Wildfire Risk Prediction with Remote Sensing and Transfer Learning

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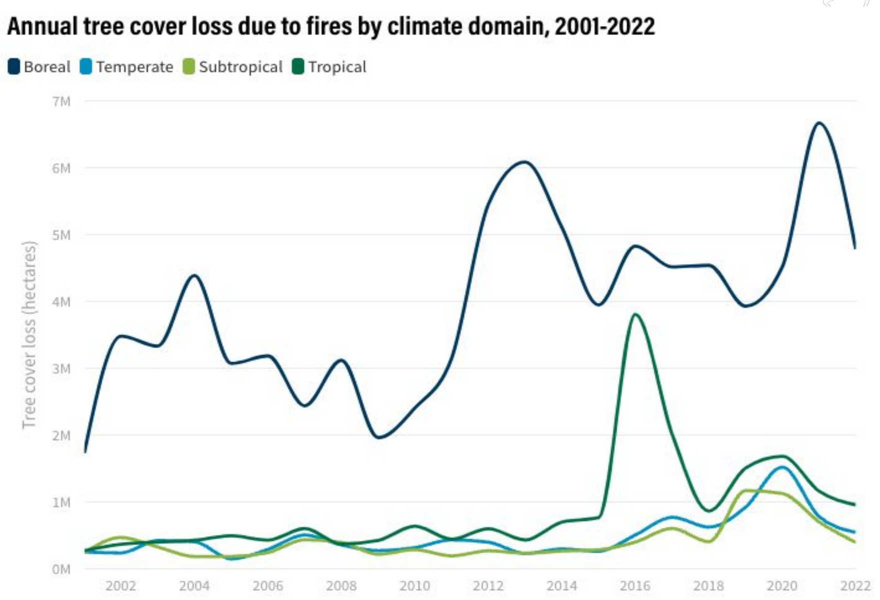
Problem Statement

- **Background:** Since the 1980s, wildfires have intensified due to factors like climate change, posing significant threats to ecosystems and economies.
- **Need for Assessment:** Early wildfire risk assessment is crucial for environmental protection and effective resource allocation by authorities.
- **Potential Impact:** By analyzing photos, machine learning models can assess areas for wildfire risk, aiding in proactive measures like vegetation management and controlled burns.



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Key Objectives

1. Assess the effectiveness of different machine learning models in analyzing satellite imagery for wildfire risk prediction.
2. Focus on understanding the performance dynamics of various model architectures rather than developing a production-ready methodology.
3. Utilize an existing repository of pre-processed satellite images to fit 10 robust models.

Performance Metrics

- Accuracy
  - correctly classified proportion
- Precision
  - true positives / all positive predictions
- Recall
  - true positive / all actual positives
- F1 Beta Score
  - the harmonic mean of precision and recall
- F2 Beta Score
  - weights recall 2x more than F1
  - false negatives are more costly than false positives

Success: >0.85 precision and recall.

Failure: <0.75 precision and recall.

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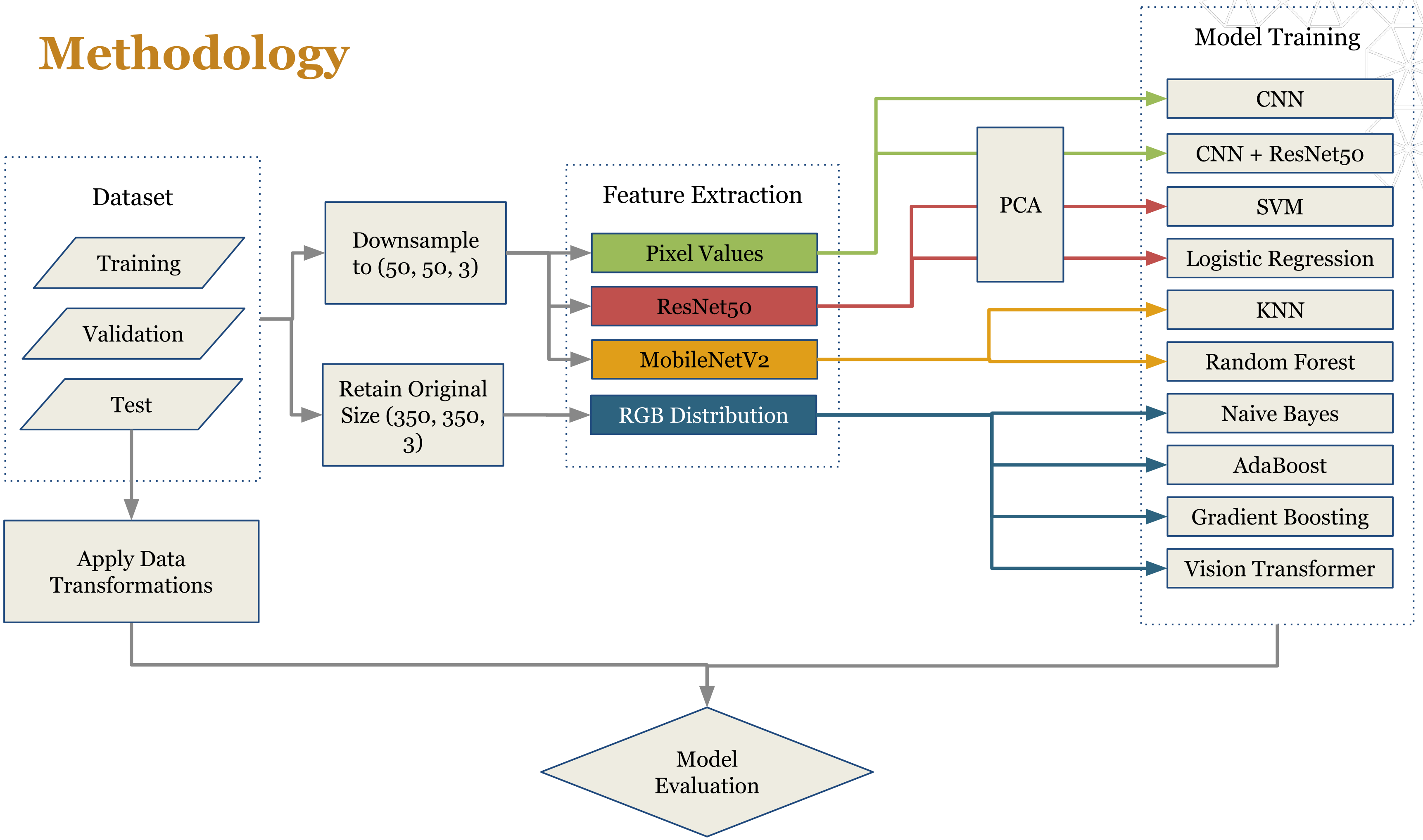
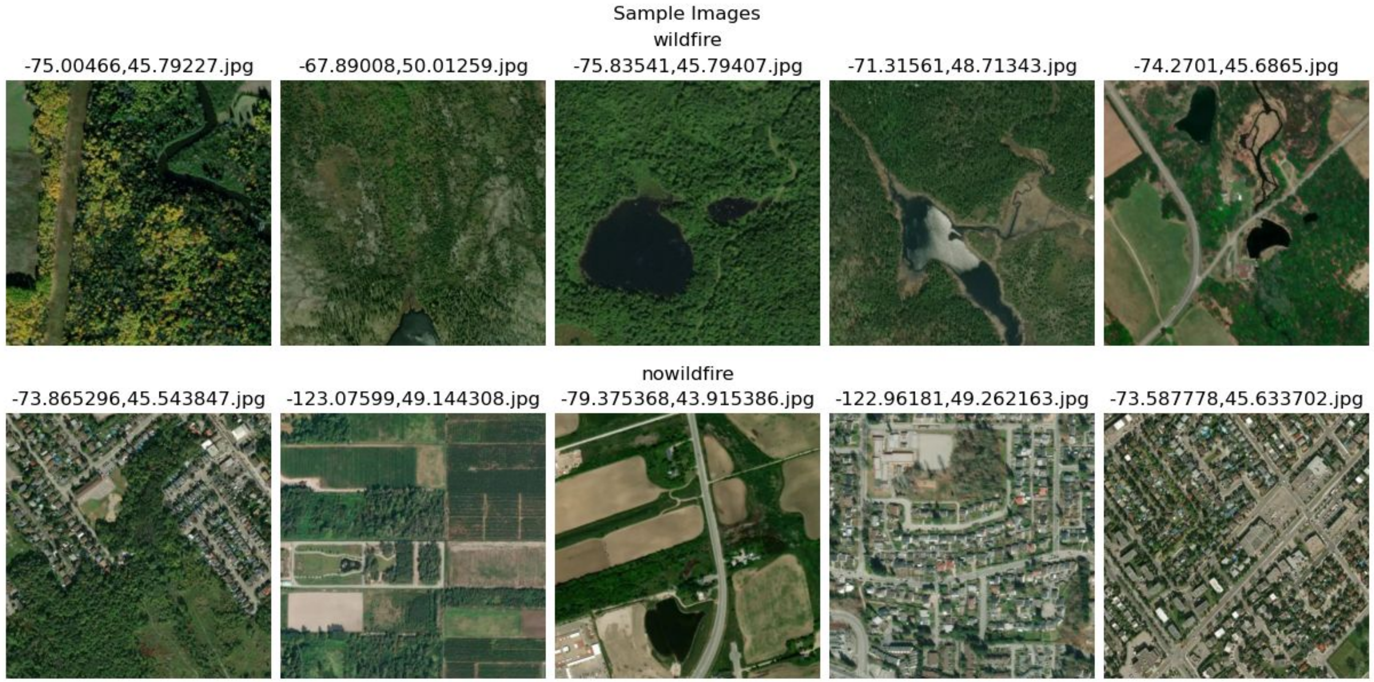
Methodology



Data Overview

- For this study, we are use the Wildfire Prediction Dataset (Satellite Images) on Kaggle.com by Abdelghani Aaba (derived from Forest Fires – Open Government Portal).



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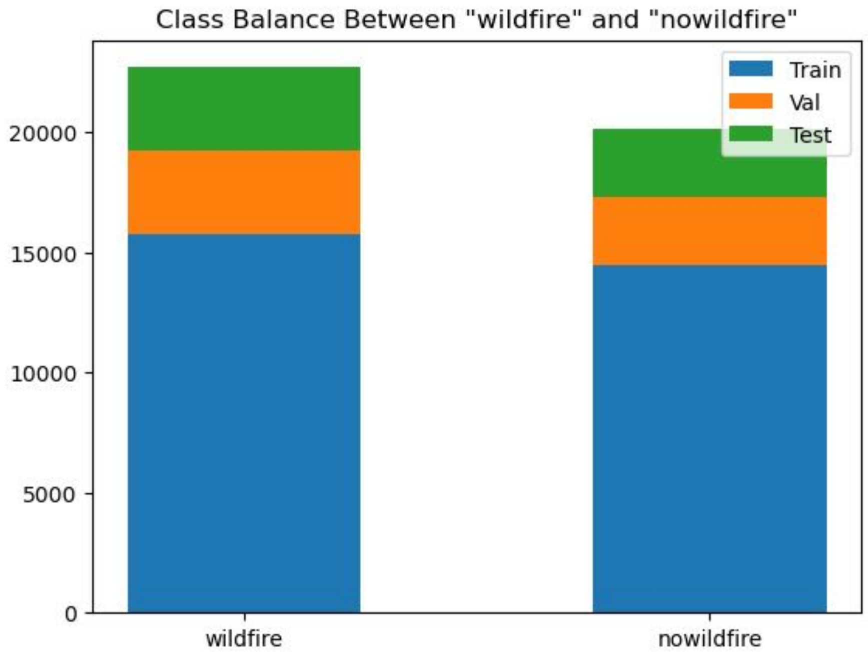
Class Balance

- Labels
  - Wildfire : 22,710 images
  - No wildfire: 20,140 images

- Train/Test/Validate:
  - Train: 30,250 images (75%)
  - Validation: 6,300 images (15%)
  - Test: 6, 300 images (15%)



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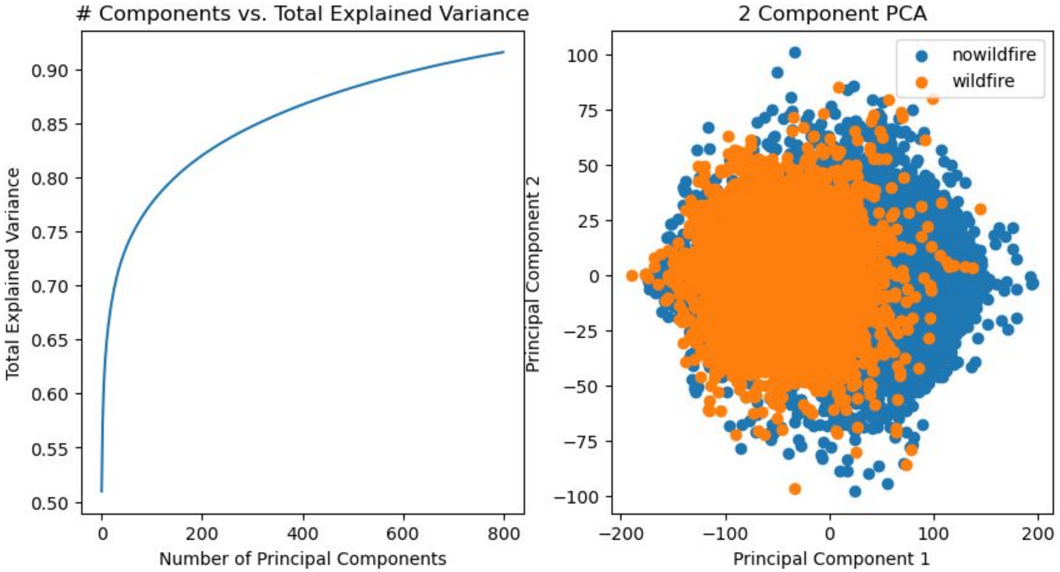
Raw Pixel Values as a Baseline Feature

- Most simple and elementary feature
- Flattens the raw pixel values into a 1D vector for each image
- Models using this feature: Baseline Logistic Regression, Baseline CNN



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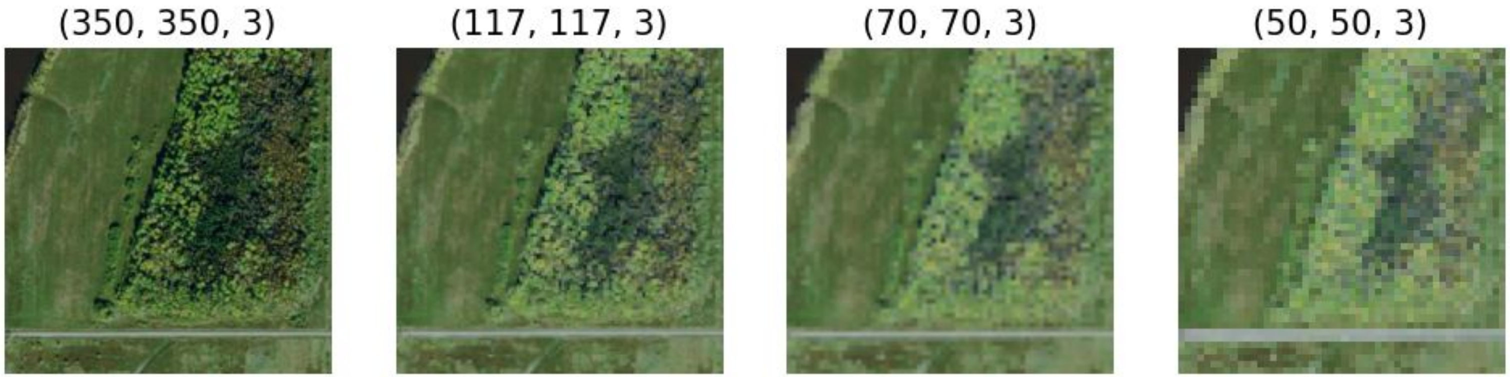
Midterm Results From Baseline Models

Metric	Logistic Regression with Image Flatten	CNN w/ Sigmoid, SGD Optimizer	CNN w/ Sigmoid, Adam Optimizer	CNN w/ Relu, Adam Optimizer
Train Accuracy	90%	53%	86%	93.2%
Validation Accuracy	89%	48%	53%	55.3%

Image Downsampling



- Used max pooling on varying block sizes
- Downsampled to (50, 50, 3) based on visual inspection
- Aids in speeding up computation time for downstream tasks without losing too much information

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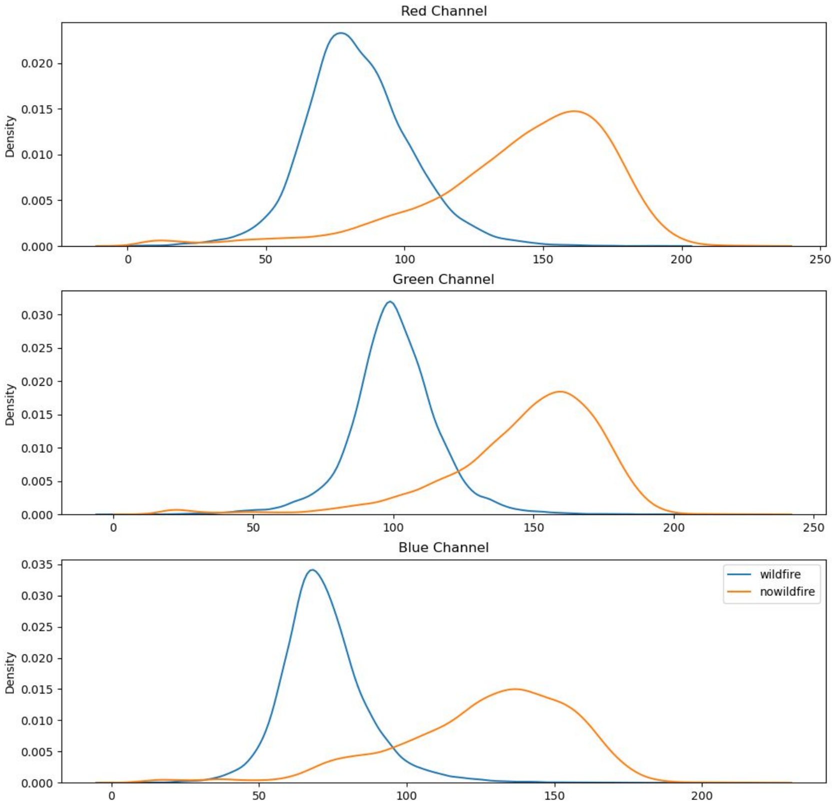
Feature: RGB Distribution

- Simple and intuitive representation of RGB color distributions
- Normalized histograms for all 3 color channels constructed as a single vector
- Robust to variations in images
- Low computational cost
- Models using these features: Naive Bayes, AdaBoost Classifier, Gradient Boosting Classifier



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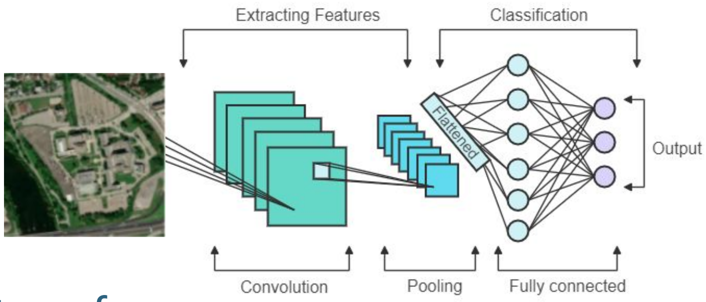
Feature Extraction: MobileNetV2

- Neural Network
- Expansion and depth-wise convolutional layers
- Linear activation function (to prevent the model from becoming too complex)
- Lightweight & accurate models
- Captures both fine-grained details and high-level patterns for classification tasks.
- Models using these features: Random Forest, KNN, and



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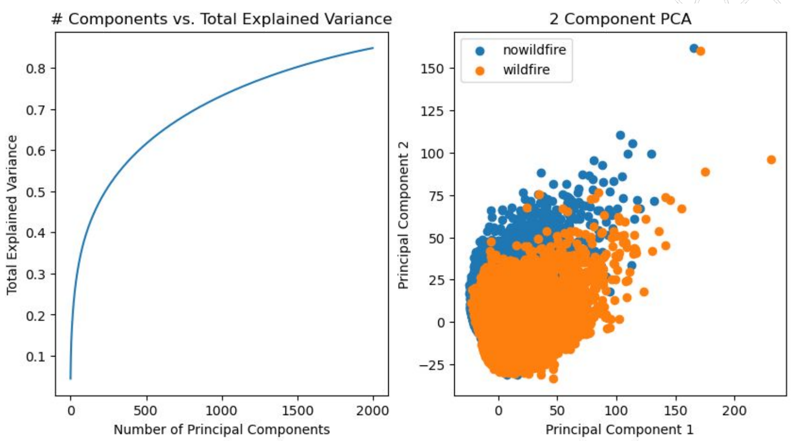
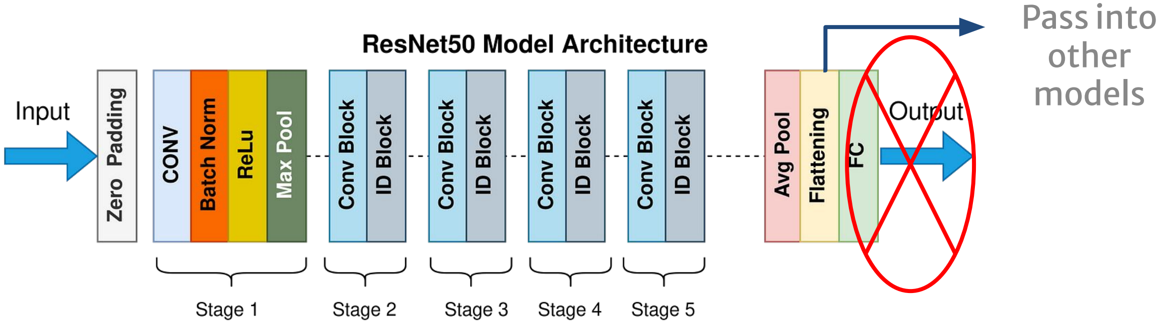
Feature Extraction: ResNet-50

- Remove fully connected layer of the ResNet50 model, keep only the convolutional base.
- Pass satellite images through the ResNet50 convolutional layers, to extract features.
- Apply global average pooling to reduce the spatial dimensionality.
- Obtain a feature vector representing each input image.
- Pass the extracted features into classifiers for wildfire prediction
- **Models using this feature:** Logistic regression, SVM





[Source: Suvaditya Mukherjee, Towards Data Science]()

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Model comparison

	Model	Accuracy	Precision	Recall	F1	F2
1	Gradient Boosting Classifier	0.969	0.980	0.964	0.972	0.967
2	CNN + ResNet50	0.961	0.968	0.961	0.964	0.962
3	Vision Transformer (ImageNet-21k)	0.916	0.957	0.941	0.927	0.956
4	AdaBoost Classifier	0.957	0.968	0.954	0.960	0.956
5	Logistic Regression + ResNet50	0.945	0.961	0.939	0.949	0.943
6	Naive Bayes	0.824	0.767	0.979	0.860	0.927
7	CNN	0.918	0.938	0.911	0.917	0.925
8	SVM + ResNet50	0.918	0.937	0.913	0.925	0.917
9	K-Nearest Neighbors + MobileNetV2	0.895	0.912	0.897	0.905	0.901
10	Random Forest Classifier + MobileNetV2	0.889	0.903	0.895	0.899	0.896

*Reference for Accuracy Metrics

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Top 3 Models based on F2 Score

1. Gradient Boost Classifier
2. CNN + ResNet 50
3. AdaBoost Classifier

Model 1: Gradient Boosting Classifier

- Used sklearn's Gradient Boosting Classifier
- Trains a robust classifier sequentially, with each new weak learner trained to correct the errors made by the previous ones.
- Gradient Boosting fitsnew weak learners to the residuals of the current ensemble
- Typically achieves high accuracy in datasets with noise

```
Gradient Boosting Classifier with Downsampling -> RGB feature extractior
Training Accuracy: 0.9585785123966942
Validation Accuracy: 0.956031746031746
Test Accuracy: 0.9625396825396826
Test Precision: 0.9674351585014409
Test Recall: 0.9646551724137931
F1 Beta: 0.9660431654676259
F2 Beta: 0.9652098907418057

Confusion Matrix (Test):
 [[2707  113]
 [ 123 3357]]
```

```
Gradient Boosting Classifier with RGB feature extraction
Training Accuracy: 0.9658512396694214
Validation Accuracy: 0.9658730158730159
Test Accuracy: 0.9696825396825397
Test Precision: 0.9804265264387964
Test Recall: 0.964367816091954
F1 Beta: 0.9723308706359554
F2 Beta: 0.9675373349478175

Confusion Matrix (Test):
 [[2753   67]
 [ 124 3356]]
```

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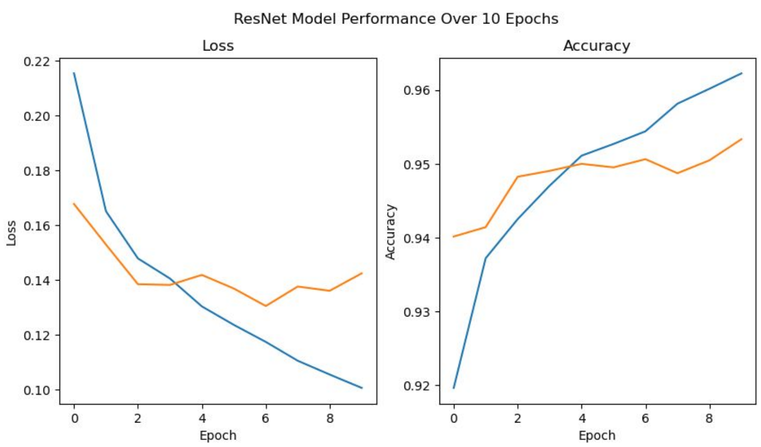
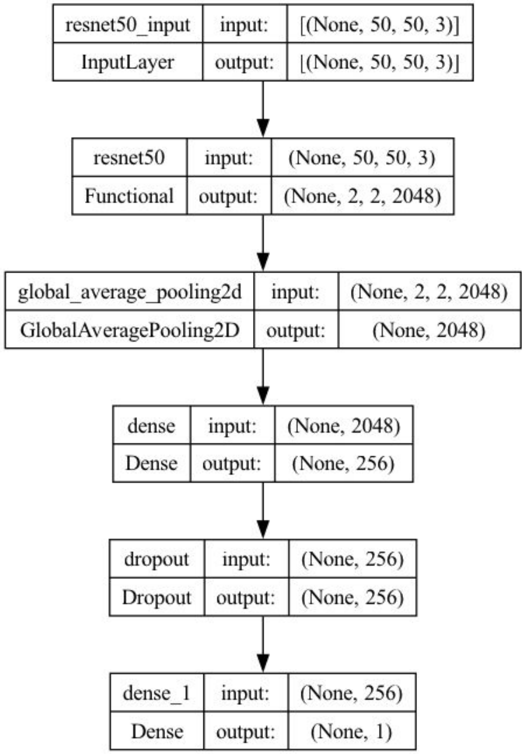
CNN with ResNet50 Pretrained Base Model

- Wrapped CNN around ResNet50 architecture using TensorFlow/Keras.
  - Utilized transfer learning by loading pre-trained ResNet50 model with ImageNet weights.
  - Extracted features using Global Average Pooling layer to reduce dimensionality.
  - Added dense layers for classification with dropout regularization.
- 24,112,513 total parameters
- 524,801 trainable parameters





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Model 2:
CNN + ResNet 50

- Wrapped CNN around ResNet50 architecture using TensorFlow/Keras.
    - Loaded pre-trained ResNet50 model with ImageNet weights.
    - Extracted features using Global Average Pooling.
    - Added dense layers for classification with dropout regularization.
- 24,112,513 total parameters
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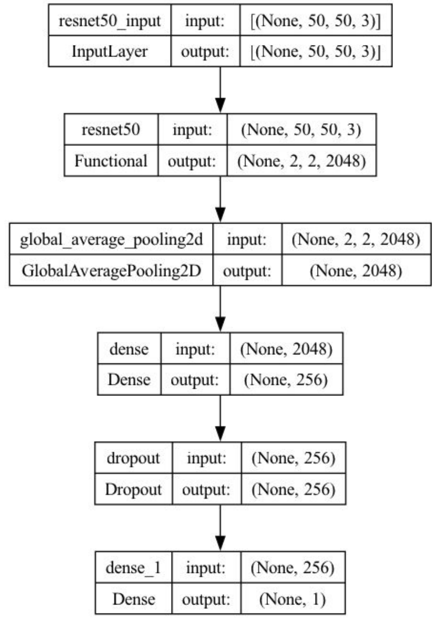

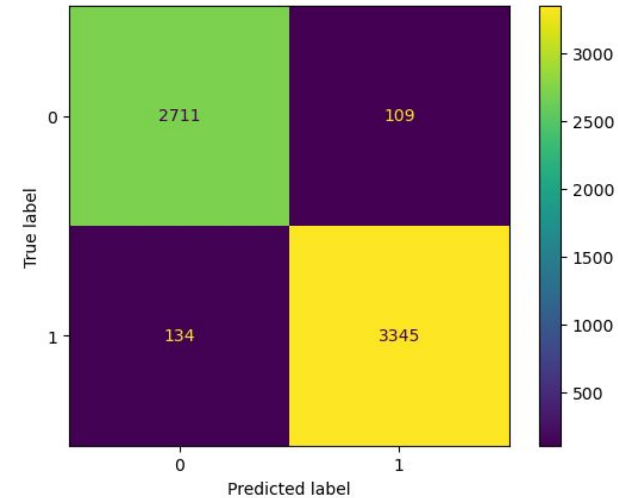

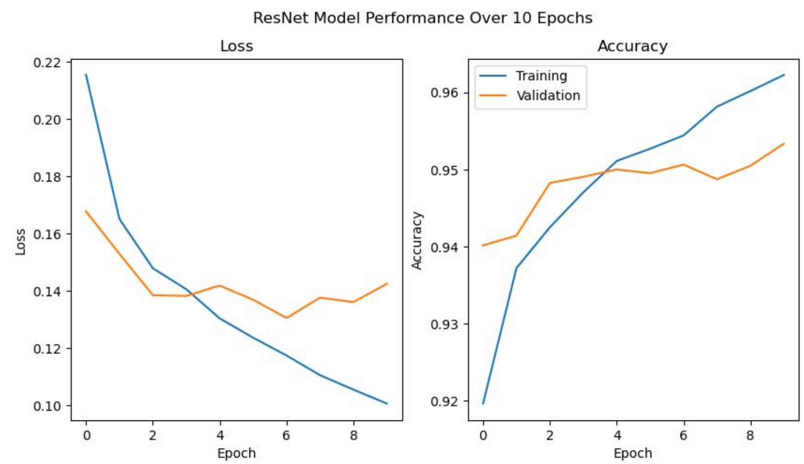

Model 3: Adaptive Boosting Classifier

- Used Sklearn's AdaBoost Classifier Package
- Robust classifier trained by iteratively combining the predictions of multiple weak learners
- Each subsequent model assigns higher weights to the misclassified samples from the previous iteration
- AdaBoost is surprisingly robust with RGB feature extraction vs downsampling

```
AdABoost Classifier with Downsampling -> RGB feature extraction
Training Accuracy: 0.9439338842975207
Validation Accuracy: 0.9480952380952381
Test Accuracy: 0.949047619047619
F1 Beta: 0.9538726828567323
F2 Beta: 0.9537904477268807

Confusion Matrix (Test):
 [[2660  160]
 [ 161 3319]]
```

```
AdaBoost Classifier with RGB feature extraction
Training Accuracy: 0.9498842975206612
Validation Accuracy: 0.9517460317460318
Test Accuracy: 0.9571428571428572
Test Precision: 0.967930029154519
Test Recall: 0.9540229885057471
F1 Beta: 0.9609261939218524
F2 Beta: 0.956772334293948

Confusion Matrix (Test):
 [[2710  110]
 [ 160 3320]]
```

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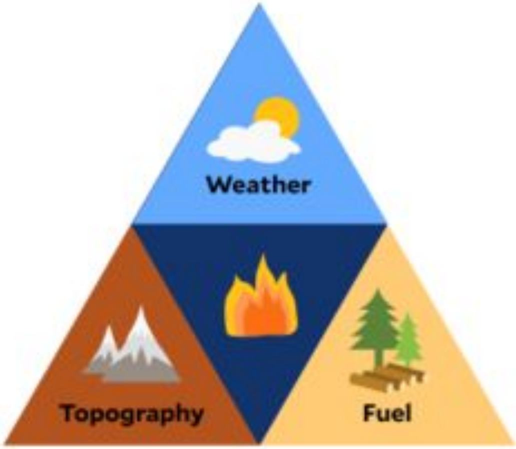
Bias and Fairness

- It is well-established that predictive AI algorithms can often be biased when applied to human beings.
- There is little research being done at the moment on geospatial biases and predictive algorithms' unintended biases in disaster prediction.
- Sampling bias:
  - Wildfire boundaries are commonly documented by forests services.
  - "nowildfire" labels need to be sampled from anywhere not within those boundaries.
  - Methods for sampling must ensure comprehensive representation of topographies, land uses, etc.
- Satellite images on the visual spectrum can only capture so much (for example, no vertical information, all birds-eye-view), and are prone to biases because of this.

Constraints and Limitations

- This study does not include data collection methodology
  - Key limitation of Kaggle data: time between photo taken and time of fire is unspecified
  - Methods for sampling images is out of our control
- Wildfire prediction largely dependent on additional factors beyond the visual spectrum
  - Infrared bands
  - Temperature, wind, humidity
- We recognize that this simplified approach to wildfire prediction



Fire Behavior Triangle

The factors involved in the severity, intensity, duration, size, and season of wildfires

Source: Yale Sustainability

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Final Takeaways

- Binary classification is suitable for wildfire prediction using visual spectrum satellite images alone.
- **All models exceeded our initial goal of >0.85 precision and recall.**
    - The Gradient Boosting Classifier performed the best (**0.964 precision, 0.972 recall, 0.967 F2**)

However

- These numbers only describe how well the models fit and generalize on the data available.
- Being able to predict wildfires in production will require more work in the data collection and sampling methodologies.

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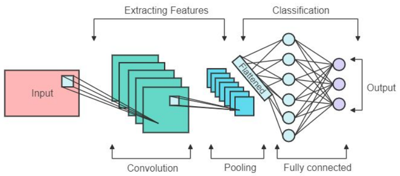
Thank you!

New and Improved CNN



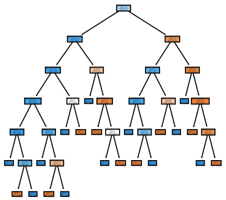
- Included another convolutional layer
  - Extract spatial hierarchies of features
- Added Max Pooling
  - Reduce dimensionality
- Dropout Layer
  - Regularization (sets a fraction of input units to zero)
  - Prevent overfitting
- Fully connected/dense layer
  - Classification

Layer (type)	Output Shape	Param #
conv_1 (Conv2D)	(None, 50, 50, 32)	2,432
pool_1 (MaxPooling2D)	(None, 25, 25, 32)	0
conv_2 (Conv2D)	(None, 25, 25, 64)	51,264
pool_2 (MaxPooling2D)	(None, 12, 12, 64)	0
flatten (Flatten)	(None, 9216)	0
fc_1 (Dense)	(None, 1024)	9,438,208
dropout (Dropout)	(None, 1024)	0
fc_2 (Dense)	(None, 1)	1,025

Validation Accuracy	Validation Loss
86.94%	0.312

Test Accuracy
87.32%

Random Forest Classifier



- Extracted features from the images using Keras MobileNet V2 (a pre-trained neural network).
- Passed these features into the random forest algorithm (Scikit-Learn).
  - Ensemble learning method
  - Constructs multiple decision trees and outputs average class among the trees
- Obtained predictions from the Random Forest model and compared to test labels.

Test Accuracy
88.90%

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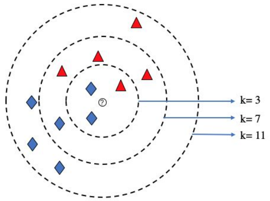
K-Nearest Neighbors Classifier



- Extracted features from the images using Keras MobileNet V2
  - Pre-trained neural network

- Passed these features into the K-Nearest Neighbors algorithm (Scikit-Learn).
  - Non-parametric
  - Classifies based on most common class of k-nearest data points

- Obtained predictions from the K-Nearest Neighbors algorithm and compared to test labels.

Test Accuracy
89.57%

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Support Vector Machine

Logistic Regression

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Baseline CNN

Used A Single-Layer Keras Sequential model with:

Activation Function	Relu
Optimizer	Adam
Loss Function	Categorical Cross Entropy
Training Epochs	10

Model Performance:

Validation Accuracy	Validation Loss
55.3%	5.97

*Note: No image preprocessing done

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