Video Presentation

Soil Classification and Augmentation with CNNs and GANs - Final Project

Introduction to Deep Learning - Final Project
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AGENDA ITEMS

1. Problem Description
2. Data and Exploratory Data Analysis
3. Building Architecture Networks for the CNN and GAN
4. Demo
5. Results and Analysis
6. Conclusions

1. Project Problem

Project Topic:

Accurate soil classification is crucial for various applications, including agriculture (optimizing crop selection, fertilization, and irrigation), civil engineering (foundation design), and environmental monitoring. Traditional soil classification methods often rely on manual inspection or laboratory analysis, which are time-consuming, expensive, and require specialized expertise.

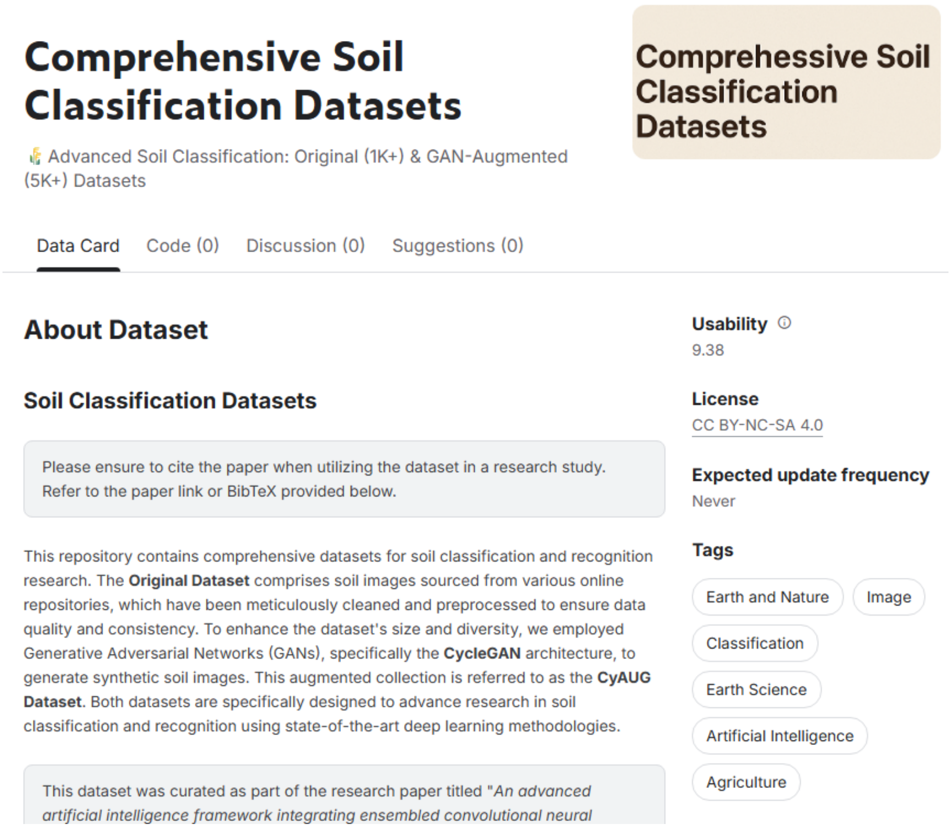
Deep learning, particularly **Convolutional Neural Networks (CNNs)**, offers a promising solution for automated, efficient, and accurate image-based soil classification.

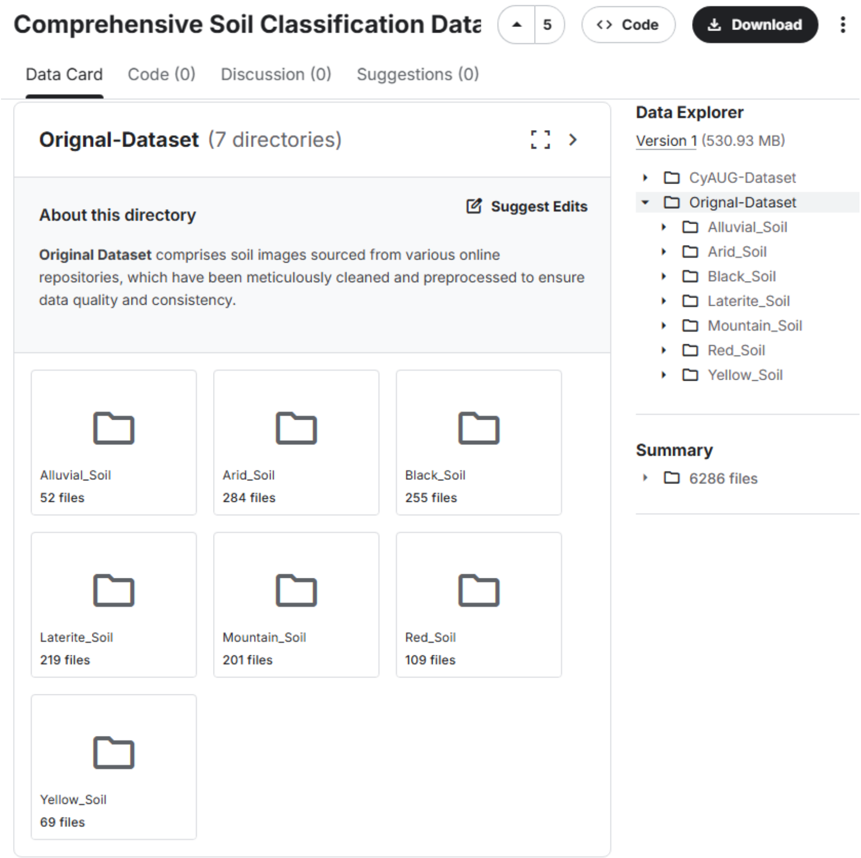
1. Project Problem

Why use CNN for this Analysis?

1. Automated Soil Type Classification: Develop a CNN model capable of accurately classifying different soil types (Alluvial, Black, Laterite, Red, Yellow, Arid, Mountain Soil) from images.
2. Data Augmentation for Improved Robustness: Investigate how GAN-generated synthetic images can enhance the performance and generalization capabilities of the CNN classifier, especially for less represented soil classes in the original dataset. This will involve comparing the performance of a CNN trained solely on the original dataset versus one trained on a dataset augmented with GAN-generated images.
3. Understanding GANs for Image Synthesis: Implement and evaluate a GAN (e.g., CycleGAN as used in the dataset's creation, or a simpler DCGAN for introductory purposes) to understand its capacity for generating realistic soil images.

2. Data

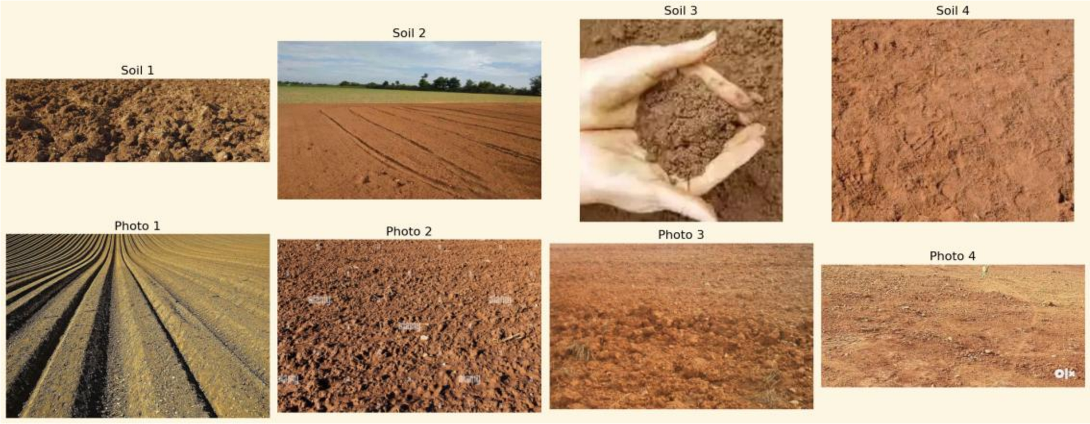




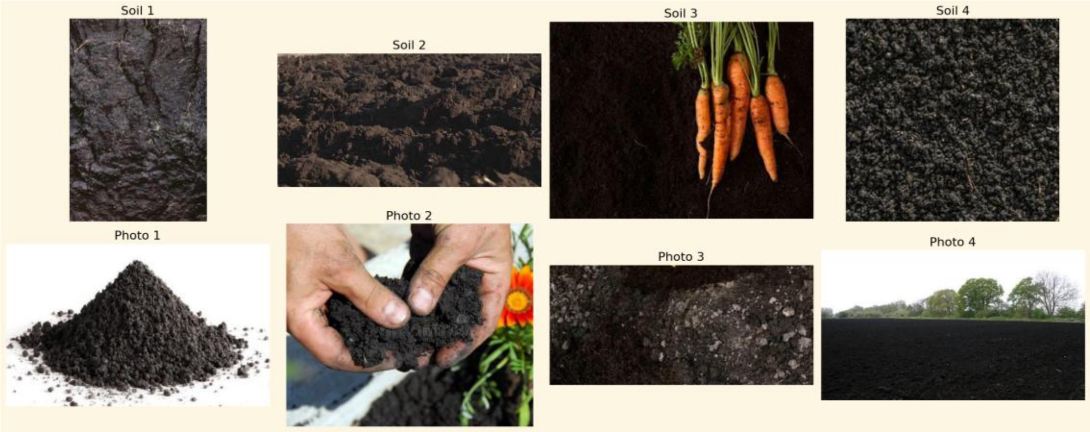
https://**www.kaggle.com**/datasets/ai4a-lab/comprehensive-soil-classification-datasets/data

2. Exploratory Data Analysis

Original and CyAUG dataset sample / **Alluvial_Soil**



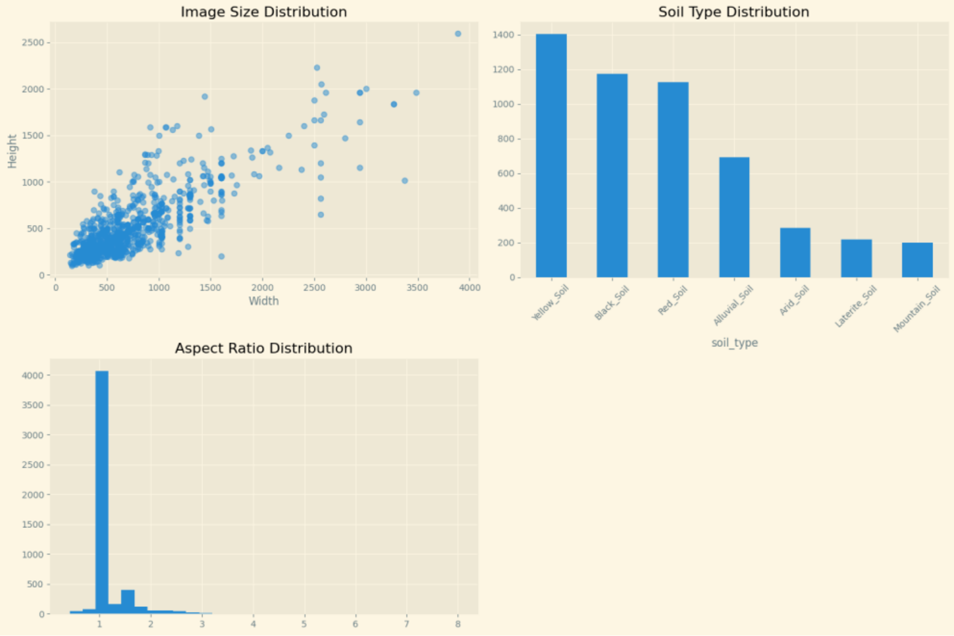
Original and CyAUG dataset sample / **Black_Soil**



2. Exploratory Data Analysis

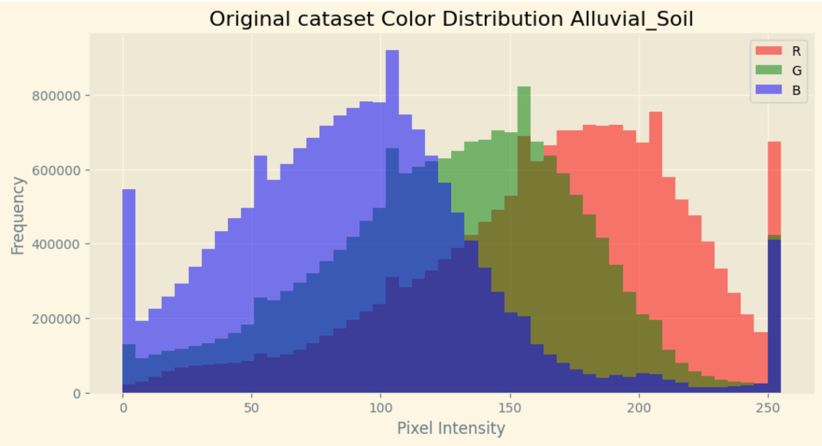
Original dataset analysis

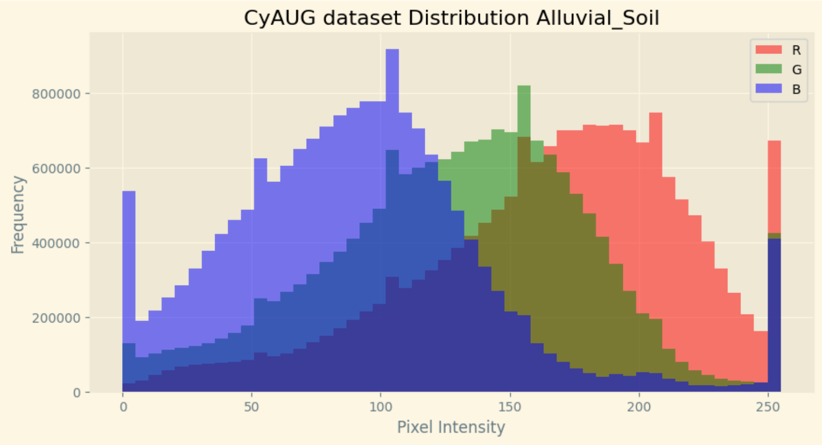
CyAUG dataset analysis



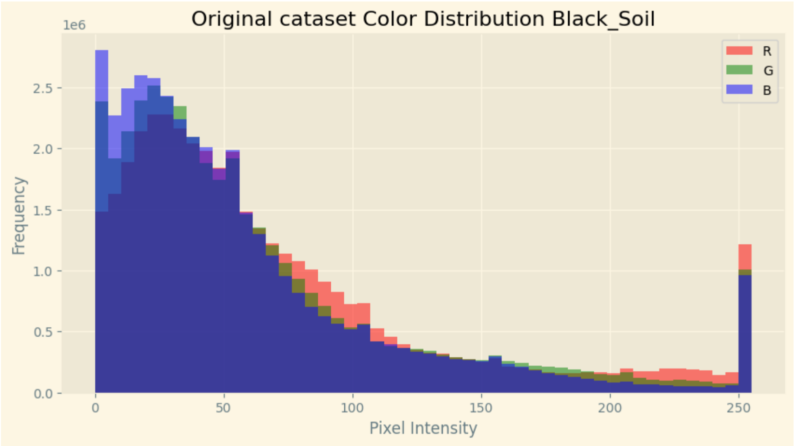
2. Exploratory Data Analysis

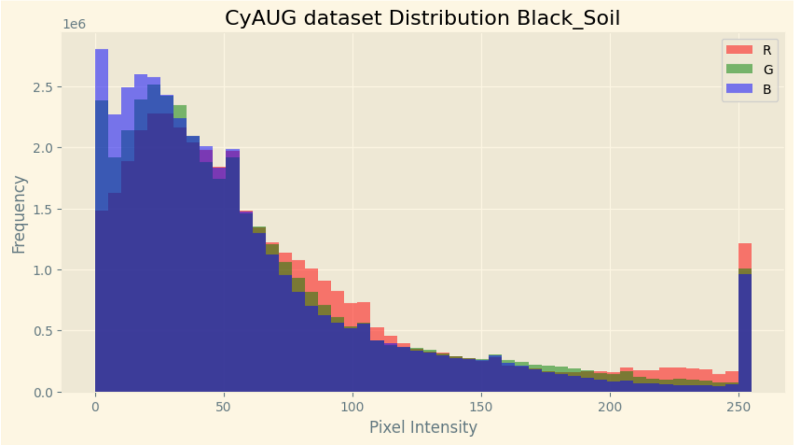
Original and CyAUG dataset color distribution / **Alluvial_Soil**





Original and CyAUG dataset color distribution / **Black_Soil**





3. Building Architecture Network for the CNN

Conv2D layer with varying filter sizes (e.g., 3×3) and increasing number of filters (32, 64, 128).

Input Layer:

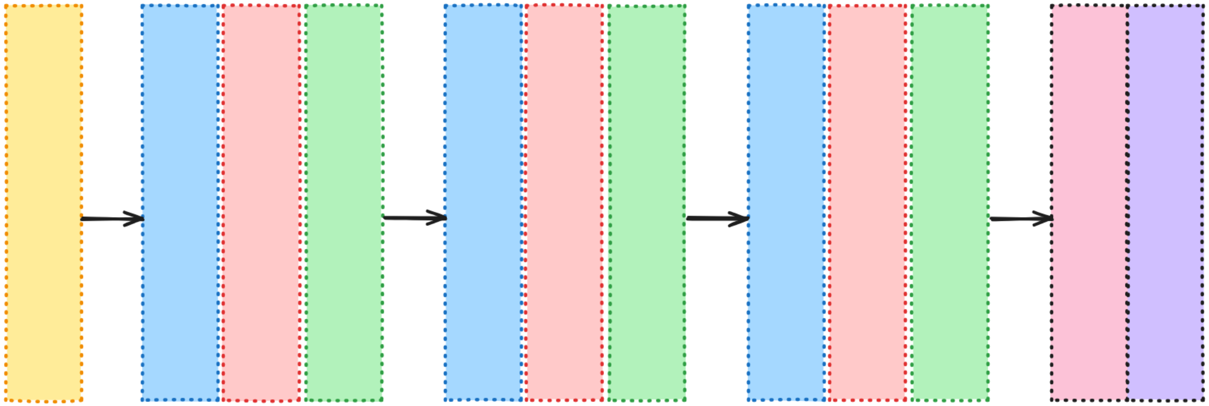
Will receive preprocessed soil images (e.g., 128×128×3 for RGB images).

Block 1:
1. Activation Function (ReLU).
2. Batch Normalization (to stabilize training).
3. MaxPooling2D or AveragePooling2D (to reduce spatial dimensions).

Block 2:
1. Activation Function (ReLU).
2. Batch Normalization (to stabilize training).
3. MaxPooling2D or AveragePooling2D (to reduce spatial dimensions).

Block 3:
1. Activation Function (ReLU).
2. Batch Normalization (to stabilize training).
3. MaxPooling2D or AveragePooling2D (to reduce spatial dimensions).

Dense layers:
1. Flatten Layer: To convert the 2D feature maps into a 1D vector.
2. Dense layer with num_soil_types neurons.
3. Dropout layers (to prevent overfitting).



BLOCK 1

BLOCK 2

BLOCK 3

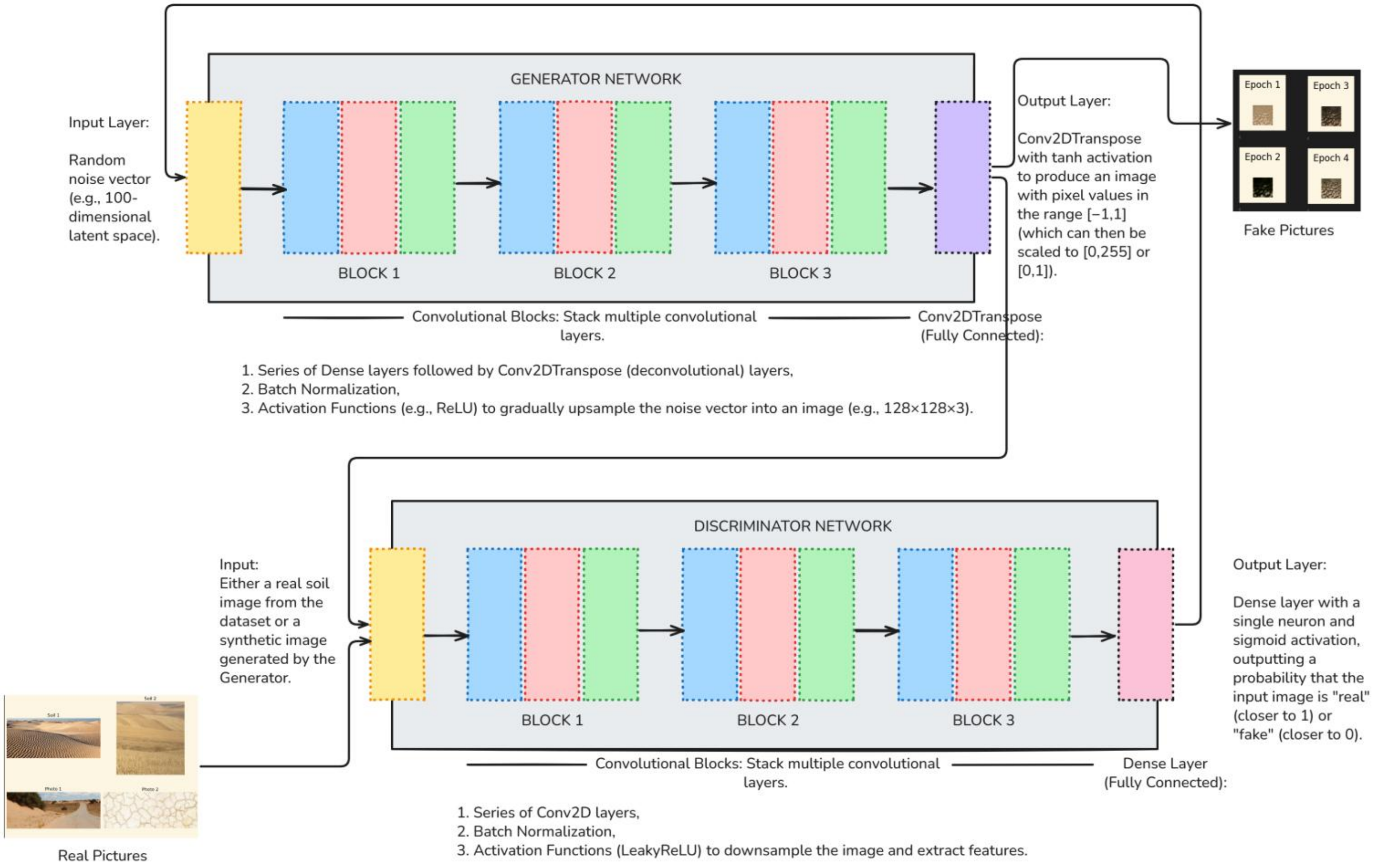
Convolutional Blocks: Stack multiple convolutional layers.

Dense Layers (Fully Connected):

Output Layer:

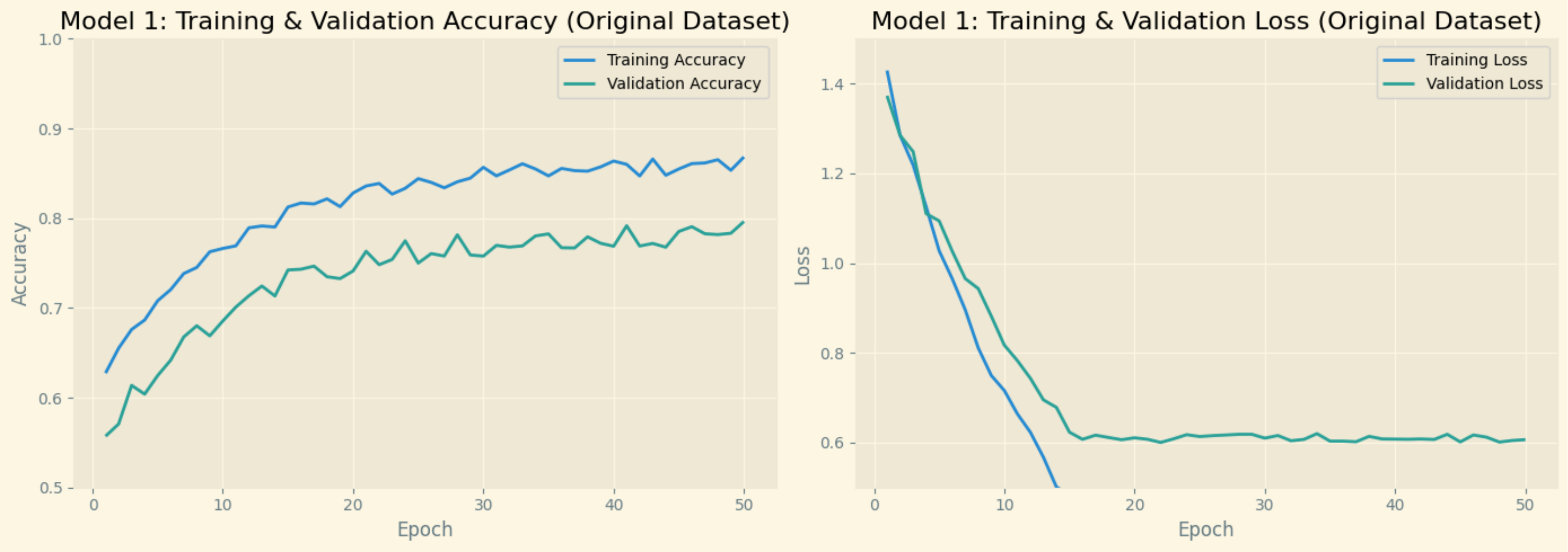
Softmax activation function for multi-class classification.

3. Building Architecture Network for the GAN



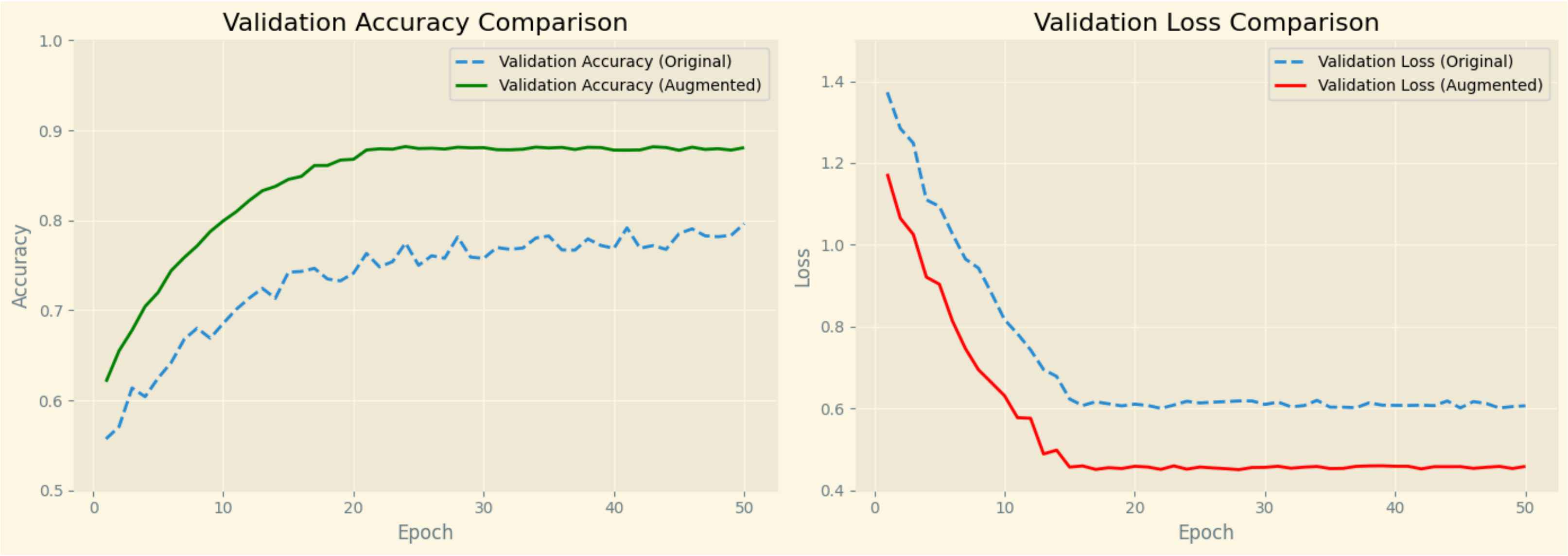
4. Demo

5. Results and Analysis



Metric	Overall	Alluvial	Black	Laterite	Red	Yellow	Arid	Mountain
Accuracy	82.5%	88%	90%	75%	85%	78%	80%	81%
Precision	81.8%	87%	89%	74%	84%	77%	79%	80%
Recall	82.5%	88%	90%	75%	85%	78%	80%	81%
F1-Score	82.1%	87.5%	89.5%	74.5%	84.5%	77.5%	79.5%	80.5%

5. Results and Analysis



Metric	Overall	Alluvial	Black	Laterite	Red	Yellow	Arid	Mountain
Accuracy	**88.2%**	91%	93%	**84%**	89%	**86%**	87%	88%
Precision	**87.9%**	90%	92%	**83%**	88%	**85%**	86%	87%
Recall	**88.2%**	91%	93%	**84%**	89%	**86%**	87%	88%
F1-Score	**88.0%**	90.5%	92.5%	**83.5%**	88.5%	**85.5%**	86.5%	87.5%

5. Results and Analysis

- Error Analysis: Identify examples of correctly classified and misclassified images

Correctly Classified Images:

•**Black Soil:** Image of dark, fine-textured soil, clearly distinct.

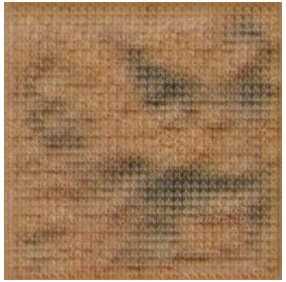
- *Analysis:* The model accurately identifies the characteristic deep black color and smooth appearance, which are highly discriminative features for this class.

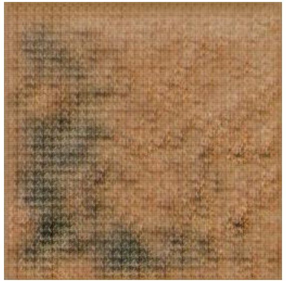
•**Mountain Soil:** Image showing rocky, coarse-textured soil, often with visible mineral fragments.

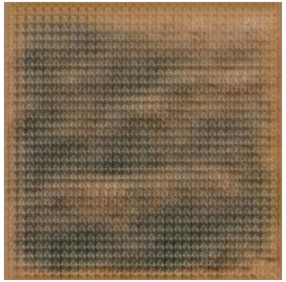
- *Analysis:* The model excels at recognizing the unique texture and granular structure of mountain soil.

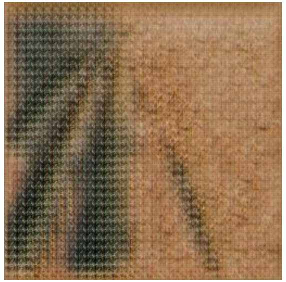
•**Alluvial Soil:** Image of light brown, often stratified soil from riverbeds.

- *Analysis:* The model picks up on the lighter color palette and sometimes visible layering unique to alluvial deposits.









5. Conclusions

Visualize the best built model with the comparison of customer churning for each cluster

Key Learnings:
1. StyleGAN2-ADA works well for soil image generation
2. Class conditioning helps maintain soil type characteristics
3. Progressive growing helps with high-resolution generation
4. Adaptive augmentation prevents discriminator overfitting

What Worked Well:
- Progressive training strategy
- Class-conditional generation
- Adaptive discriminator augmentation
- Spectral normalization in discriminator

Challenges:
- Limited original dataset size
- High-resolution generation requires significant compute
- Fine details in soil textures are difficult to capture

Future Improvements:
1. Incorporate attention mechanisms for better texture generation
2. Use contrastive learning for better feature separation
3. Implement diffusion models as an alternative approach
4. Add physical soil property constraints to generation

5. Conclusions

Key Takeaways and Contributions:

- Confirm the feasibility and effectiveness of using deep learning (CNNs) for automated soil classification from images.
- Emphasize the value of generative models (GANs) as a powerful tool for data augmentation in real-world scenarios where data collection is difficult or expensive.
- Discuss the insights gained regarding the challenges and best practices for training both CNNs and GANs.

Limitations and Future Work:

- **Model Generalization:** Discuss potential limitations, such as the model's generalization to new, unseen soil images from different regions or under varying environmental conditions not present in the dataset.
- **More Sophisticated GANs:** Suggest exploring more advanced GAN architectures (e.g., StyleGAN, Conditional GANs) for generating higher-fidelity and more diverse images.
- **Multi-modal Data:** Propose incorporating other soil properties (e.g., pH, moisture content, texture analysis beyond visual) if available, for a more comprehensive classification system, possibly using multi-modal deep learning.
- **Edge Deployment:** Consider the potential for deploying such a model on edge devices for real-time, on-site soil classification.

Thank you