Applying deep learning techniques to remote sensing data for orchard age classification

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Background

Orchard Age & Trellises

- Orchard age is correlated with orchard yield and thus orchard value
- Trellised orchards (right) tend to be younger and more densely planted as opposed to orchards without trellises (left)

Figure #1. Example images of orchards

- An accurate way to predict orchard age on a broad scale will help inform decisions about water and fertilizer allocation

Data & Study Area

- Obtained images (right) of central Washington state from the RapidEye satellite constellation, spanning 2009-2019, covering 124,000 km^2
- Received field information for 1004 fields (left) from Washington State University including position, shape, crop type, trellis presence, and rough age estimates

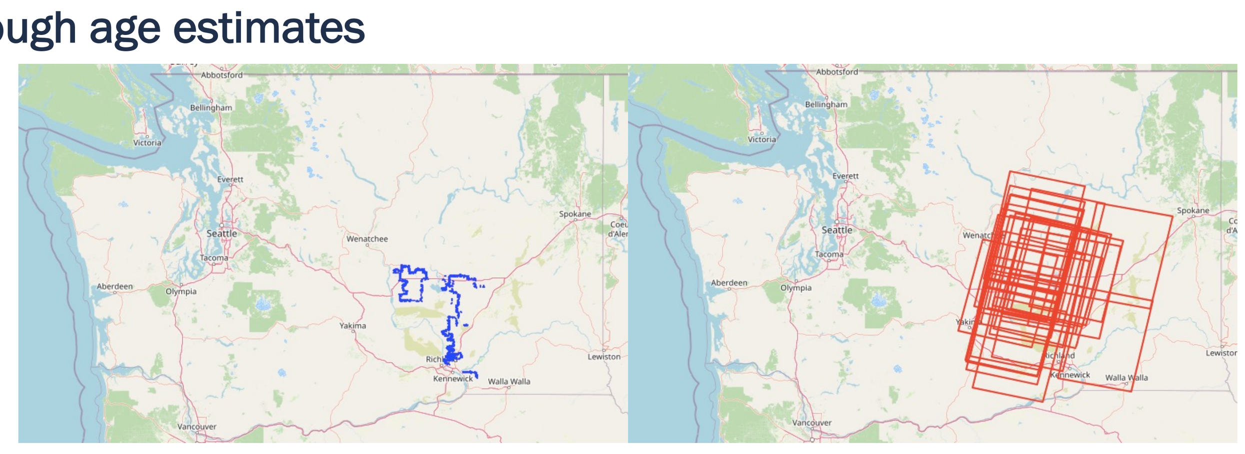

Figure #2 & Figure #3. Maps of fields and images

Purpose

To develop a deep learning algorithm that can accurately predict orchard age while requiring less historical data than traditional methods

Methods

Orchard Patch Extraction

- Prior to age prediction, the satellite images were standardized to one another via histogram matching
- Each orchard was divided into overlapping square patches

NDVI Z-score Method

- Calculated normalized difference vegetation index (NDVI) and constructed a time series for each orchard
- Converted each value in the time series to a z-score
- Identified potential planting years based on three rules
  - 1) Select years below a certain threshold
  - 2) For each selected year, check if the following year's z-score does not drastically increase
  - 3) Take the most recent year as the planting year

AlexNet for Trellis Classification

- AlexNet is a convolutional neural network (CNN) designed for image classification
- Based on AlexNet, created a CNN to classify patches as trellised or not
- Aggregated the votes of each patch within an orchard to classify the entire orchard as trellised or not

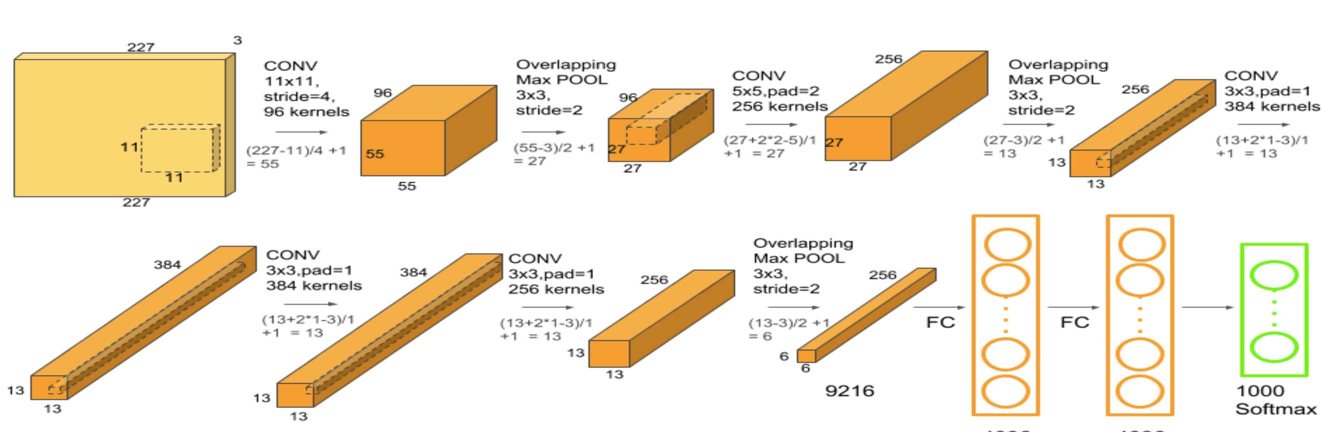

Figure #4. Illustration of AlexNet's architecture

Experiments

Modified NDVI Method

- Applied the NDVI Z-score method to the orchards which had a rough age estimate, which consisted of 19 orchards
- Attempted to convert the age estimates to quantitative labels in order to evaluate the accuracy of the method
- Omitted the second rule to allow for more predictions

AlexNet 10-Fold Cross Validation

- Trained the CNN on patches from the fields which had a trellis label, which consisted of 113 fields total
- Evaluated the accuracy of the model on patches and fields
- Performed 10-fold cross validation by withholding fields

Results

NDVI Method Accuracy

- The mean absolute error (MAE) of the NDVI method was 2.526 years
- Randomly guessing years gave a MAE of 3.004 years
- These metrics may be misleading because they were calculated based upon imprecise labels
- In Figure 5, the left's age was 1 year off; the right's age was 5 years off

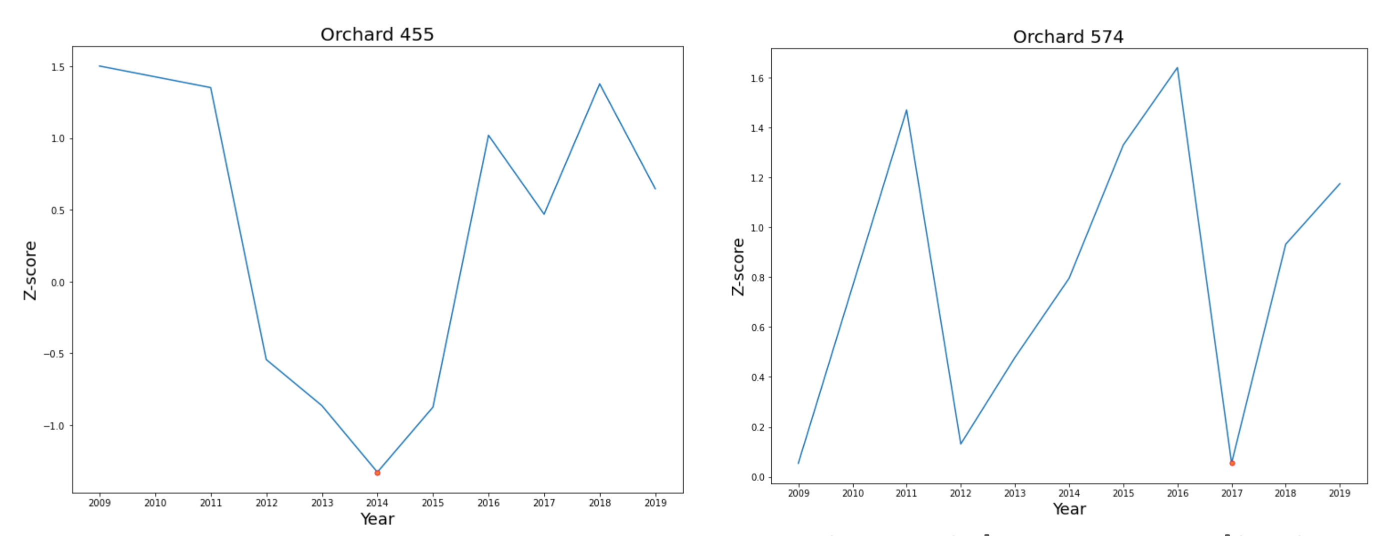

Figure #5. Example NDVI time series with age predictions

AlexNet Performance

- Within 40 epochs, the CNN reached a patch accuracy of above 0.99 with a validation accuracy of above 0.98
- Possibility of overfitting, worse at classifying non-trellised images

Cross Validation Results

- Across all ten folds, the CNN successfully classified 89 out of 98 fields, or 90.82%
- Within the folds, the CNN had an average accuracy of 90.52% with a standard deviation of 10.46%
- Struggled to generalize; for unseen orchards, always voted for trellised

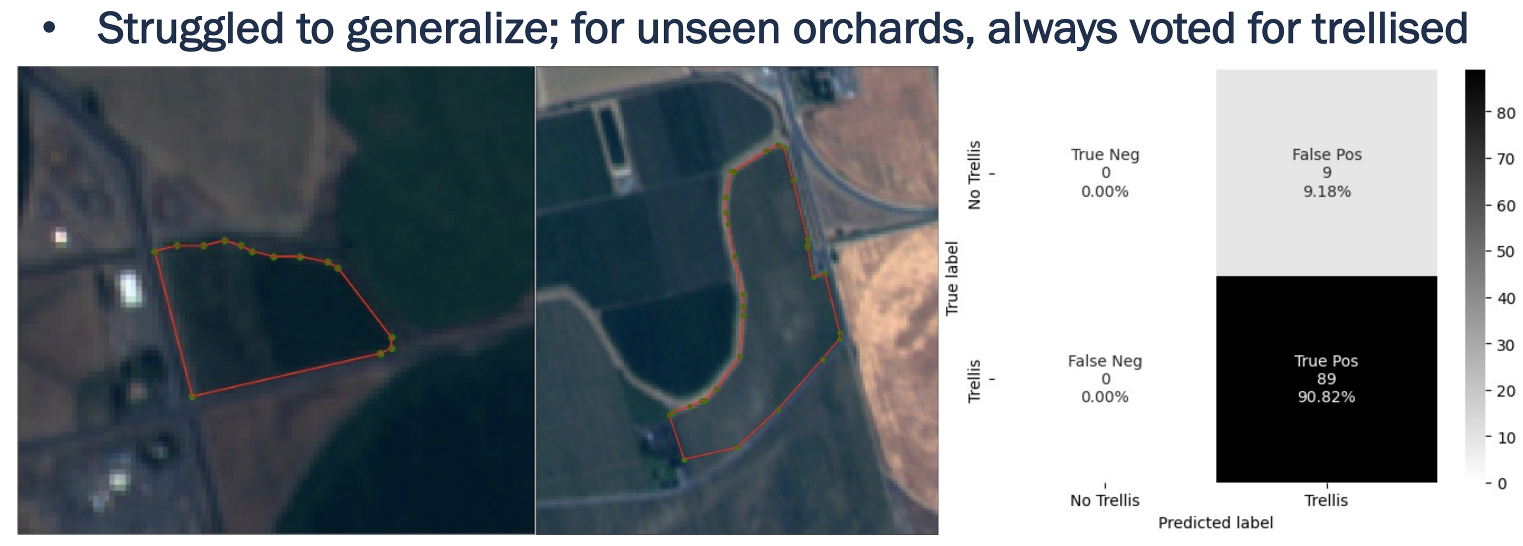

Figure #6 & Figure #7. Misclassified fields and confusion matrix

Future Work

- Utilize the trellis labels to bolster age prediction methods
- Acquire more precise and numerous age labels to enable more methods for age prediction
- Analyze the performance of different CNN architectures to determine the best available model

References

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