



Objectives

Goal: Implement a model using both low and high-resolution satellite data to identify anomalies in tree health

- Once anomalies are identified, determine whether it indicates that a tree is unhealthy or healthy.
 - Using unsupervised data, no preexisting labels
- Alert landowner of the severity of the problem in the tree(s)
- Track and continue to monitor issues

Overall Process

- Conduct research into literature reviews on forest health issues solved with remote sensing
 - Pest Detection (ex. Emerald Ash Borer)
 - Forest Fire detection (☹ an issue in Indiana)
- Narrowed focus to identifying signs of tree infestation
 - Sudden tree death
 - Color change
 - Out of Season Behavior
- Working with Unsupervised Data
 - Manually find anomalies
 - No distinct labels without additional work
 - No confirmation labels are fully correct

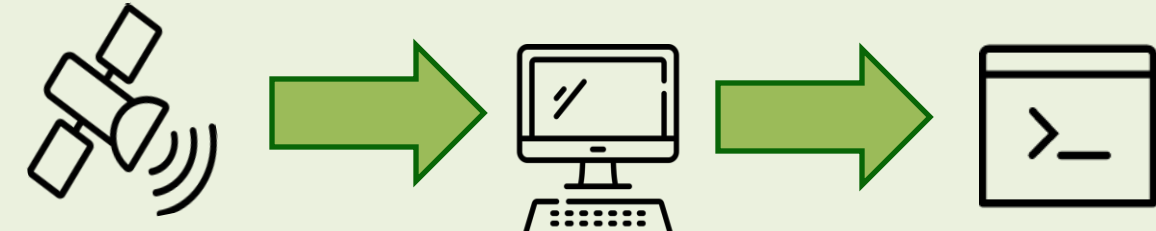


Semester 1 Progress

- Researched forest issues and potential
 - Forest Fires
 - Pests
 - Disease Detection
- Researched possible Machine Learning Solutions
 - Anomaly detection
 - Time Series Analysis
- Constructed an **autoencoder** to read in images
 - Differentiated between images with trees and images without trees
 - Then tested with images that had more green areas, but not necessarily trees

Sentinel 2 Dataset

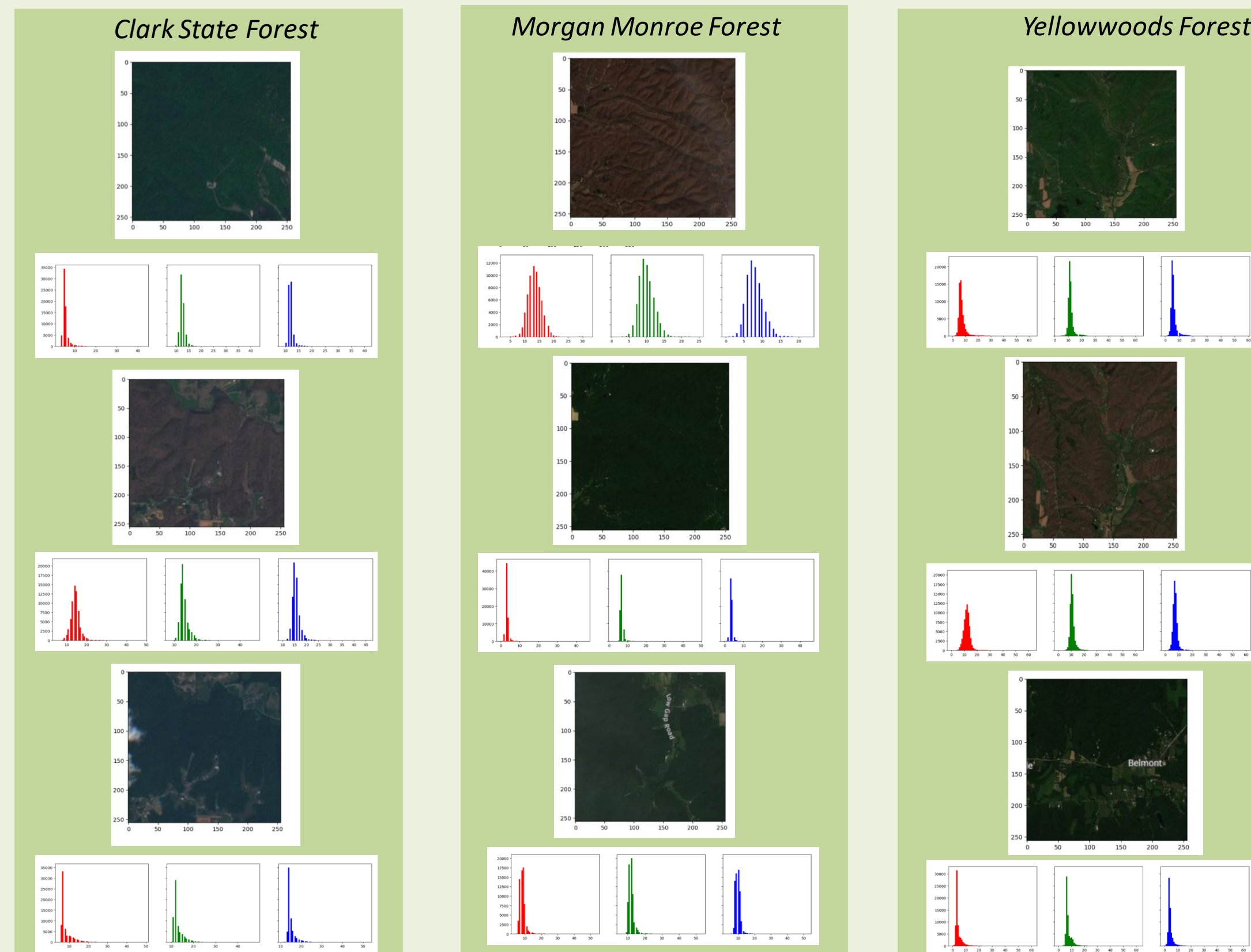
- Gathered from large forests in Indiana from March – August each year from 2018 to 2022
- Over 300 images tiled to over 1000 256X256 images
- Unable to identify anomalies without further steps
- 10 meter – 60 meter per pixel resolution
 - Intelinair's imagery is 10cm per pixel resolution



Sentinel Images – Low Resolution

Forest Color Histogram Analysis

- Processed images using b64 decode to find BGR values in images
- Flipped values using cv2, so images look correct and are RGB
- Plotted density and range of pixel values per pixel using pyplot



Color Histogram Conclusions

- Color histograms showed patterns for specific commonalities in the dataset
 - The more red colored images from late winter to early spring
 - The more green/blue images from later spring into summer
 - The mean of the images RGB values can be used to find large scale anomalies that show widespread forest damage.

Autoencoder Conclusions

- The autoencoder has an accuracy of about 68.9%
- Model can reconstruct images, though they appear blurry
- Switching from the first to second dataset caused some errors, but the model was able to compensate

Future Goals

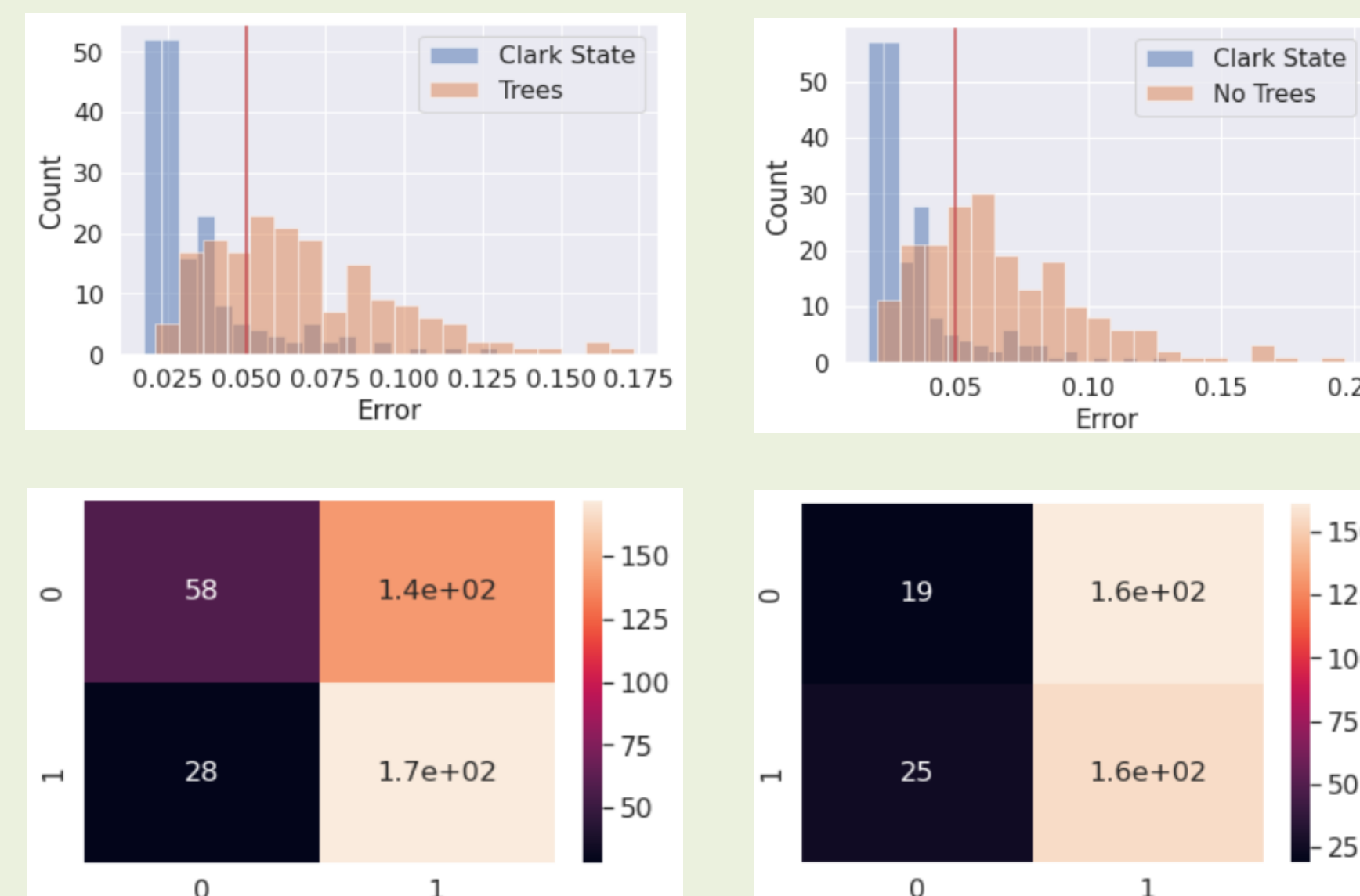
- Test our models on a larger variety of datasets
 - Intelinair's Data
 - Other similar high resolution data
- Expand the model to assess forest health by season (time-series)
- Be able to define the characteristics/cause of an unhealthy tree



Image above is from a model that identifies health in palm trees

Anomaly Detection Using Auto-Encoders

- Trained an auto-encoder model on data of a particular label (grassland/trees) and
- Plotted mean squared error (MSE) after testing the model on both the previous label and a new, unfamiliar label (barren land/no trees)
- Observe the presence/ lack of groups which could indicate what the auto-encoder sees as unfamiliar and therefore an anomaly



References and Acknowledgements

References:

- Bradski, G. (2000). The OpenCV Library. <https://opencv.org/>
- Copernicus Sentinel 2 data (2018-2022), processed by ESA.
- Chollet, Francios (2015) Keras Library, <https://keras.io>
- Lenhardt, Julia (2019) "Use deep learning to assess palm tree health", <https://hub.arcgis.com/documents/LearnGIS::use-deep-learning-to-assess-palm-tree-health/explore>

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