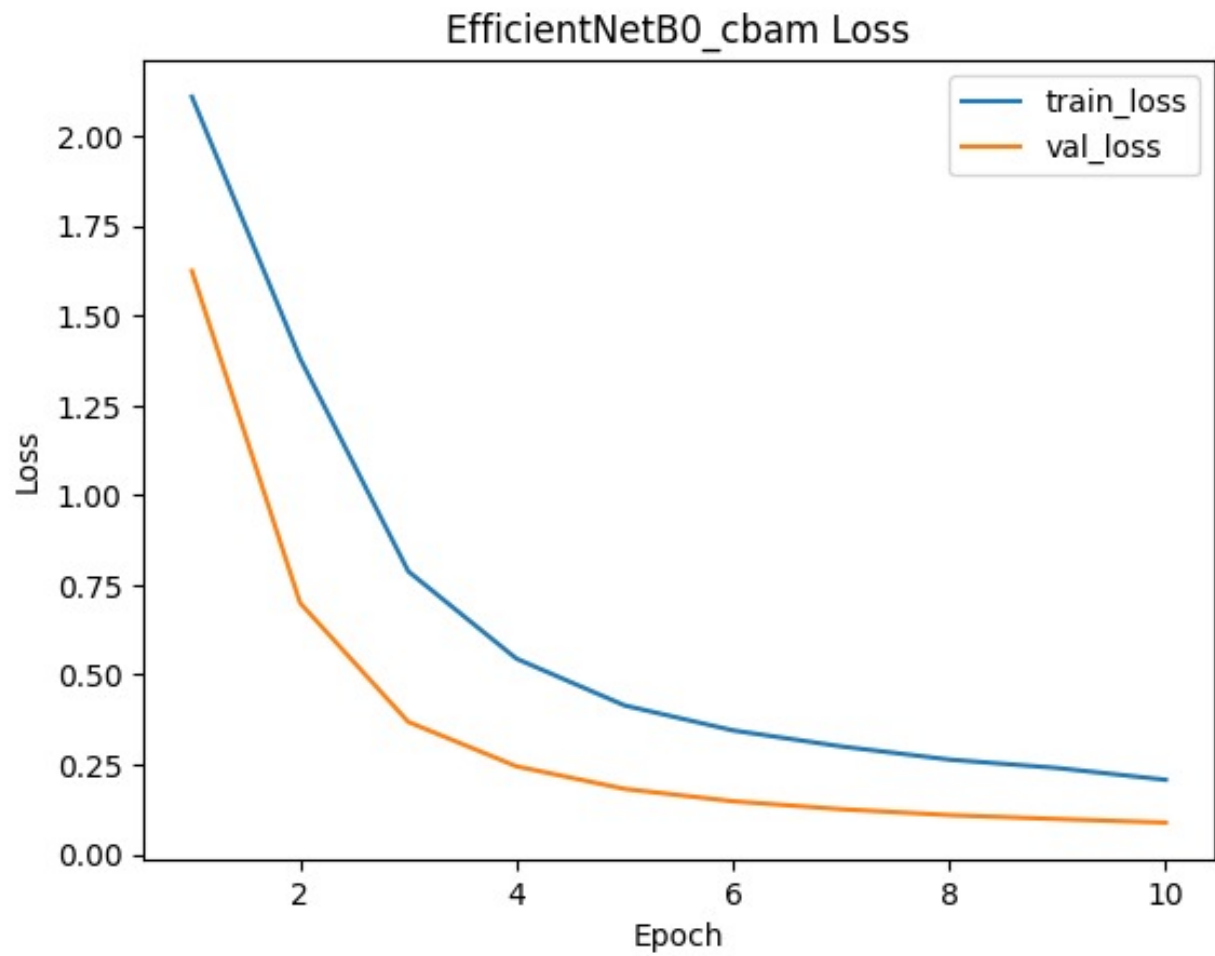
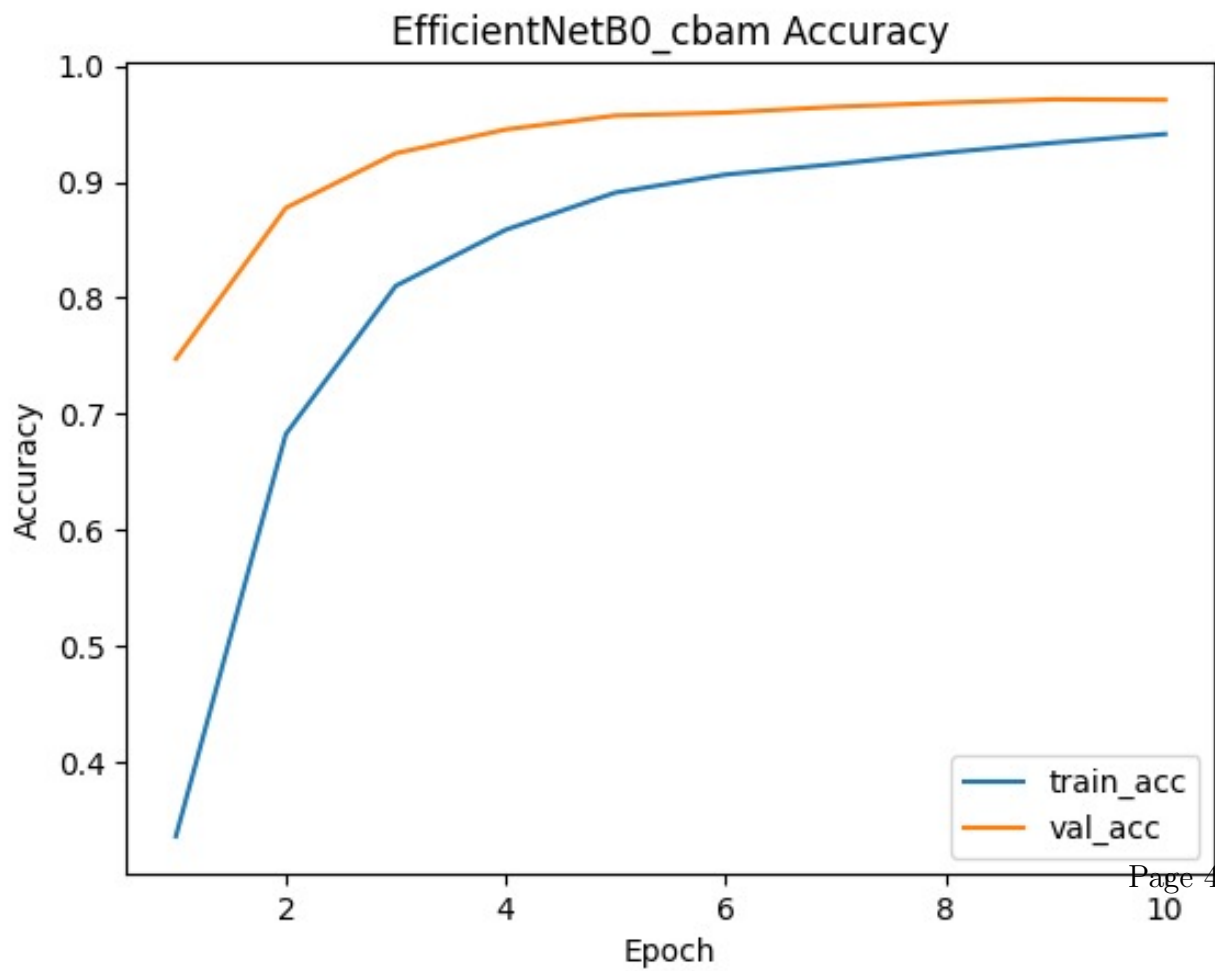


Figure 9: EfficientNetB0 + cbam Loss



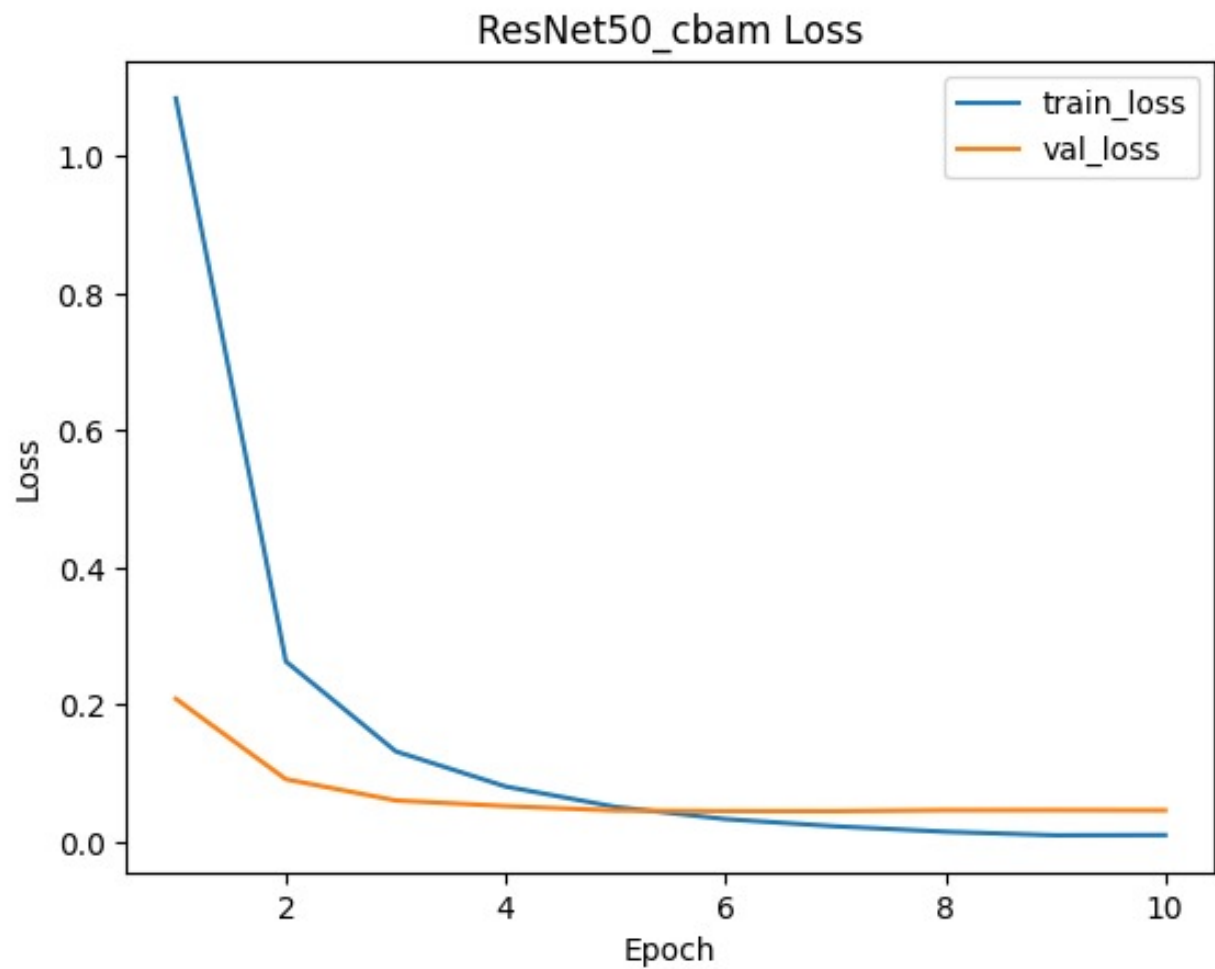
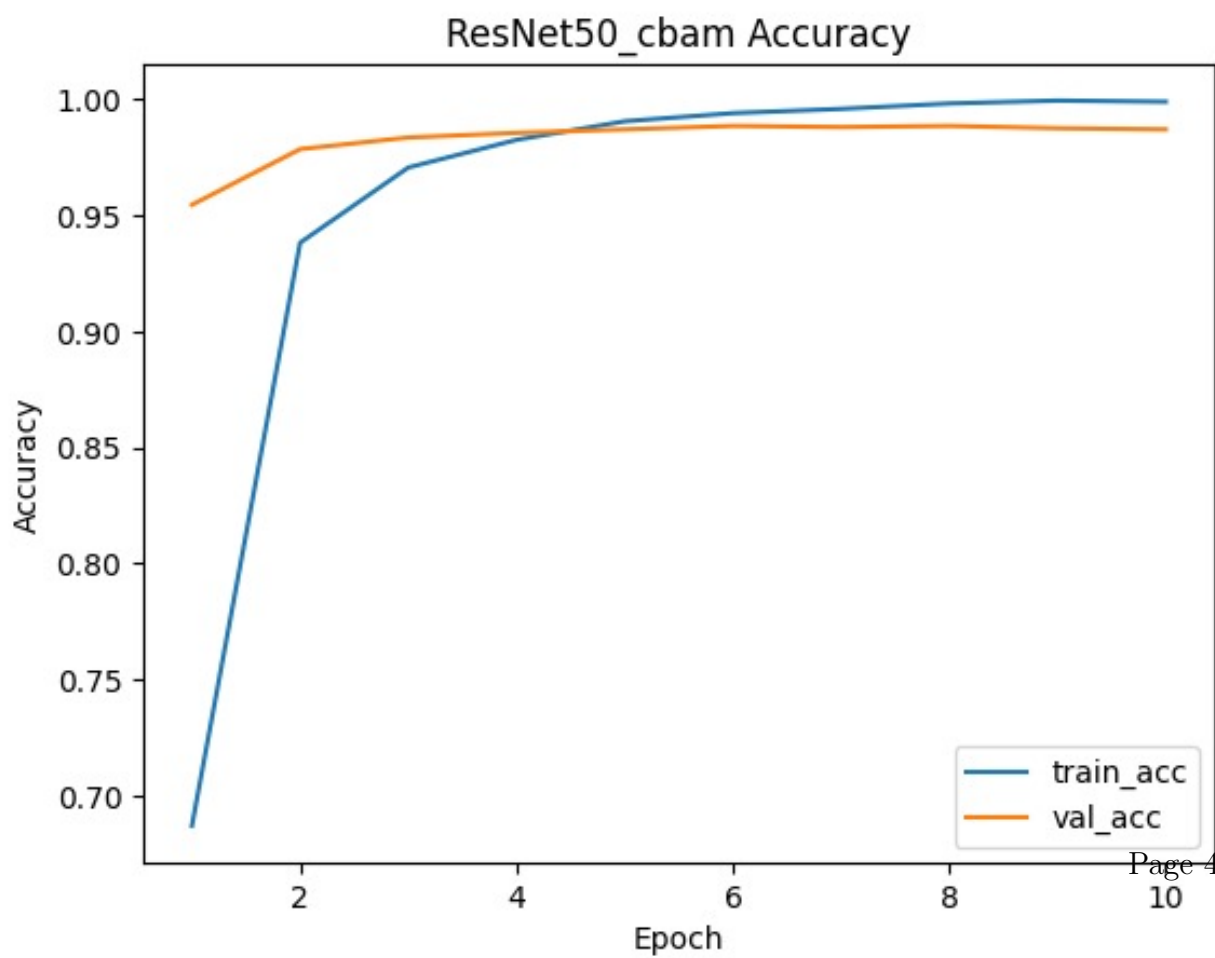


Figure 11: RestNet50 + cbam Loss



6.8 Counterfactual Generation Performance

- **Model:** A fine-tuned version of ResNet50 with the CBAM module.
- **Dataset:** MNIST, a dataset of handwritten digits.
- **Metrics:** We focus on visualizations through different XAI techniques, examining the feature maps, saliency maps, and counterfactuals.
- **Techniques:**
 - Grad-CAM: Highlights the regions in the input image most important for the model's decision.
 - SmoothGrad: Adds noise to the input to smooth out the saliency maps and reduce noise.
 - LIME: Uses local surrogate models to explain the prediction of a complex model.
 - Score-CAM: A variation of Grad-CAM that replaces gradients with activations.

The experimental procedure involves running the model on MNIST test data and generating explanations for the predictions using these methods. The following describes the steps and key results obtained from applying each method.[\[13\]](#)

7 Result Analysis

7.1 Feature Map Visualizations

By extracting the output from various layers of the ResNet50 model (such as conv1_conv, conv3_block4_out, and conv5_block3_out), we analyzed the feature maps at different stages of the network. The visualizations highlight how the model captures various low-level and high-level features of the input image.

- **Conv1 Layer:** In the initial layer, the model detects basic features such as edges and textures. The feature maps appear relatively uniform, detecting simple patterns in the image.
- **Conv3 Layer:** As we move deeper into the network, the feature maps start to focus on more complex patterns such as shapes and contours. At this stage, the network is learning more abstract features.
- **Conv5 Layer:** The feature maps in the final layers focus on highly discriminative regions that are crucial for the model's final decision-making process.

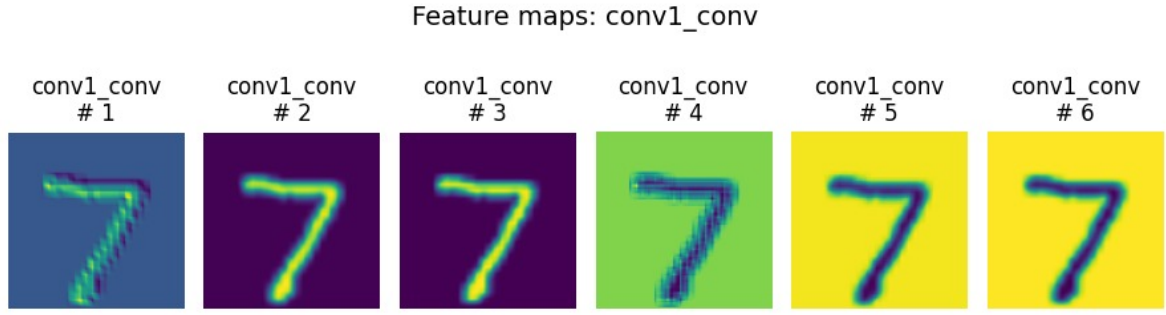


Figure 13: Feature Maps From Convolutional Layer 1

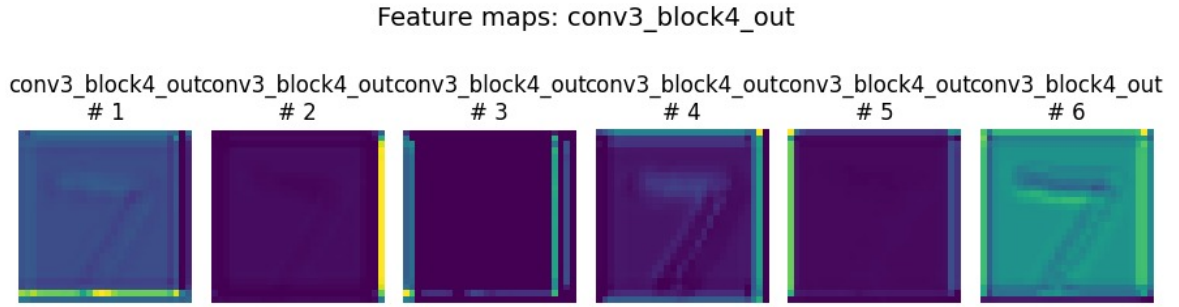


Figure 14: Feature Maps From Convolutional Layer 3

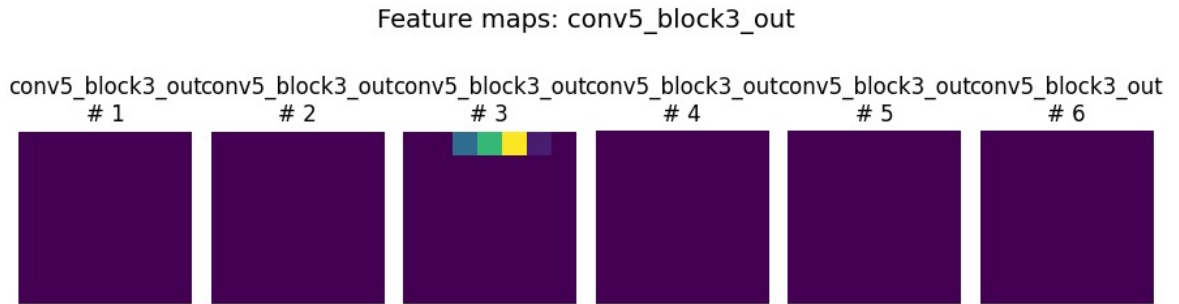


Figure 15: Feature Maps From Convolutional Layer 5

The visualized feature maps from each layer were plotted, revealing the progressive abstraction of features across layers. The model's capacity to focus on relevant patterns increases as we go deeper in the network as evident in Figure 13, 14 and 15.

7.2 Grad-CAM Visualizations

Grad-CAM was applied to visualize the regions of the image that the model focuses on during classification. The heatmaps generated show areas of high importance, helping us understand the model's focus when making predictions. For each test image, Grad-CAM highlighted key regions that contributed most to the classification decision shown in red.^[6]

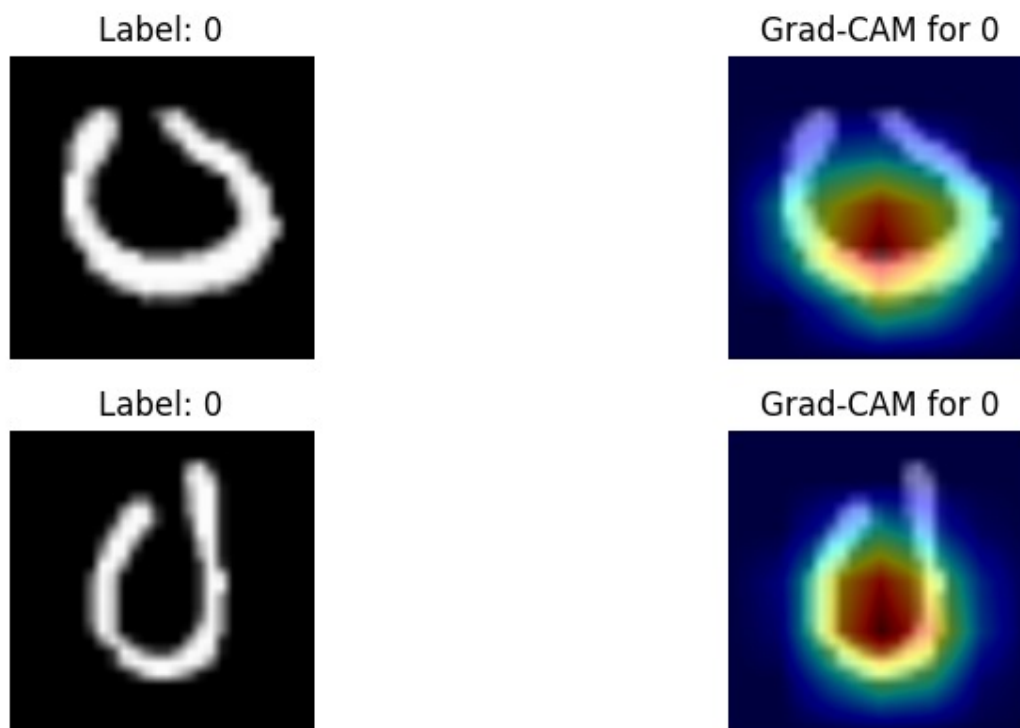


Figure 16: Grad-CAM Visualization for label 0

7.3 SmoothGrad Visualizations

SmoothGrad is a technique designed to reduce noise in saliency maps. By adding random noise to the input image and averaging the resulting gradients, SmoothGrad helps create clearer and more stable saliency maps. This technique was applied to the model to generate saliency maps for each test image.

The results in Figure 17 showed that SmoothGrad generated less noisy saliency maps compared to standard saliency, providing a clearer understanding of which parts of the image are important for classification. For example, when analyzing the digit "3", the saliency map showed a stronger focus on the central part of the digit, indicating the model's emphasis on the shape of the number rather than background noise.

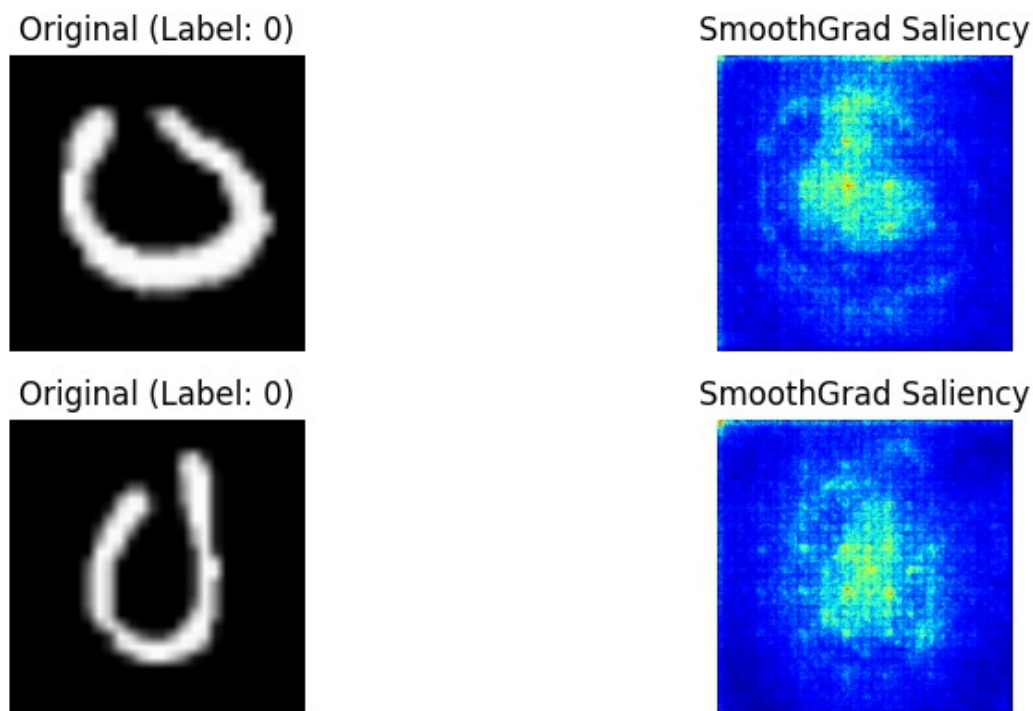


Figure 17: SmoothGrad Visualization for level 0

7.4 LIME Explainer

LIME was used to explain model predictions by approximating its behavior locally around a test sample. It perturbs the input image, fits a simple interpretable model to the perturbed data, and highlights the regions most influential to the prediction.

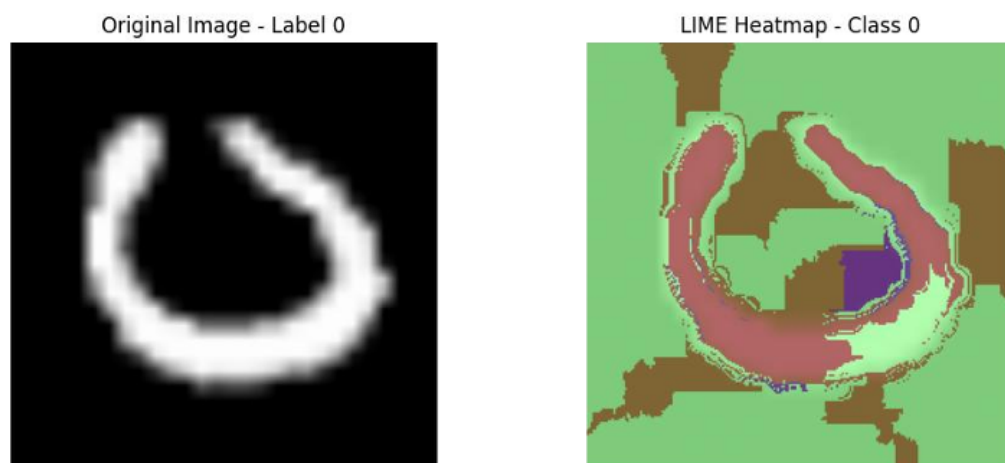


Figure 18: Lime HeatMap for label 0

The LIME-generated heatmaps revealed that the model relies on a combination of features from different parts of the image, such as edges and central features of the digits. This method provided a more granular understanding of the model's decision process by showing which regions were crucial for individual predictions as evident in Figure 18.

7.5 Score-CAM Visualizations

Score-CAM is another method for visualizing feature importance, which differs from Grad-CAM by using activation maps instead of gradients. It calculates class discriminative activation maps and applies them to the input image.

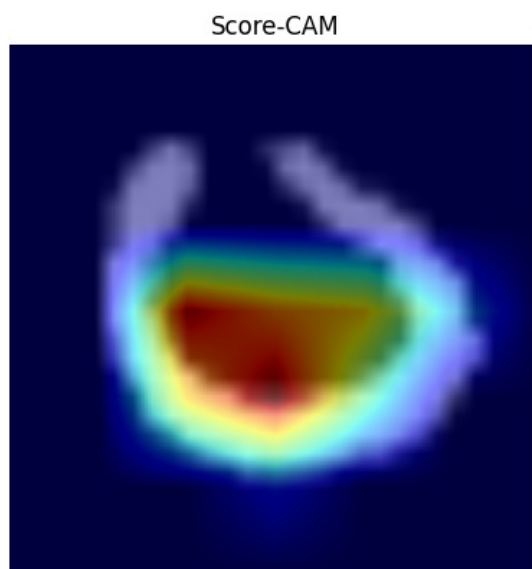


Figure 19: Score Cam for label 0

As seen in Figure 19, the Score-CAM visualizations were similar to Grad-CAM, with both methods highlighting the central parts of the digits, but Score-CAM provided a smoother and more consistent heatmap. The visualizations from Score-CAM were also overlaid on the input image, providing intuitive insight into the model's focus.

7.6 Counterfactual Explanations

Counterfactual explanations were generated by modifying the input image slightly to flip the model's prediction. This was done by creating perturbations on the input image and observing how small changes in the image affected the model's output. The method used here involves optimizing a counterfactual image that results in a target class prediction while remaining as close as possible to the original image.

7.7 What is a Counterfactual Explanation?

Counterfactual explanations attempt to answer the question: "What minimal changes would I need to make to the input to change the model's decision?" In the context of image classification, it means tweaking the input image just enough so that the model switches its classification to another class, all while keeping the changes minimal and the image as similar as possible to the original.

7.8 How is a Counterfactual Image Generated?

The process typically involves the following steps:

7.8.1 Initial Model Prediction

- Start with an input image, such as a digit (e.g., the digit "0").
- The model makes a prediction, say, it classifies the image as "0".

7.8.2 Target Prediction

- You select a target class to which you want to change the model's prediction. For instance, the target could be the digit "2".

7.8.3 Generating Perturbations

- The key idea is to create a counterfactual image where the prediction changes from "0" to "2". This involves modifying the original image by perturbing some of its pixels (slightly altering certain regions of the image) while ensuring that the modified image remains visually similar to the original as seen in Figure 20.
- The process of perturbation typically involves applying small shifts to the image's pixels, such as slightly altering the color or brightness of certain areas or adding small noise that might influence the model's decision.

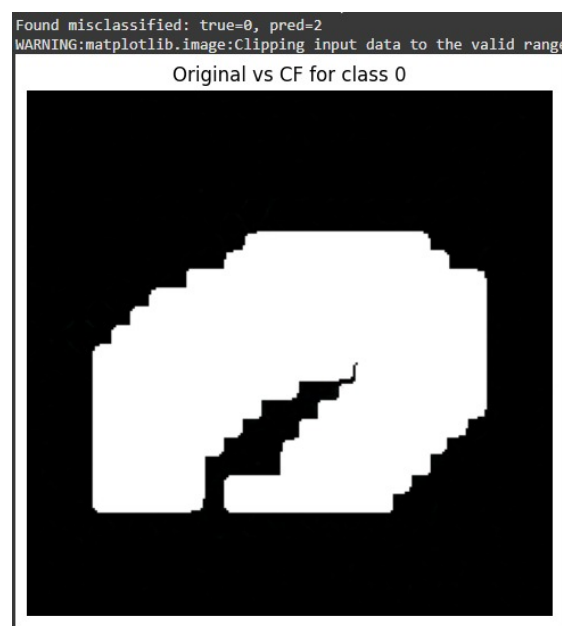


Figure 20: Counterfactual Map for label 0

7.8.4 Optimization Process

- An optimization algorithm is used to find the minimal perturbation that results in the model predicting the target class. This is typically framed as an optimization problem:

```

minimize perturbed_image - original_image_p
subject to model_prediction(perturbed_image) = target_class
\text{minimize} \quad \|\text{perturbed\_image} - \text{original\_image}\|_p
\quad \text{subject to} \quad
\text{model\_prediction}(\text{perturbed\_image}) = \text{target\_class}

```

- Here, the optimization minimizes the distance between the perturbed image and the original image, typically using a norm like L2 (Euclidean distance), while ensuring that the model now classifies the perturbed image into the desired target class like in Figure 21.

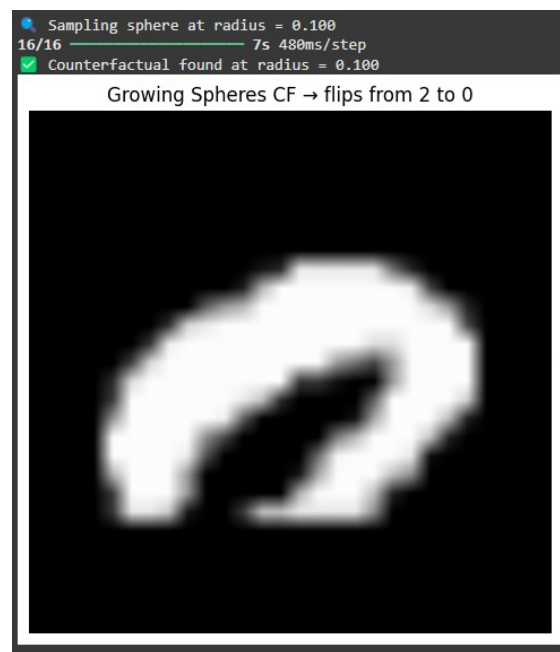


Figure 21: Applying Growing Spheres to flip predicted value '2' to '0'

7.9 Iterative Adjustment

- The optimization iterates, adjusting the image slightly in each step, gradually converging to a perturbed image that causes the model to predict the target class.
- At each iteration, the model's output is monitored. If the predicted class still matches the original prediction (e.g., still "0"), the perturbation continues until the model's prediction changes to "2".

- During this process, the algorithm attempts to minimize the perturbations to ensure that the counterfactual image remains as similar as possible to the original image, keeping the changes subtle as shown in the heatmap in Figure 22.

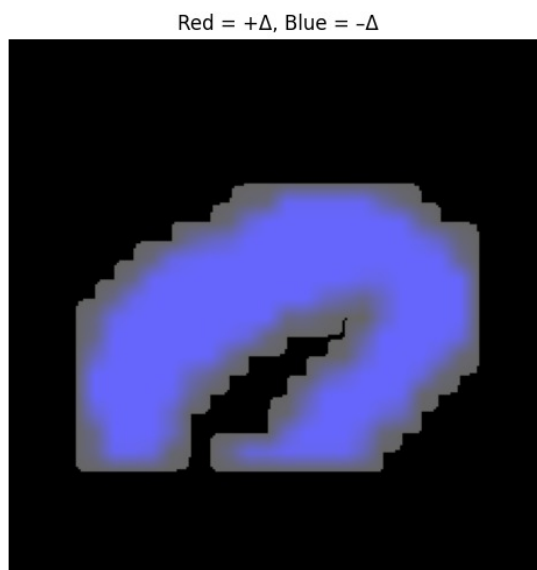


Figure 22: Applying Heatmap to the Counterfactual

7.10 Example: Digit "0" Misclassified as "2"

Consider an image of the digit "0", which the model incorrectly classifies as "2". In this case, the counterfactual explanation seeks to understand what small adjustments can be made to the image to cause the model to change its prediction from "0" to "2".

- **Original Image:** The model sees a "0" and incorrectly predicts it as "2".
- **Counterfactual Explanation:** By slightly changing the shape of the "0" (for example, by tweaking the curvature or the top part of the digit, which is slightly more open, or adding a little curve to the right), the model might shift its classification to "2".

These changes may include adjusting the angle or width of certain lines in the digit, altering pixel intensities, or changing the placement of specific segments to make the image appear more like a "2" than a "0" to the model. The goal is that the changes are small enough that, to a human, the image still looks like a "0" with minimal alteration as shown in Figure 23.

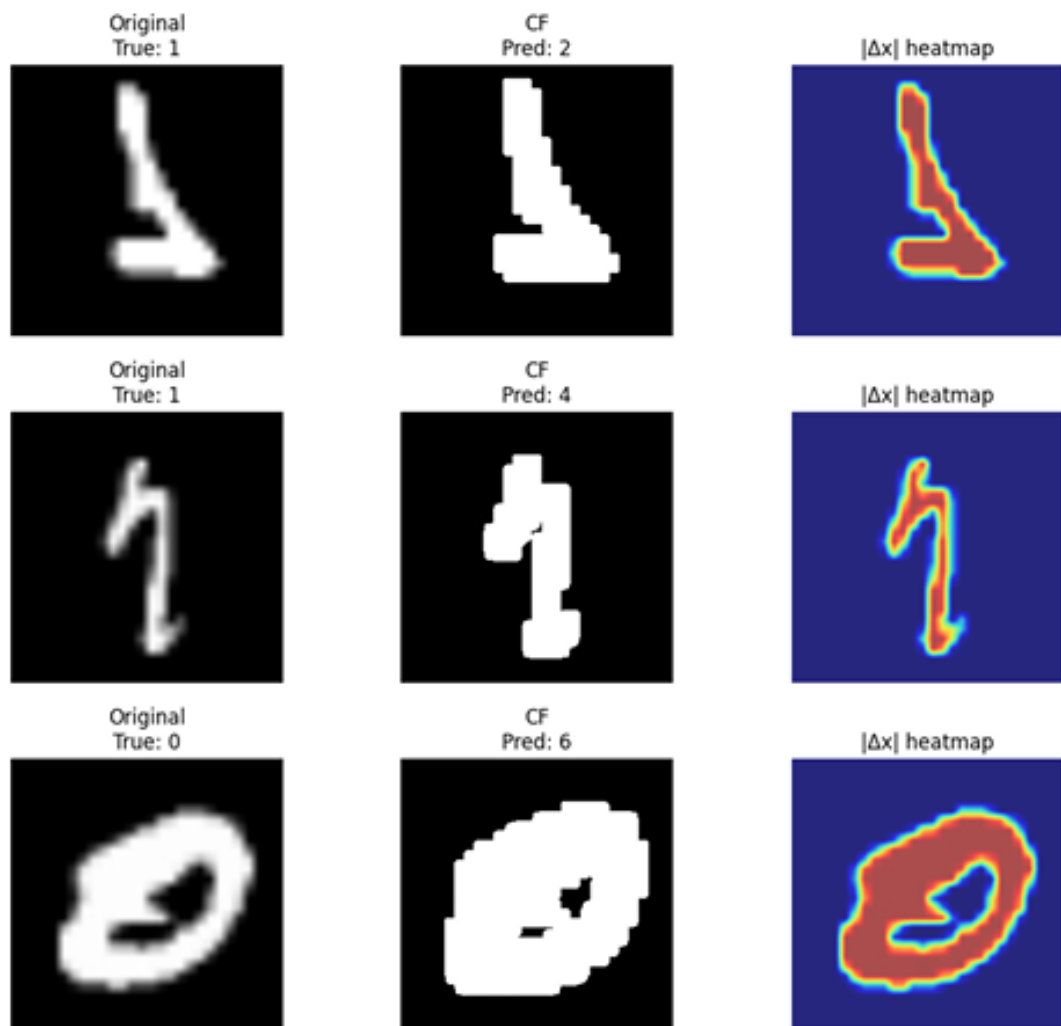


Figure 23: Comparing Original Labels with Growing Spheres CF Image and the Differential Heatmap

7.11 Why is This Important?

Counterfactual explanations provide insight into the model's decision-making process. Here's why they're valuable:

- **Understanding Model Behavior:** By studying the counterfactual explanation, we can understand the key features of the input image that led the model to misclassify it. In the case of the "0" misclassified as "2", the counterfactual explanation tells us that the model might be overly sensitive to certain pixel changes in the shape of the "0", which makes it mistake the digit for a "2".
- **Model Debugging:** This technique can be used to debug models by identifying edge cases where small changes in the input lead to significant changes in prediction. If counterfactual explanations reveal that the model is making decisions based on irrelevant or spurious features, it can guide the model's improvement.
- **Transparency and Trustworthiness:** For applications where interpretability is crucial (e.g., healthcare, autonomous driving), counterfactual explanations help make the model's behavior more transparent. Users can see what changes would need to occur for the model to make a different decision, which can build trust in the model's output.
- **Identifying Vulnerabilities:** Counterfactuals can also highlight vulnerabilities in the model, such as susceptibility to adversarial attacks. If small perturbations can cause a drastic change in prediction, the model might be too fragile and could be vulnerable to adversarial manipulation.

7.12 Challenges in Counterfactual Explanations

While counterfactuals are powerful tools, they come with challenges:

- **Optimization Complexity:** Generating a meaningful counterfactual image that minimally alters the original while ensuring a change in prediction can be computationally expensive. It often requires iterative optimization, which may take a long time, especially for high-dimensional inputs like images.
- **Ambiguity in Results:** In some cases, there might be multiple counterfactuals that could result in a change of prediction. This means counterfactuals might not always provide a clear or unique explanation.
- **Interpretability of Perturbations:** For images, it's not always straightforward to interpret the exact changes made. While small pixel perturbations might be understandable from a technical standpoint, the impact of these changes might not always be clear to end-users, especially when they don't align with human perception.

7.13 Use in Explainable AI

Counterfactual explanations fit within the broader field of explainable AI (XAI), offering one of the many ways to interpret and understand model predictions. Alongside other techniques like LIME, SHAP, and saliency maps, counterfactuals provide a complementary toolset that helps model developers and end-users alike gain clarity on how and why a model arrives at a particular decision. In summary, counterfactual explanations involve finding minimal perturbations to an input that flip the model’s prediction. By understanding these minimal changes, we gain insights into how the model is making decisions, which features are most influential, and how the model might be prone to errors or adversarial inputs.

8 Future Scope

8.1 Extending Model Complexity and Application Domains

8.1.1 Beyond MNIST: Complex Image Benchmarks

- **High-Resolution Multi-Object Scenes:** Transition from single-digit MNIST to datasets such as CIFAR-10/100 and ImageNet to evaluate counterfactual methods on color imagery with multiple objects and backgrounds.
- **Domain-Specific Visual Tasks:** Apply the framework to medical imaging (e.g., chest X-rays, MRIs), satellite imagery, and autonomous-driving datasets, assessing both accuracy and interpretability under domain constraints.

8.1.2 Real-World Systems Regulatory Compliance

- **Interactive Decision Support:** Integrate counterfactual explanations into human-in-the-loop interfaces where users can adjust input features and observe real-time model responses.
- **GDPR-Aligned Explanations:** Implement “right to explanation” mechanisms that provide actionable counterfactuals without exposing proprietary model internals

8.2 Advancing Counterfactual Generation Techniques

8.2.1 Generative Model Integration

- **GAN-Based Plausibility:** Leverage generative adversarial networks or diffusion models to produce on-manifold counterfactuals, ensuring visual realism and avoiding noisy perturbations
- **VAE-Guided Perturbations:** Use variational autoencoders to constrain counterfactuals to the learned data manifold, improving interpretability.

8.2.2 Real-Time Explanations

- **Low-Latency Pipelines:** Architect end-to-end systems capable of generating counterfactual overlays in milliseconds to support interactive applications.
- **Incremental Refinement:** Implement streaming solvers that iteratively improve counterfactual quality, allowing early termination with approximate yet informative explanations.

9 Conclusion

This project has demonstrated the feasibility and utility of integrating explainability techniques—ranging from Grad-CAM overlays to contrastive counterfactuals—into deep CNN classifiers for digit recognition. By benchmarking multiple backbones, augmenting them with attention modules, and evaluating a suite of XAI methods, we have shown how interpretability can coexist with high performance. Going forward, the outlined future scope will enable the extension of this framework to more complex data modalities, real-world applications, and human-centric evaluation settings, ultimately advancing the state of responsible and trustworthy AI systems.

Moreover, these methodologies offer a concrete path toward transparent AI audits and compliance in regulated industries, ensuring that model decisions can be scrutinized and justified. By providing actionable insights into decision boundaries, stakeholders—from data scientists to domain experts—can more effectively identify and mitigate biases, thereby enhancing fairness and accountability. The interactive and visual nature of the explanations also fosters stronger collaboration across interdisciplinary teams, aligning technical innovation with user needs and ethical considerations. As AI systems continue to permeate critical sectors, this work lays a replicable blueprint for scalable, transparent, and trustworthy deep learning pipelines, catalyzing future advancements in human-centric XAI.

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