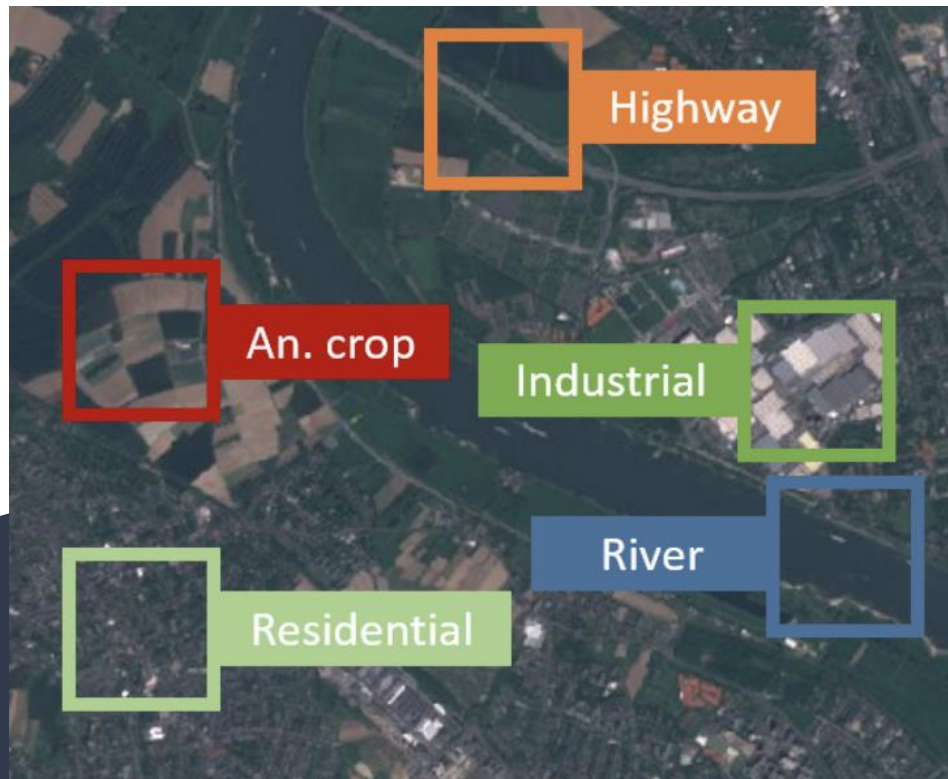


# Land Use and Land Cover Classification of Satellite Imagery

Andrew Loeber, Yeshwanth Somu, Zhifei Dong



# Dataset Information

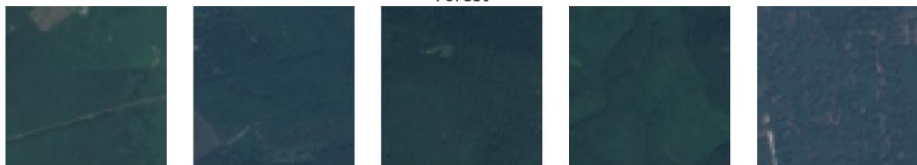
- Data comes from **EuroSAT** dataset
- **27,000** satellite images of land cover in JPEG format
- Each image is a **64x64 RGB** pixel grid
- Labeled into **10 classes**, shown on the right
- Split into train/validation/test in **70%/15%/15%**, stratified by class label

Class ID	Class Label	Number of Images
0	Industrial	2500
1	Residential	3000
2	Highway	2500
3	Annual Crop	3000
4	Permanent Crop	2500
5	Pasture	2000
6	Herbaceous Vegetation	3000
7	Forest	3000
8	River	2500
9	Sea Lake	3000

AnnualCrop



Forest



HerbaceousVegetation



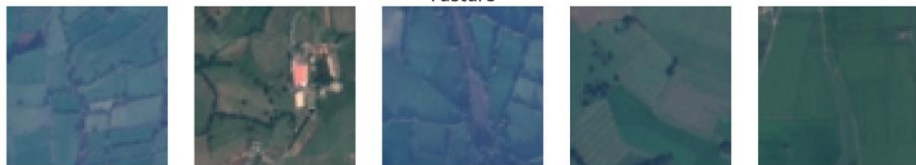
Highway



Industrial



Pasture



PermanentCrop



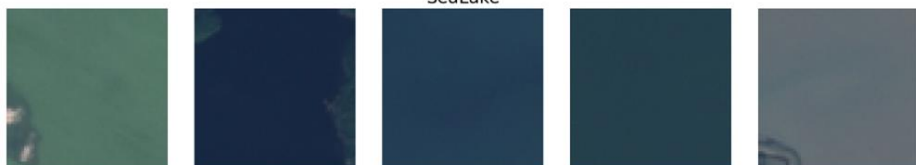
Residential



River



SeaLake



# Input Features

## Color

**Average RGB Values**

**K-Means Color Bin  
Histograms**

## Texture

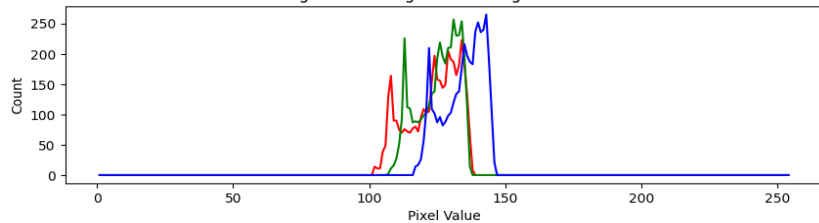
**Gray-Level Co-  
occurrence Matrix (GLCM)**

## Complex

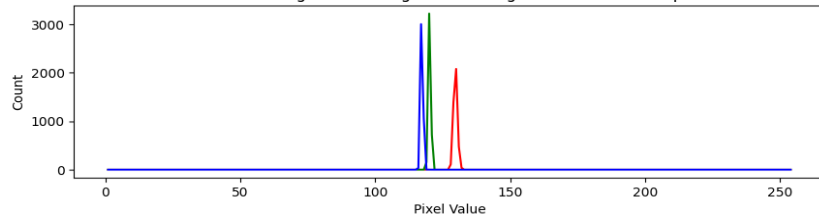
**EfficientNet Embeddings**

# Average RGB Values

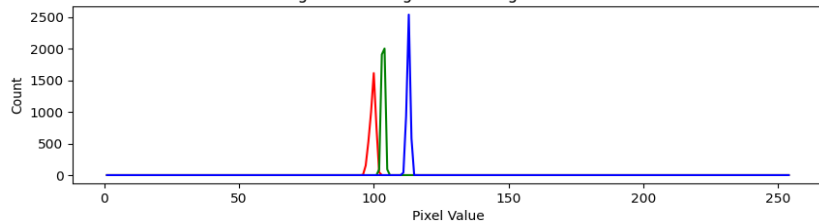
RGB Histogram for images in training data for Industrial



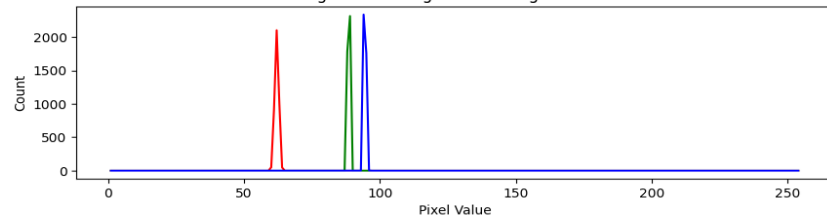
RGB Histogram for images in training data for AnnualCrop



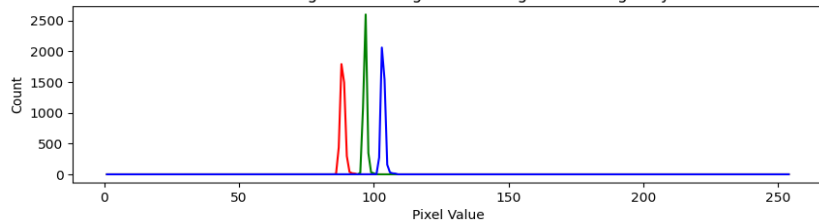
RGB Histogram for images in training data for Residential



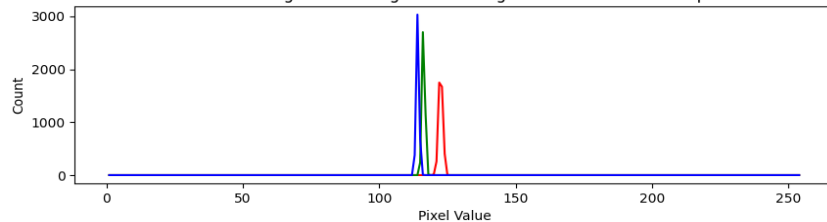
RGB Histogram for images in training data for Pasture



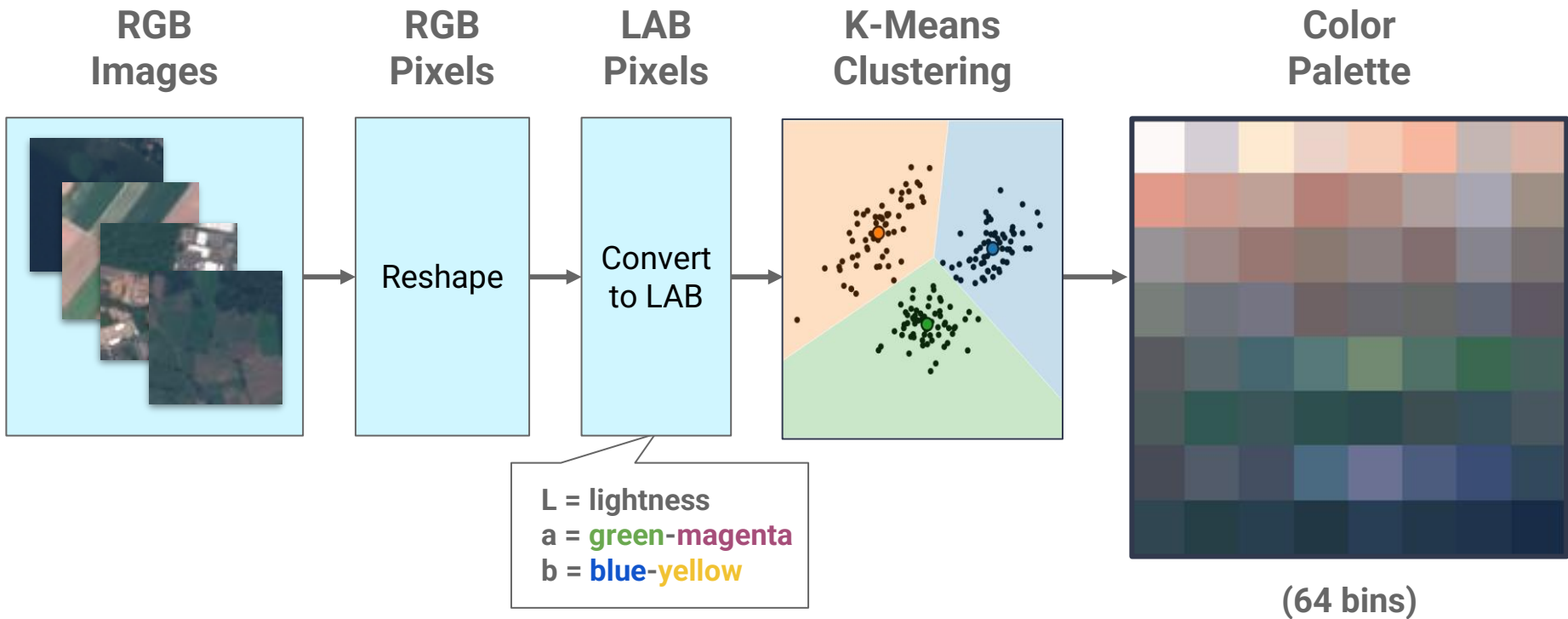
RGB Histogram for images in training data for Highway



RGB Histogram for images in training data for PermanentCrop

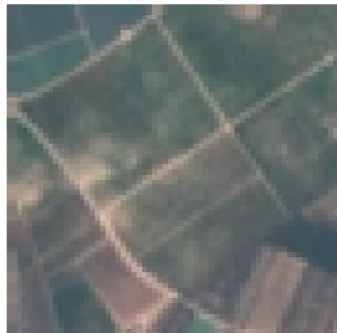


# K-Means Color Bin Histograms



# K-Means Color Bin Histograms

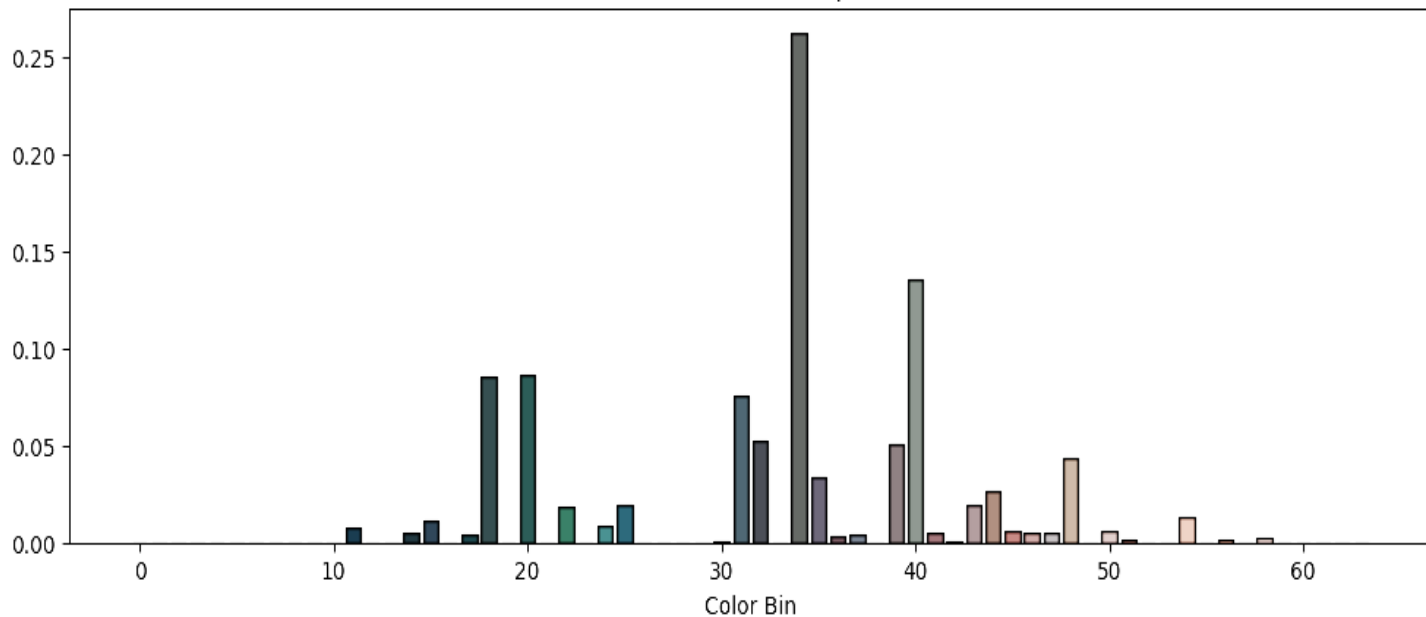
Original Image



K-Means Color Quantized - 64 Bins

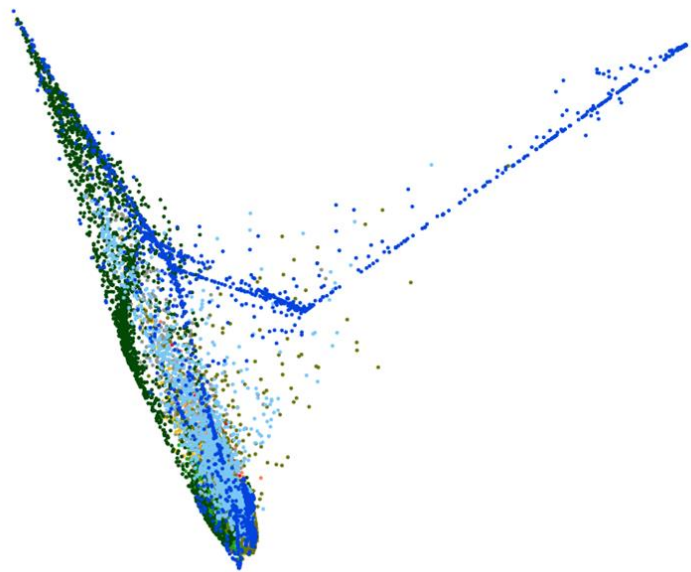


K-Means Color Bin Frequencies

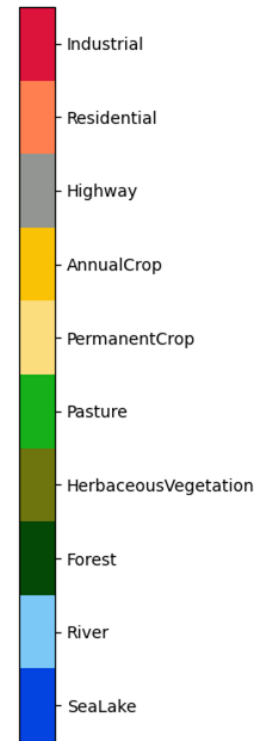
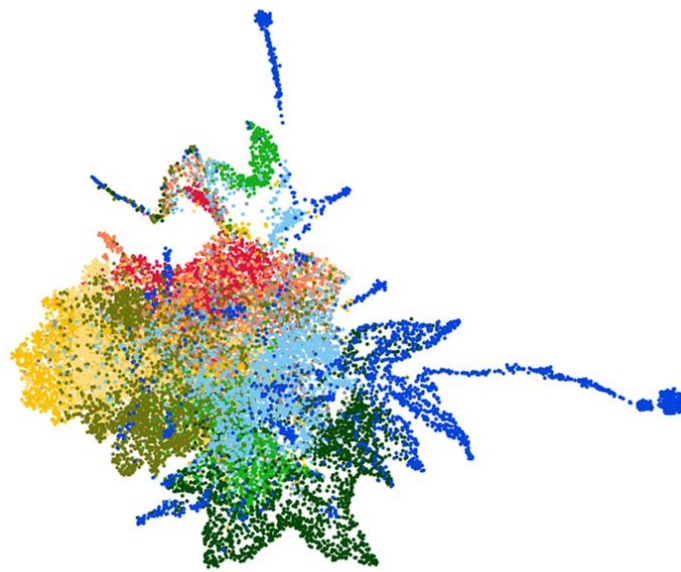


# K-Means Color Bin Histograms

PCA



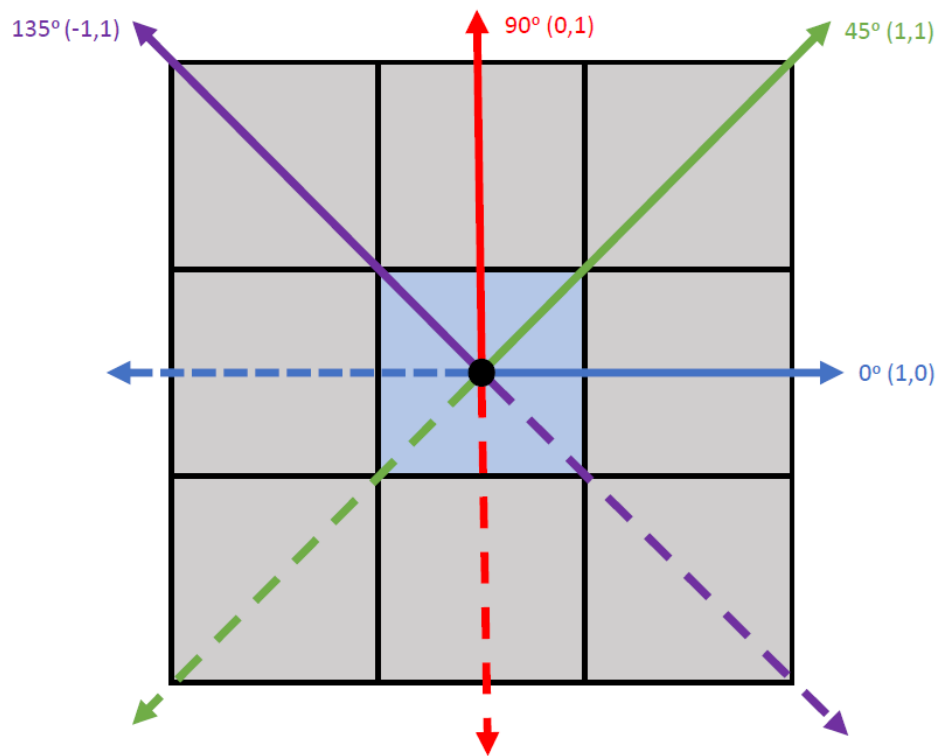
UMAP












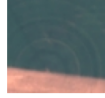


# Gray-Level Co-occurrence Matrix (GLCM)

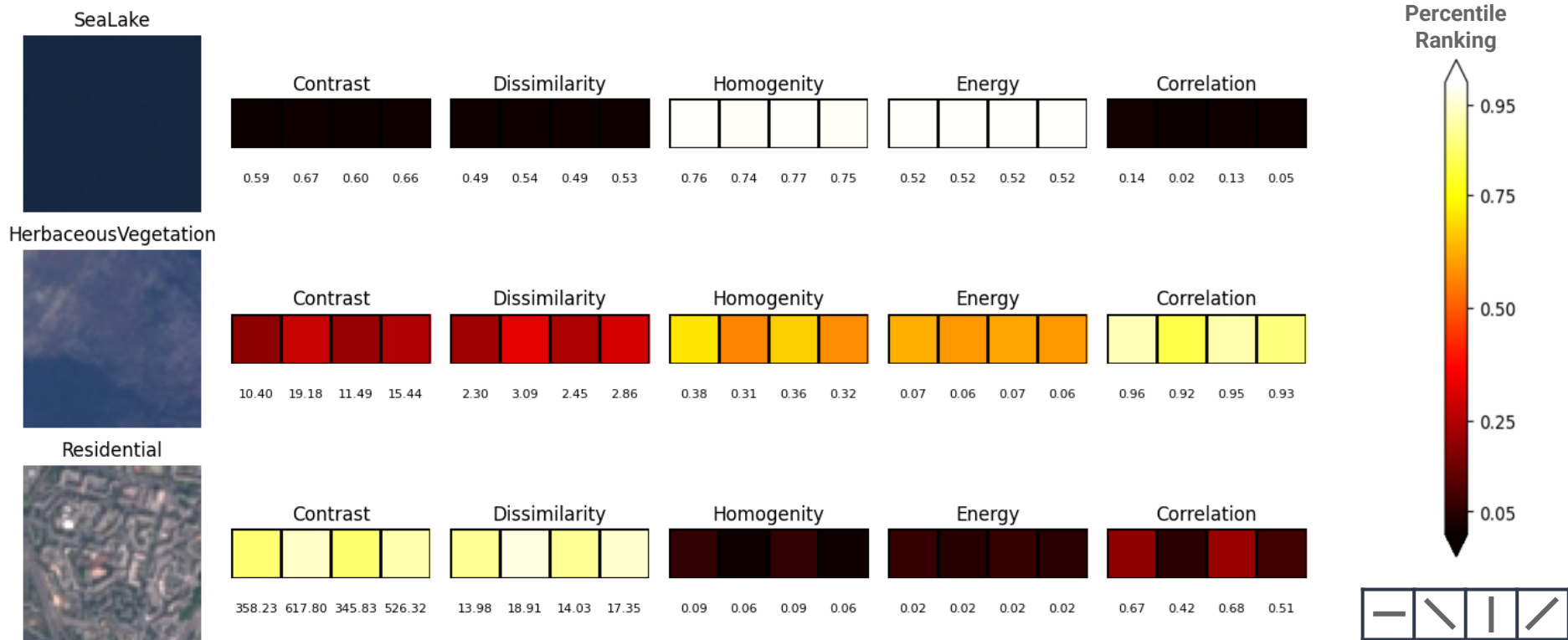
- GLCM is a statistical method of examining texture that considers the spatial relationship of pixels.
- The construction of GLCM needs two inputs: **pixel distance** and **direction**
- GLCM accounts for the frequency of pixel pairs occurring at the specified distance and direction.
- The matrix shape is determined by the number of gray levels, which in our case is (256, 256)
- Statistical properties of GLCM to include: **Contrast, Dissimilarity, Homogeneity, Energy, Correlation**



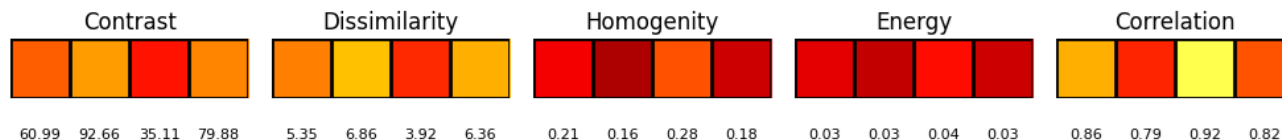
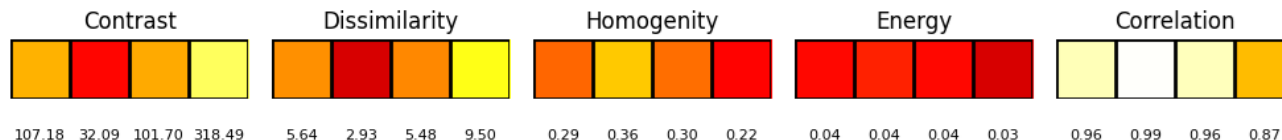
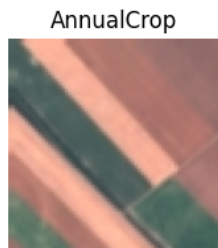
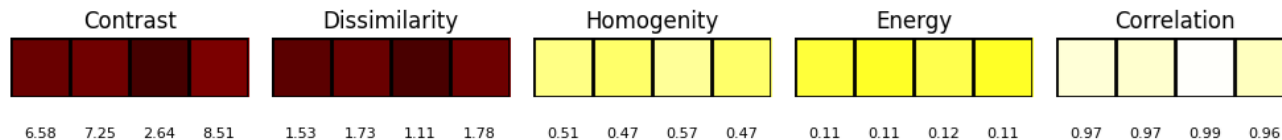
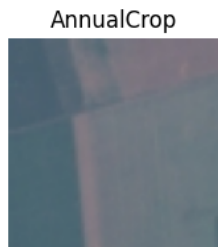
# Gray-Level Co-occurrence Matrix (GLCM)

Feature	Description	Formula	Sample w/ Low Value	Sample w/ High Value
<b>Contrast</b>	Measures the local variations in the GLCM	$\sum_{i,j} P(i,j)(i-j)^2$		
<b>Dissimilarity</b>	Similar to Contrast, but takes the absolute difference, making it less sensitive to larger differences	$\sum_{i,j} P(i,j) i-j $		
<b>Homogeneity</b>	Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal	$\sum_{i,j} P(i,j)/(1+(i-j)^2)$		
<b>Energy</b> (Angular Second Moment)	Sum of squared elements in the GLCM	$\sum_{i,j} P(i,j)^2$		
<b>Correlation</b>	Measures how correlated a pixel is to its neighbor over the whole image	$\sum_{i,j} P(i,j)((i-\mu_i)(j-\mu_j))/(\sigma_i\sigma_j)$		

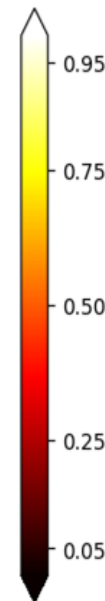
# Gray-Level Co-occurrence Matrix (GLCM)



# Gray-Level Co-occurrence Matrix (GLCM)

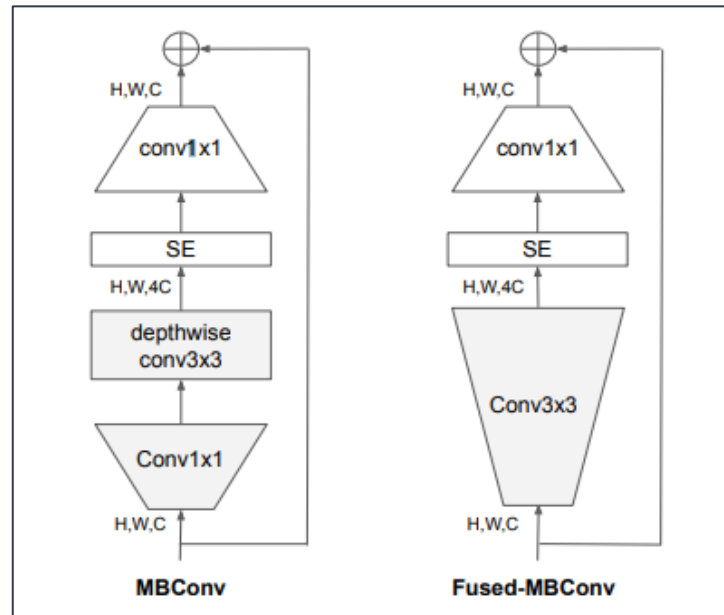


Percentile  
Ranking

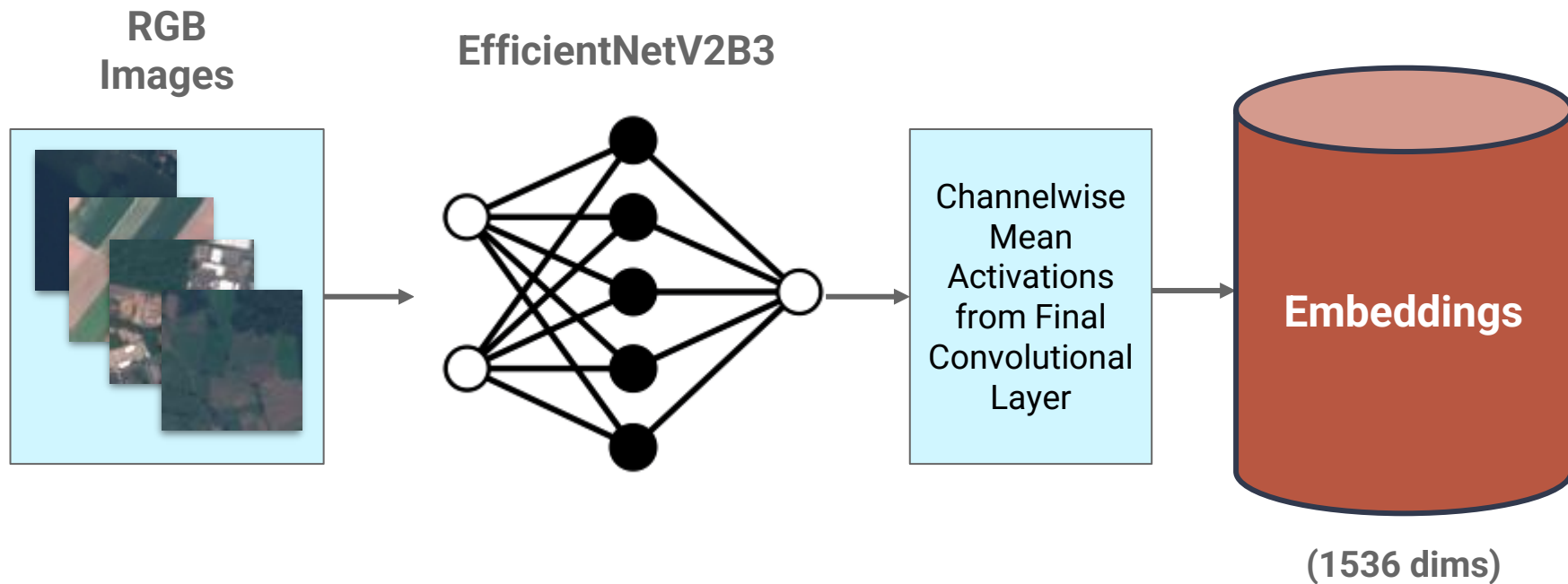


# EfficientNet

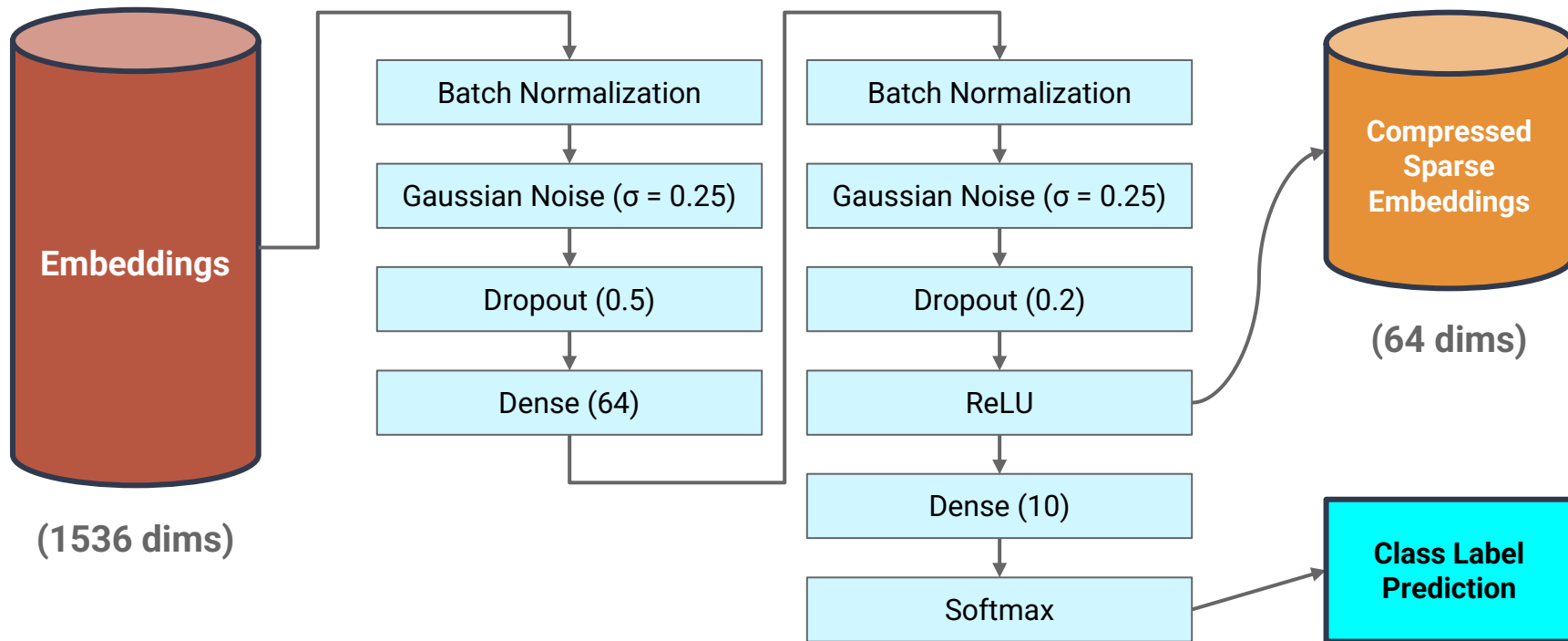
- CNN model architecture developed by two Google researchers
- Designed to be as accurate as SOTA image classifiers with fewer parameters, lower computational burden, and faster inference speed
- Final selection: **EfficientNetV2B3**
  - ImageNet-pretrained checkpoint available through Keras
  - Built-in pre-processing & transfer learning functionality
  - Can natively handle 64x64 resolution



# EfficientNet Embeddings



# EfficientNet Embeddings – Compression

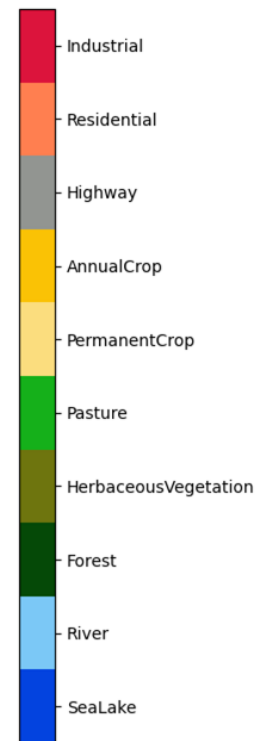
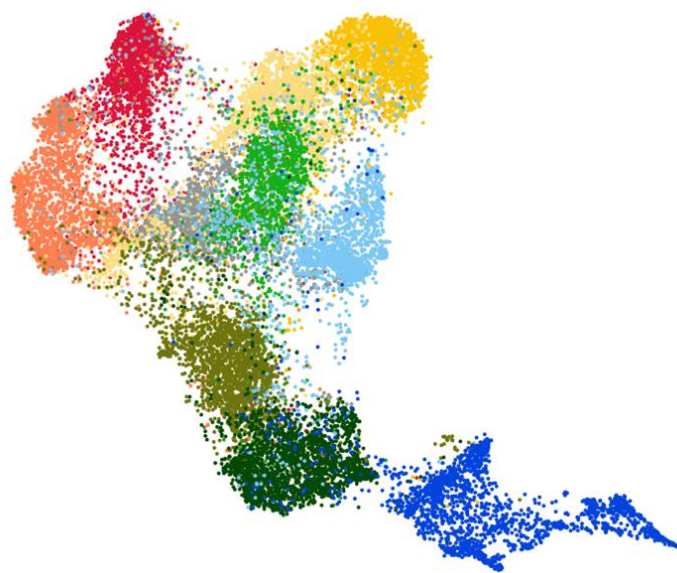


# EfficientNet Embeddings

PCA



UMAP



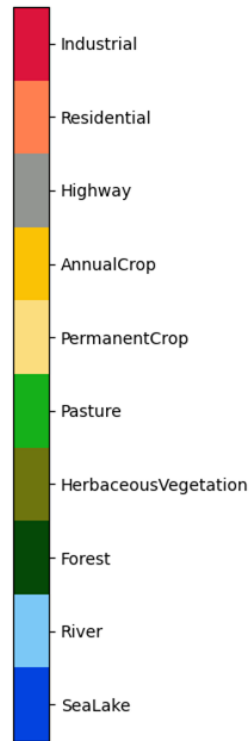
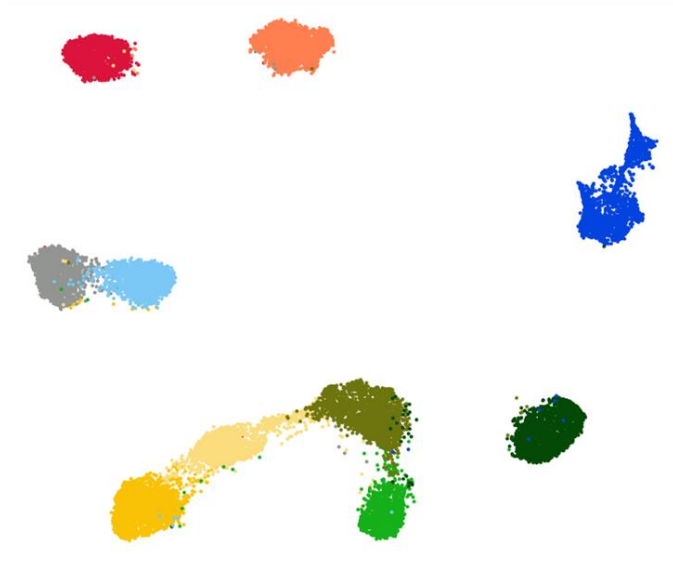


# EfficientNet Embeddings – Compressed

PCA



UMAP



# Model Architectures

## Logistic Regression

- Multiclass classification using multinomial regression
- Pros:
  - Computationally cheap
  - Easy interpretability
  - Less prone to overfitting
- Cons:
  - Limited to linear relationships
  - Sensitive to feature scaling
- Searched **regularization coefficient** ('C') and **max iterations** parameters

## eXtreme Gradient Boosting (XGBoost)

- Uses results of multiple decision trees to capture complex non-linear relationships between features and class labels
- Pros:
  - Incorporates gradient boosting and regularization
  - Early stopping
  - Handles non-linearity
- Cons:
  - Computationally expensive
  - Black box in nature
- Searched **n\_estimators**, **max\_depth**, **learning\_rate** parameters

# Preliminary Results

Model Type	Feature Set	Best Configuration	Training Time (sec)	Training Accuracy	Validation Accuracy
Logistic Regression	Basic	C = 1000 max_iter = 3000	61.6	87.3%	85.7%
	Full	C = 1 max_iter = 100	2.36	99.3%	95.2%
XGBoost	Basic	learning_rate = 0.1 max_depth = 7 n_estimators = 200	48.6	100.0%	92.8%
	Full	learning_rate = 0.1 max_depth = 3 n_estimators = 100	18.4	99.7%	94.7%

+ 9.5%

+ 1.9%

Basic = Avg RGB Values, Kmeans Color Bin Histograms, GLCM Features = **107** columns  
Full = Basic + EfficientNet features = **171** columns

# Confusion Matrix – Test Set

