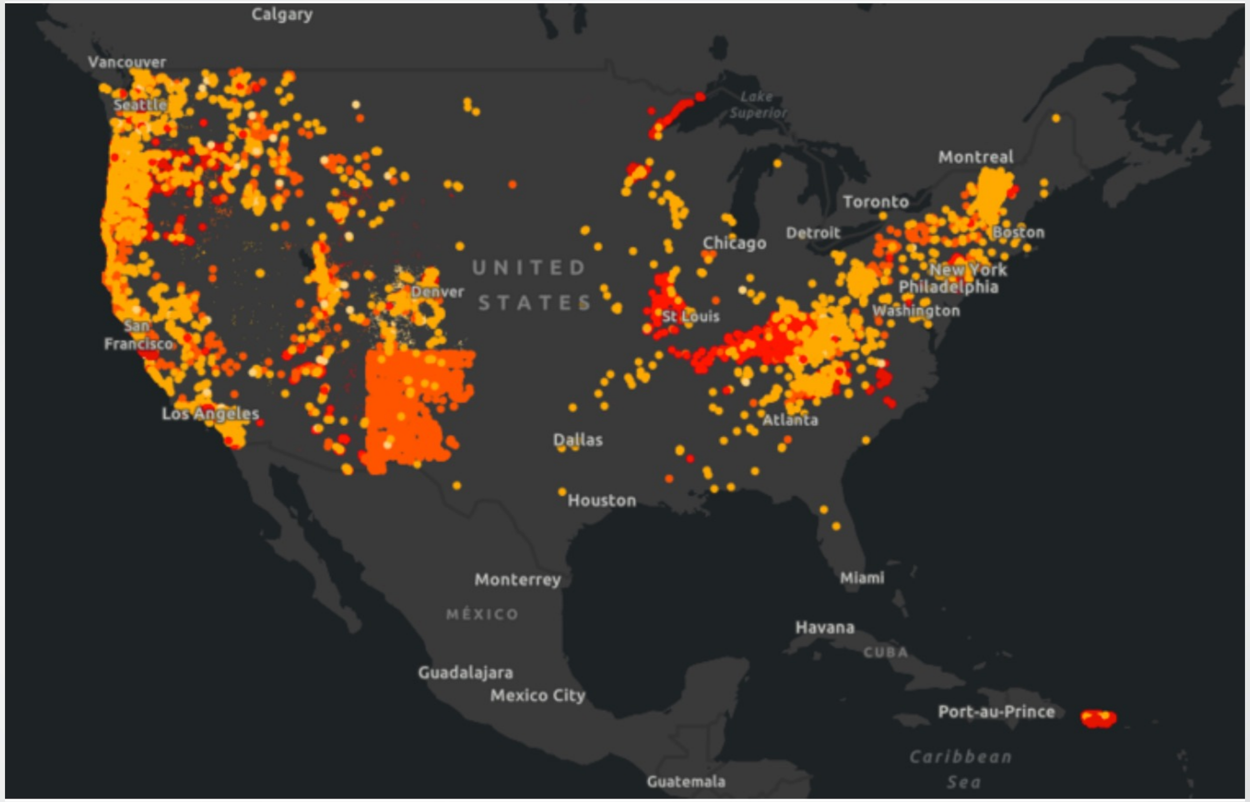

Graphic Sourced – USGS.gov /U.S. Landslide Inventory, September 2023

Landslide Identification

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Motivation

Background

Many research projects are focused on analyzing and identifying the susceptibility of landslides, but they require **accurate inventories.**

Statement of Purpose

Given increasing national and global attention on climate change, our team's objective is to apply deep learning architectures to detect/classify landslide events, even in remote areas regardless of timing.

Application

Help government and academic researchers build accurate inventories of landslides for susceptibility analysis.

Aerial Images for CNN

Landslide Images Saved to Two Classes:
0: Landslide, 1: Non-Landslide

Final Data Setup:

- **7132** Train/Validation Images
  - 6964 sourced from repositories
  - 168 sourced from Google Earth / NASA review
- **62** Unique Test Images
  - Google Images / NASA Earth Observatory

Review of NASA Landslide Observation Database

	167	246	265	288
sat_capture	captured	captured	captured	captured
latitude	36.501295	35.864314	37.680405	-23.913001
longitude	-83.028366	-121.430499	-119.748654	-65.465766
event_id	9779	9734	9691	9723
event_date	2017-05-13 00:00:00	2017-05-20 22:00:00	2017-06-12 12:00:00	2017-01-10 00:00:00
event_title	Rockfall blocks SR 70	Mud Creek Slide on SR 1	Large rockslide blocks access to Yosemite Nati...	Landslide in Volcan, Argentina
event_description	Rockfall sends large boulders onto road expect...	Massive section of hillside on Big Sur at Mud ...	Landslide on Parkline Slab cliff deposits 4,00...	Large landslide in Argentina almost entirely w...
landslide_size	medium	very_large	large	large
landslide_setting	above_road	above_road	above_road	urban
fatality_count	0.0	0.0	0.0	2.0
country_name	United States	United States	United States	Argentina

Image Processing

Key Data Pre-processing Steps

- Storage in DropBox with modified url's for proper direct downloading to Jupyter-Notebooks
- Directory structuring within .zip files for classification requirements
- Batch processing w/ Photoshop to generate:
  - .jpg file formats
  - Appropriate cropping to square formats
  - Sizing below 1000px for easier memory usage (data file ~3GB)
  - EfficientNet required specific pixel sizes across model versions; 300x300 for B3

Model Performance Comparison

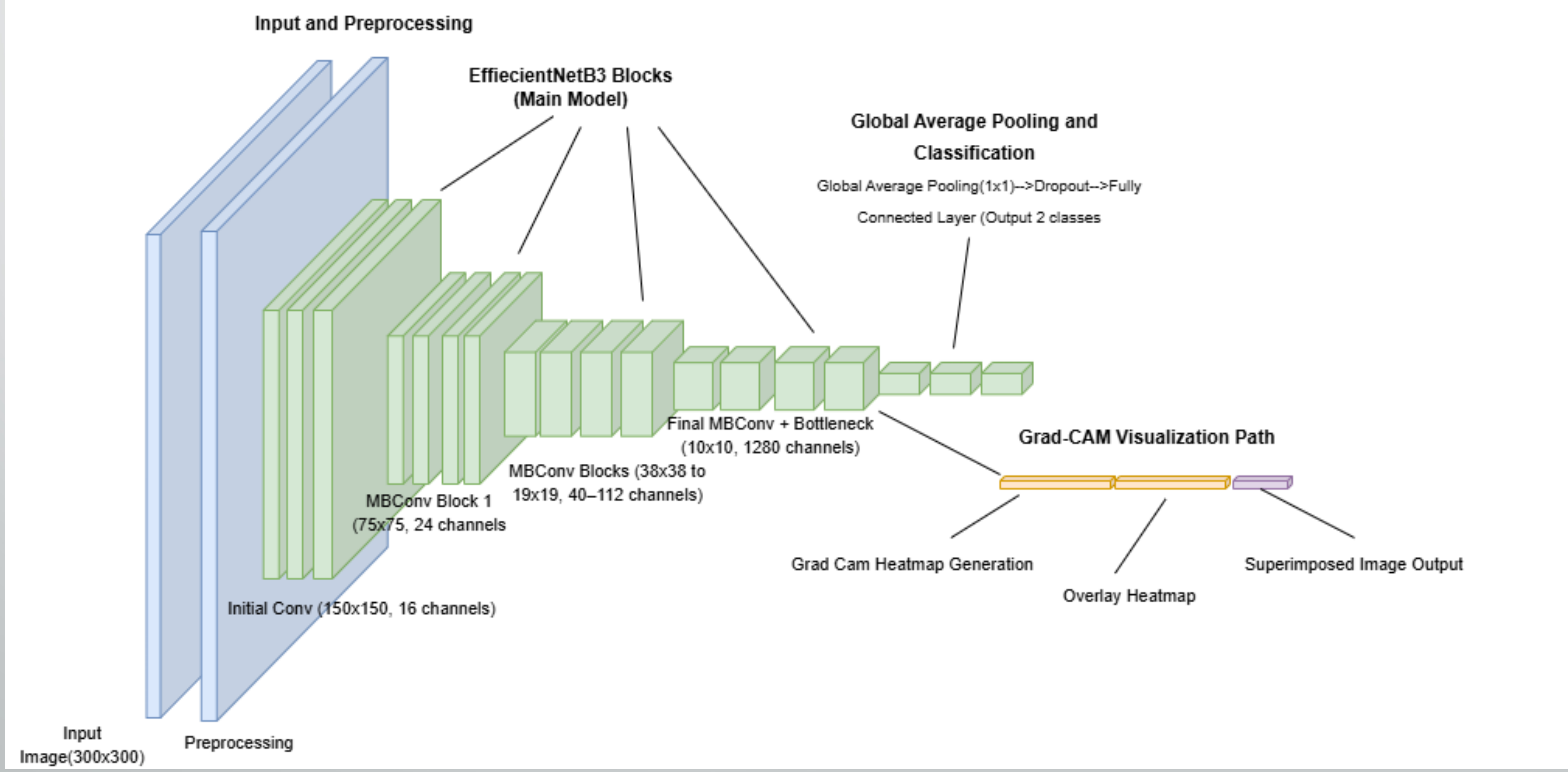
Model	Training Accuracy	Validation Accuracy	Test Accuracy	Test Precision	Test Recall
Baseline CNN	0.8898	0.8953	0.5053	0.5800	0.7230
EfficientNetB3	0.9905	0.9969	0.6340	0.6140	0.5380
ResNet50	1.0000	0.9984	0.5252	0.6538	0.3863
MobileNet	0.9688	0.9589	0.5269	N/A	N/A
DenseNet121	0.9062	0.9700	0.5526	N/A	N/A
NasNetLarge	0.6903	0.7437	0.6270	0.7130	0.2920

Model Architectures

Pre-trained Model	Size (MB)	Parameters	Depth
Baseline CNN	10.47	2.8M	5
EfficientNetB3	48	12.3M	210
ResNet50	98	25.6M	107
MobileNet	16	4.3M	55
DenseNet121	33	8.1M	242
NasNetLarge	343	88.9M	533

EfficientNetB3

- **EfficientNetB3 Architecture:** EfficientNetB3 forms the core model, leveraging MBConv blocks and bottlenecks for feature extraction from satellite images.
- **Grad-CAM Integration:** Grad-CAM visualizations enhance interpretability by highlighting image regions linked to landslide predictions.



Experiments

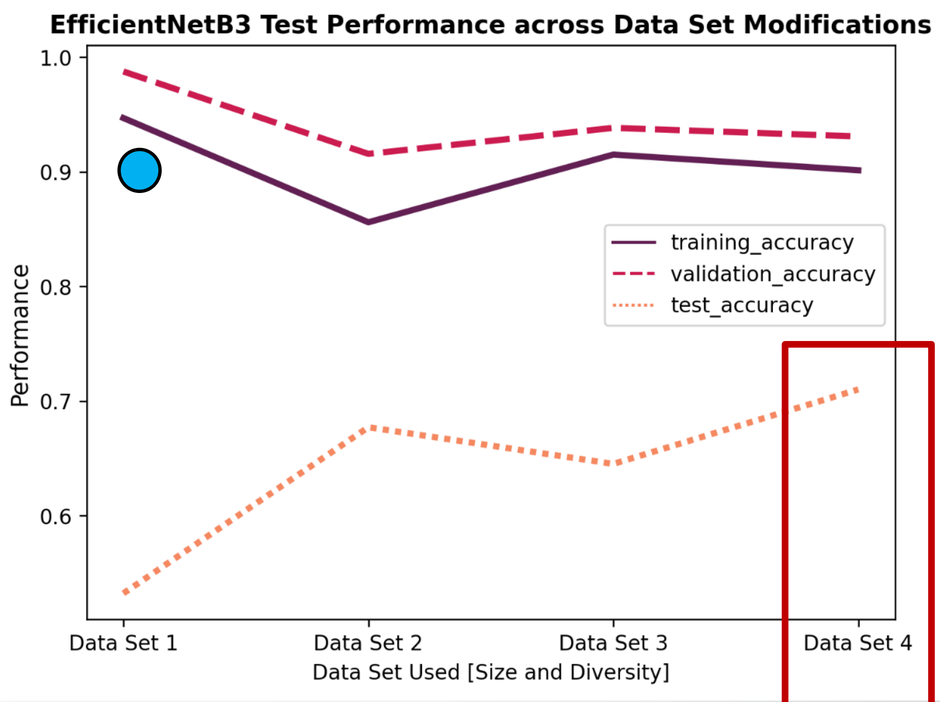
Primary Key Deep Learning Architectures

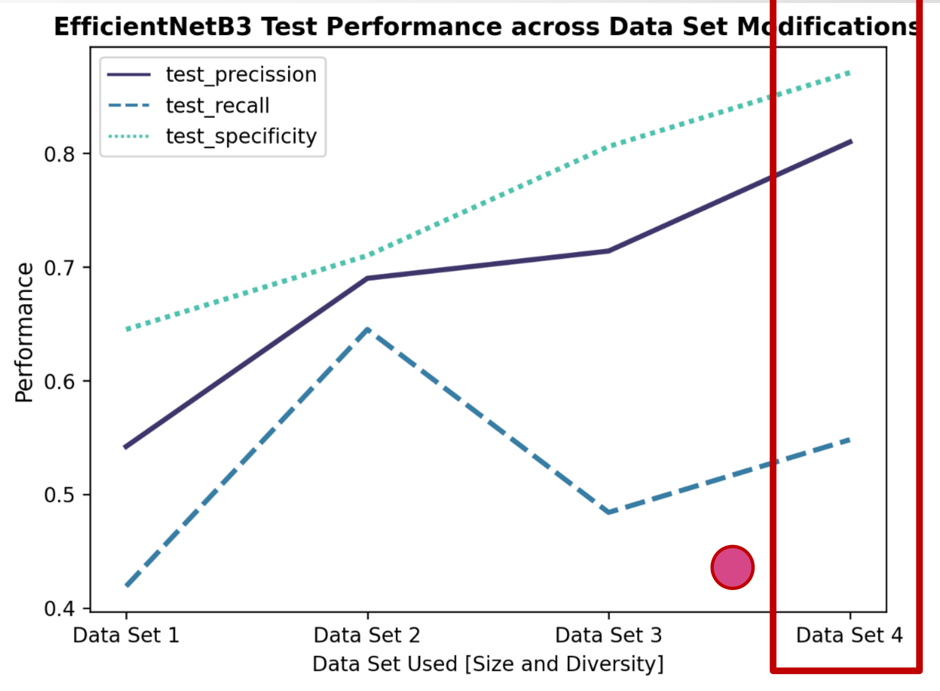
1. Start with training a **CNN model** to classify imagery to identify landslides, trying our top 2 performers: ResNet50 and ENB3.
2. **Transfer Learning** with ResNet and/or other pre-trained models focusing on Feature Extraction (e.g., extraction of meaningful features from new samples) and Fine-Tuning for joint layer training. Attempted multiple approaches to unfreezing layers.
3. **Weight Transfer** by saving the model, then unfreezing and continuing training. Layer vs Block.
4. **Multi-modal CNN** (e.g., bring in tagging data for size) to go add more descriptive classification.
5. **Grad CAM** to help us illustrate which areas contribute the most to the prediction.

Analysis of Varying Data Size & Diversity

- Per our Literary Review, diversity of data in prior landslide detection cases was noted as a key factor.
- We observed how homogeneity within the image space caused overfitting as noted in Set 1.
- We're surprised by the power of a small 2.4% increase in image variation. We observed a large impact on test accuracy once integrating our more diverse NASA image set into the data.

Data	Size
SET 1 (Train/Validate)	2000
SET 2 (Train/Validate)	3200
SET 3 (Train/Validate)	6974
SET 4 (Train/Validate)	7132
Set 7 (Test)	62





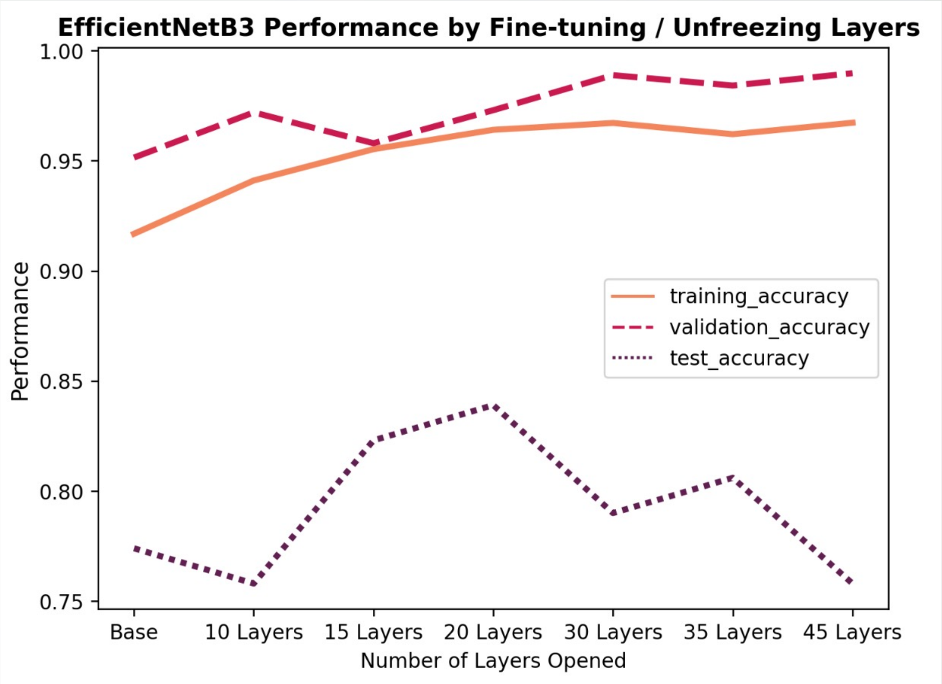
Model Performance w/o Fine-Tuning

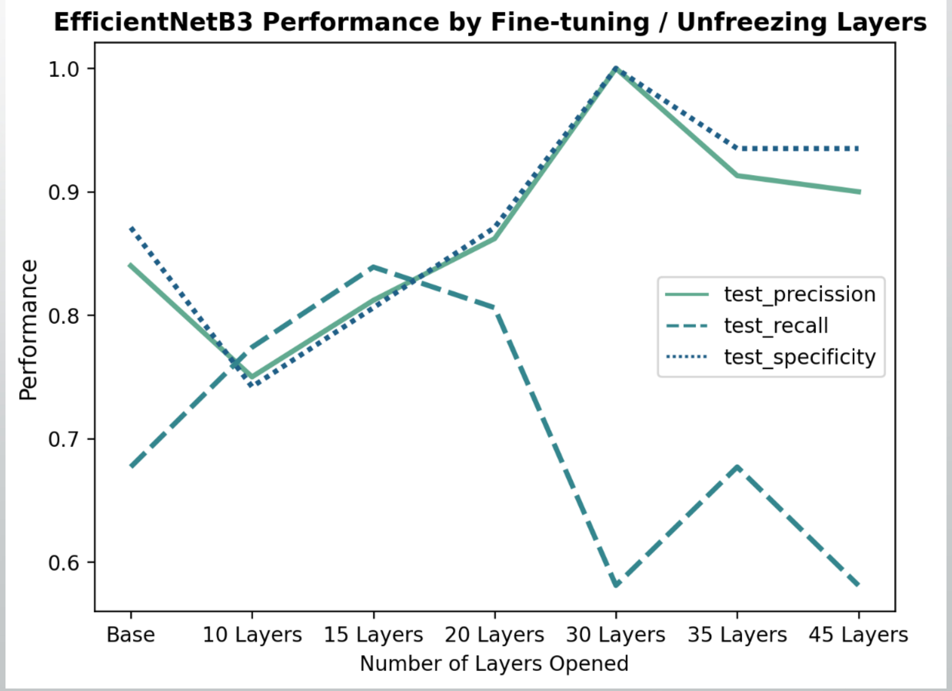
EfficientNetB3 Fine-Tuning

- **Pretrained Weights:** Initialized with ImageNet.
- **Layer Freezing Strategy:**
  - Froze initial layers to retain general features.
  - Unfrozen final layers to adapt to landslide-specific features.
- **Optimizer and Learning Rate:**
  - Adam optimizer, learning rate: 0.001.
  - Reduced learning rate on plateau for stability.
- **Training Configuration:** 15 epochs, batch size of 32.

Fine-Tuning Scenarios

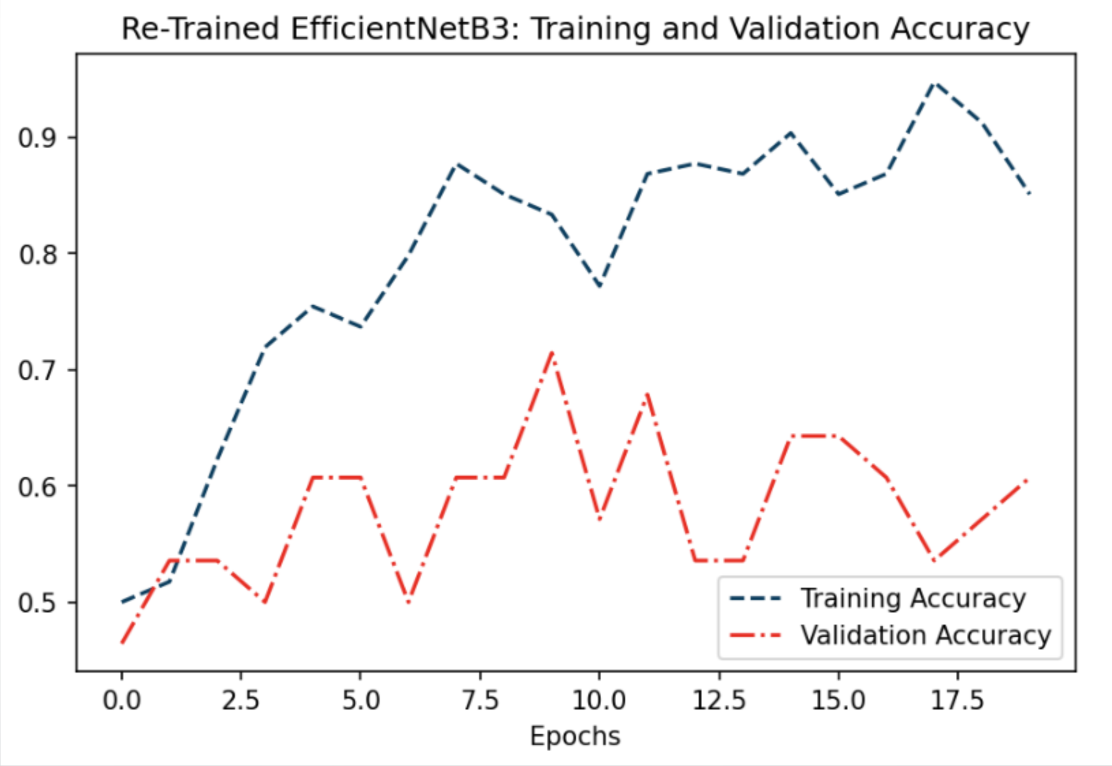
- Experimented with a variety of Layer Tuning depths with our Combined-Training data.
- Further training of higher-level features within models / EfficientNetB3 is an industry practice to customize for task-specific cases.
- Observed that further training of higher-level features improved performance; but as more layers are refined, are improvements steady and consistent ?
- We monitored impacts to:
  - Overall Accuracy
  - Recall – the % of Landslide images identified from the classification.
  - Precision – the % accuracy of landslides predicted by the model.
  - Specificity – the % of non-landslides identified from the classification.



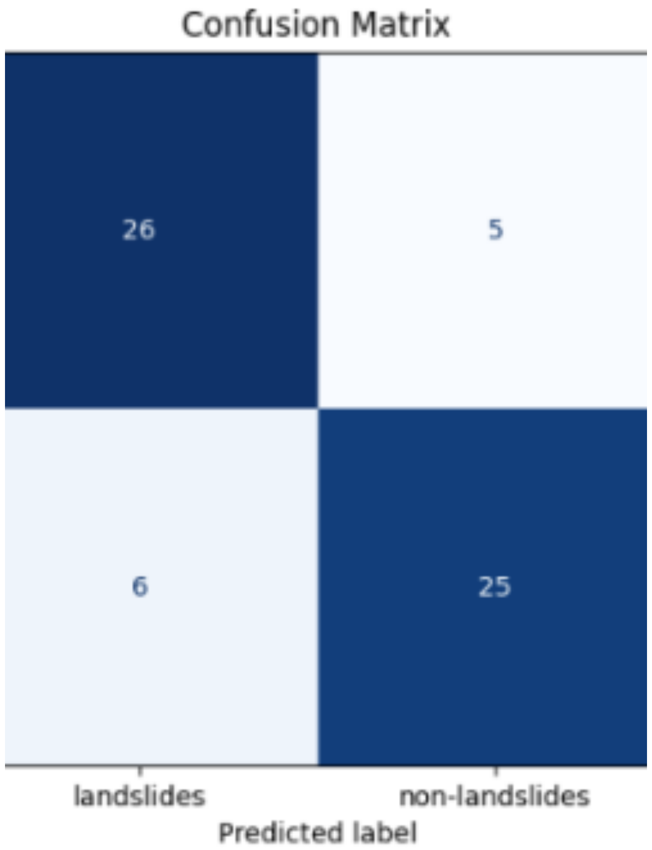


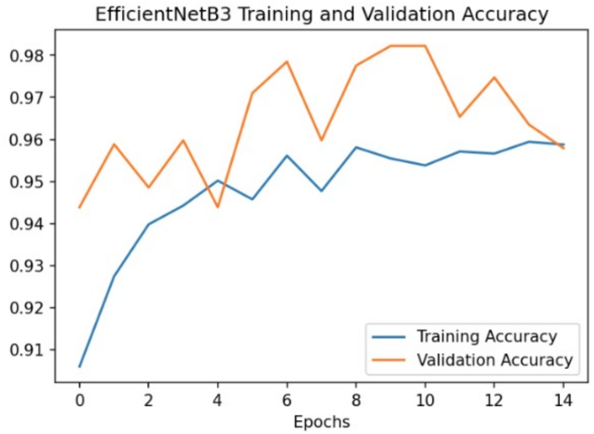
Weight Transfer – 2nd Model Training

- Attempted a multi-model approach which did not perform as hypothesized.
- Hypothesis – Initial fine-tuned training on a pre-trained model to learn basic landslide type features from a more homogenic data set.
- Transition of weights to a new model environment through **'.Keras API'**. **(Note – not fully stable due to multi-Tensorflow versions)**
- Further training / fine-tuning with a more diverse but smaller training set to improve on the already exposed model weights.
- **Validation Accuracy** did not come close to other design achievements, with accuracy coming out at ~60% across the epochs.



EfficientNetB3 Results

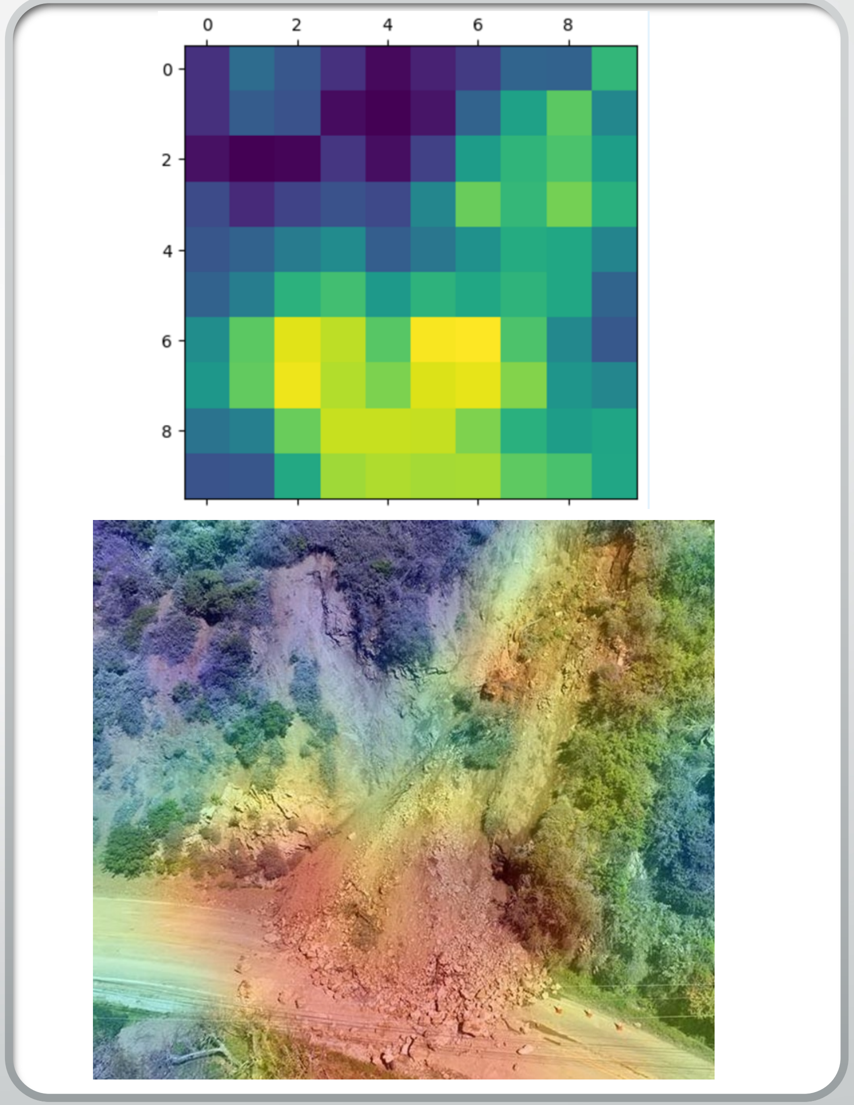




Metric	Value
Training Accuracy	.9552
Validation Accuracy	.9579
Training Loss	.1186
Validation Loss	.1281
Test Accuracy	.8230
Test Precision	.8120
Test Recall	.8390
Test Sensitivity	.8060
Test F1 Score	.8250

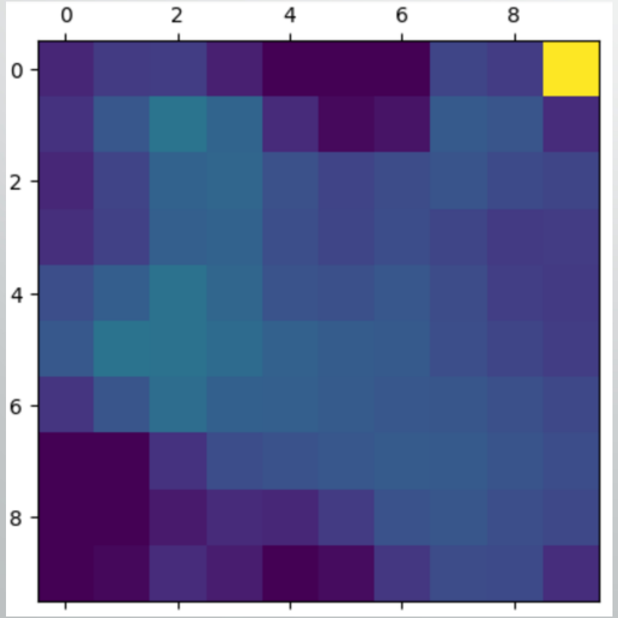
Grad-Cam Visualizations

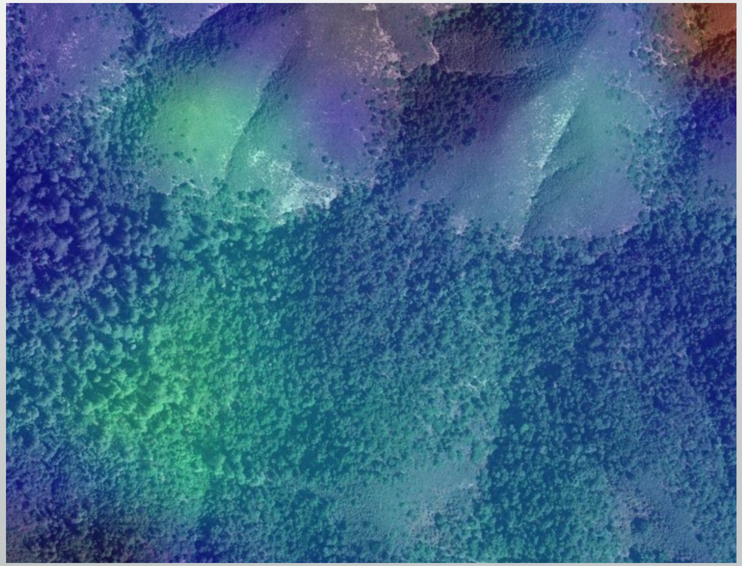
- Bright areas align with landslide-specific features (e.g., slopes, vegetation loss).
- Dark areas indicate irrelevant regions excluded by the model.
- Used confusion matrix results from the test set to understand where the network focused its attention when predicting correctly and incorrectly
- Improved trustworthiness for end-users



Grad CAM on False +/-

- An apparent pattern in the false positives and false negatives was a tendency for the network to focus on some of the corners of the images, particularly the top right corner
- Further work is needed to understand when and why this occurs.





Limitations

- **Data Constraints**:
  - Insufficient labeled datasets for rare landslide conditions.
  - Geographic bias in existing datasets limits global applicability.
- **Model Constraints**:
  - Performance variability when tested on unseen regions.
  - Computational costs limit scalability to large-scale applications.

Conclusions

- **EfficientNetB3** excelled in landslide detection with higher accuracy, precision, and recall than other pre-trained models.
  - Utilized transfer learning to enhance performance and generalization across datasets.
- **Grad-CAM Visualizations:** Improves interpretability and trust in predictions.
  - Expand datasets with diverse environmental conditions.
  - Incorporate temporal data for dynamic landslide prediction.
  - Optimize models for scalability and deployment efficiency.

Summary

Team will apply deep learning architectures to build out a landslide inventory and attempt to build probability model to help predict future events. Will apply:

- CNN; Multi-modal CNN
- ResNet (transfer learning)
- Grad CAM

Data: Thousands of images of landslides from around the world. Higher resolution images captured manually using USGIS dataset for the location & impact, applying data augmentation due to only 100-200 of these high-resolution images.