



DATS6103 Data Mining Final Project

# Landscape Classification

Jeongwon Yoo

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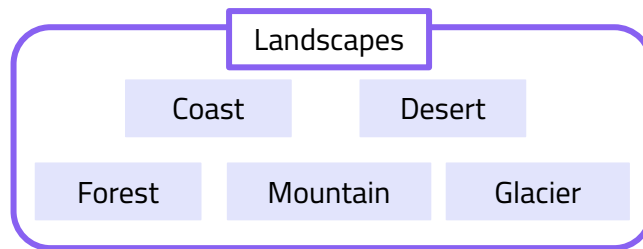
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# Introduction



## Project Objective

- Build a model that classifies landscape images into five categories using deep learning



## Why Landscape Classification

- Landscape types often appear similar
- Automated classification helps large-scale environmental analysis



## Problem Definition

- High visual similarity creates misclassification challenges
- Environmental diversity makes the dataset fine-grained



02

# Dataset & EDA

# Dataset Composition

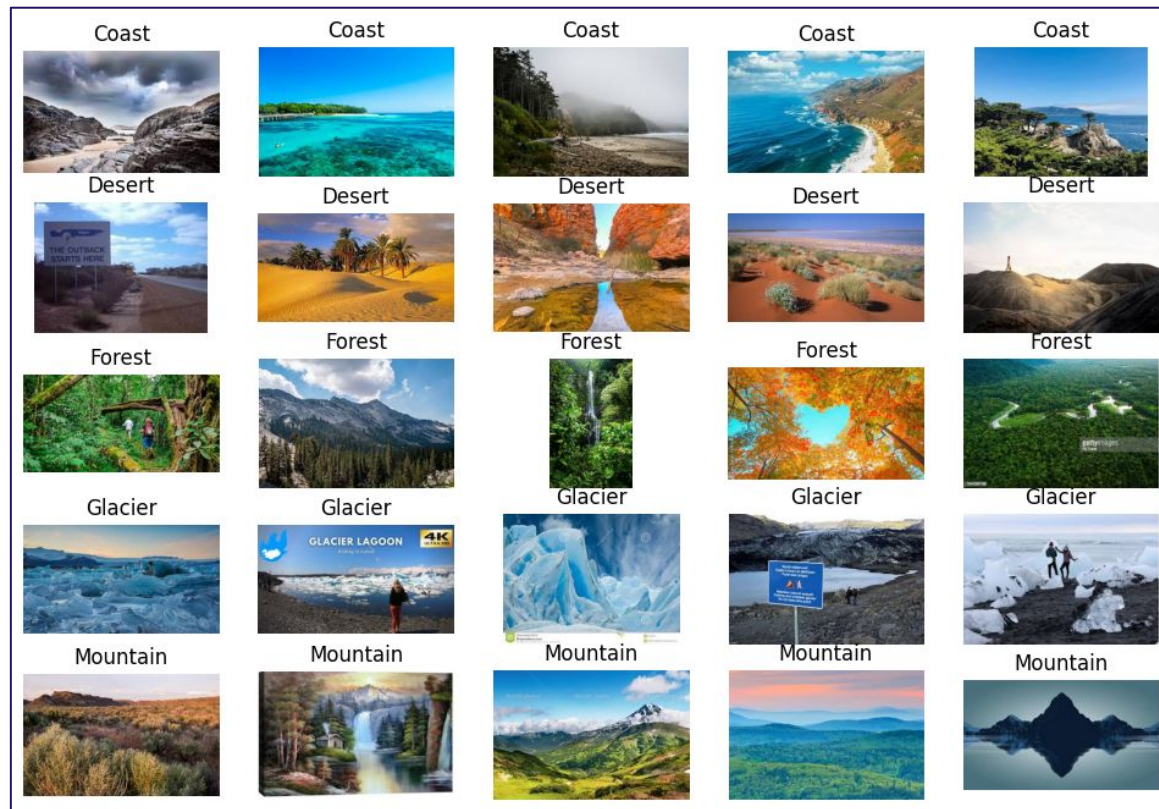
Landscape Classification	
Name	
▼	Testing Data
>	Coast
>	Desert
>	Forest
>	Glacier
>	Mountain
▼	TFrecords
>	Test
>	Train
>	Valid
▼	Training Data
>	Coast
>	Desert
>	Forest
>	Glacier
>	Mountain
▼	Validation Data
>	Coast
>	Desert
>	Forest
>	Glacier
>	Mountain



- Kaggle Data:  
Landscape Recognition Dataset
- 10,000 train | 1,500 validation | 500 test images
  - ◆ All five classes are evenly balanced

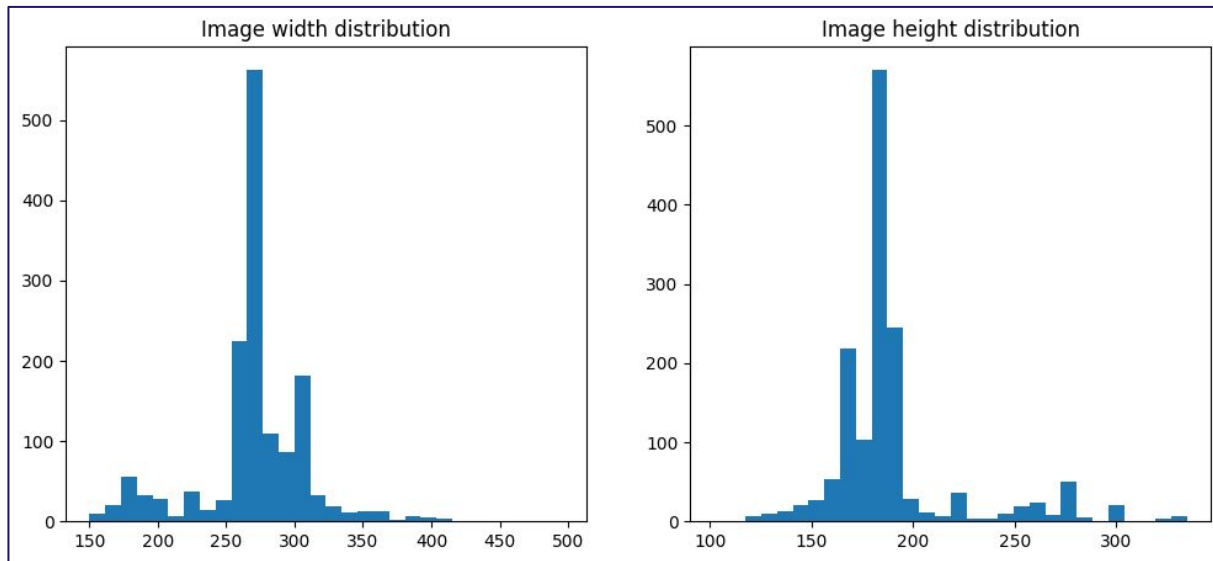


# Class Overview



Random samples from each class

# Image Size Distribution



- Image dimensions vary widely, but most cluster around 250–300 px
- Resizing was necessary for consistent model input





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# Methodology

# Methodology



## Preprocessing Pipeline

- Resize all images to 224x224
- Apply data augmentation
- Normalize images using EfficientNet built-in preprocessing

```
data_augmentation = keras.Sequential([
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(0.05),
    layers.RandomZoom(0.1),
])
```

```
input_shape = (224,224,3)

inputs = keras.Input(shape=input_shape)
x = data_augmentation(inputs)
x = normalization_layer(x)

preprocessed = x
```



## Data Pipeline

- Use TensorFlow `cache()` and `prefetch()` for faster data loading
- Batch size: optimized for GPU memory
- Ensures efficient input flow during training

```
train_ds = train_ds.cache().shuffle(1000).prefetch(AUTOTUNE)
val_ds = val_ds.prefetch(AUTOTUNE)
test_ds = test_ds.prefetch(AUTOTUNE)
```

```
img_size = (224, 224)
batch_size = 32

train_ds = tf.keras.preprocessing.image_dataset_from_directory(
    train_dir,
    image_size=img_size,
    batch_size=batch_size,
    shuffle=True
)

val_ds = tf.keras.preprocessing.image_dataset_from_directory(
    val_dir,
    image_size=img_size,
    batch_size=batch_size,
    shuffle=True
)

test_ds = tf.keras.preprocessing.image_dataset_from_directory(
    test_dir,
    image_size=img_size,
    batch_size=batch_size,
    shuffle=False
)
```



## Model Architecture

### Baseline: **ResNet50**

- Used as the initial benchmark
- Showed signs of underfitting (accuracy ~0.40)

### Improved Model: **EfficientNetB0**

- Lightweight architecture
- Strong transfer learning
- Significantly improved test accuracy



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# Models & Experiments

# Experiment Settings

<b>Epochs</b>	10
<b>Optimizer</b>	Adam (learning rate = $1e-3$ )
<b>Loss</b>	Sparse Categorical Crossentropy
<b>Batch size</b>	32

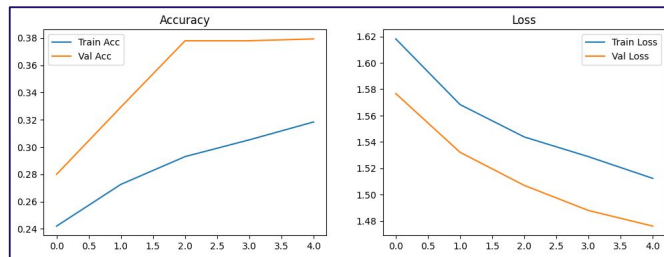
- **Data augmentation + EfficientNet** preprocessing
- **Prefetch()** and **cache()** used to accelerate training

# ResNet50 (Baseline)

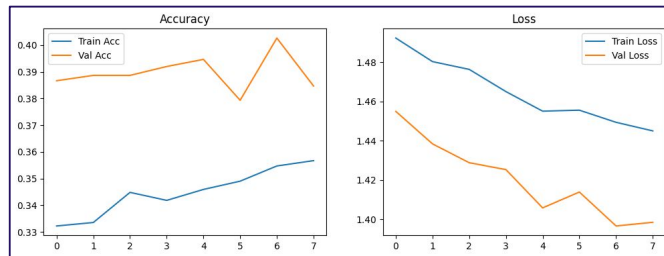
- Used as the initial benchmark
- **Validation accuracy** reached **~0.40**

Helped reveal dataset difficulty and need for stronger architecture

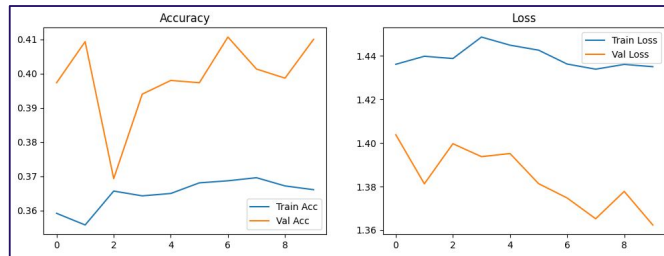
Epochs = 5



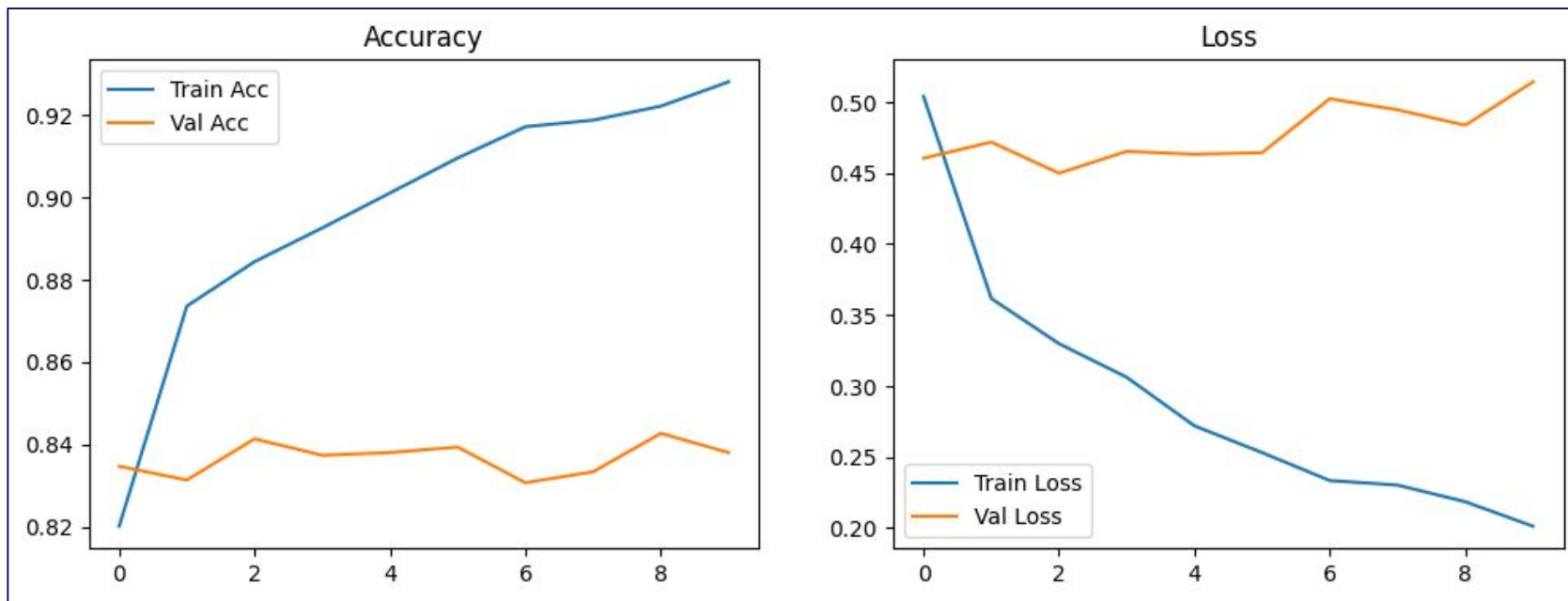
Epochs = 8



Epochs = 10



# EfficientNetB0 (Improved)



→ Efficient and effective for natural image features

→ Validation accuracy ~0.83, Test accuracy 0.884

Stable learning patterns and high accuracy





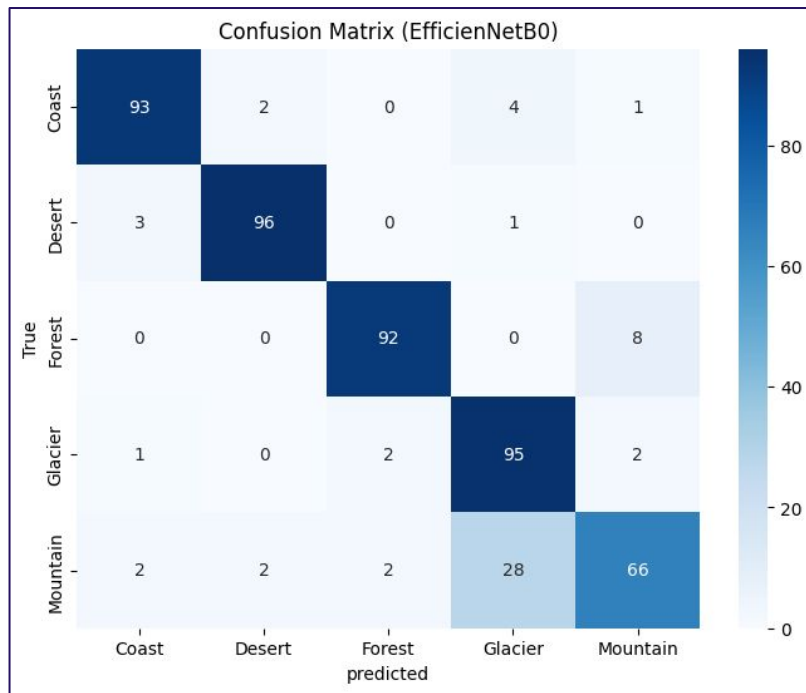
05

# Results & Evaluation

# Model Comparison

Model	Test Accuracy	Macro F1	Notes
ResNet50	~0.40	low	Underfitting
EfficientNetB0	<b>0.884</b>	0.88	Strong generalization

# Confusion Matrix



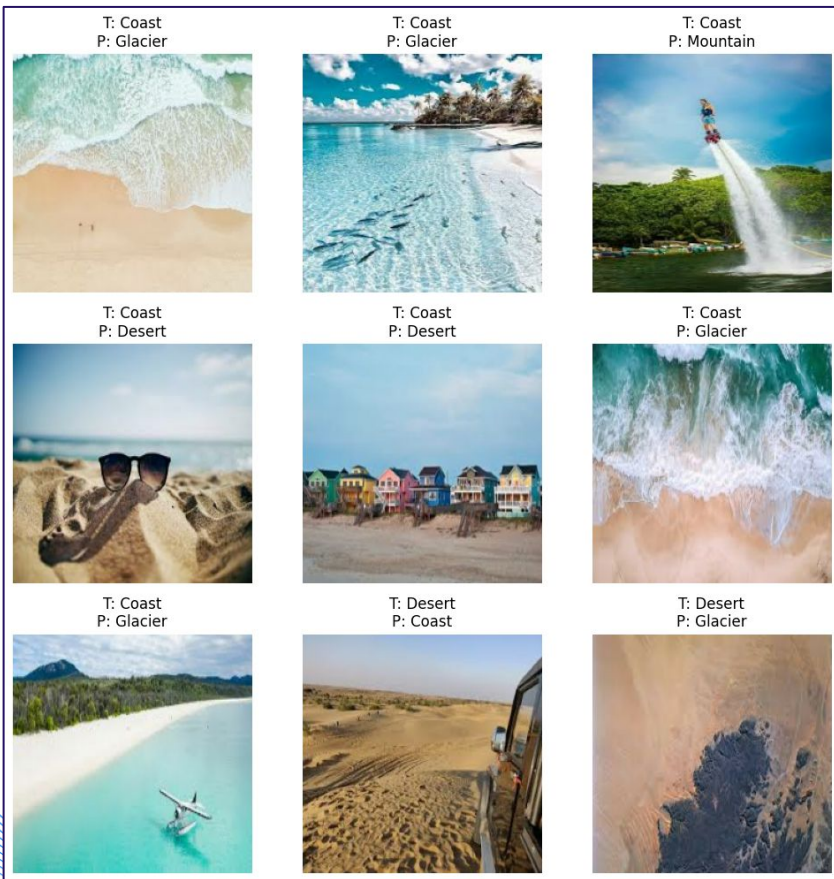
- Strong performance across most classes
- Major confusion occurs in **Mountain and Glacier** classes

# Classification Report

Classification Report:		precision	recall	f1-score	support
Coast	0.94	0.93	0.93	100	
Desert	0.96	0.96	0.96	100	
Forest	0.96	0.92	0.94	100	
Glacier	0.74	0.95	0.83	100	
Mountain	0.86	0.66	0.75	100	
accuracy		0.88	500		
macro avg	0.89	0.88	0.88	500	
weighted avg	0.89	0.88	0.88	500	

- High precision and recall for Coast, Desert, Forest, Glacier
- Mountain shows lower recall due to visual overlap
- Macro F1-score: 0.88

# Key Error Pattern



- Most misclassifications are **Mountain, Glacier**
- Most errors occurred in scenes with mixed landscape elements, such as blue water or coast–mountain combinations.

Expected in fine-grained natural scene classification tasks



## Glacier



shutterstock.com - 556661092



## Mountain



shutterstock.com - 2202790739







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# Conclusion & Future Work



## Conclusion

- EfficientNetB0 clearly outperformed the baseline and achieved strong generalization
- Most errors came from visually similar categories, mainly Mountain and Glacier
- The project successfully demonstrated the value of transfer learning for landscape recognition



## Future Work

- Fine-tuning EfficientNet variants (B1–B3)
- More targeted augmentation for snowy terrain
- Including metadata or elevation data to improve separation

# Thank You

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