Machine Learning for Quality Prediction in Additive Manufacturing

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Introduction to Laser Based Additive Manufacturing (LBAM)

What is LBAM?

- Products are made when metallic powder is melted layer-by-layer by a laser until the product is complete
- A much more cost effective option over subtractive engineering

Applications of LBAM

- Can produce many different types of complicated parts or models
- Benefiting industries like
  - Aerospace
  - Bioengineering / Medical
  - Consumer Products

Problems is LBAM

- Defects due to Porosity
  - Prevented adoption on a large scale
- No reliable / cost-efficient way of detecting these porosity defects
  - No in-situ detection
  - Post-production detection is expensive

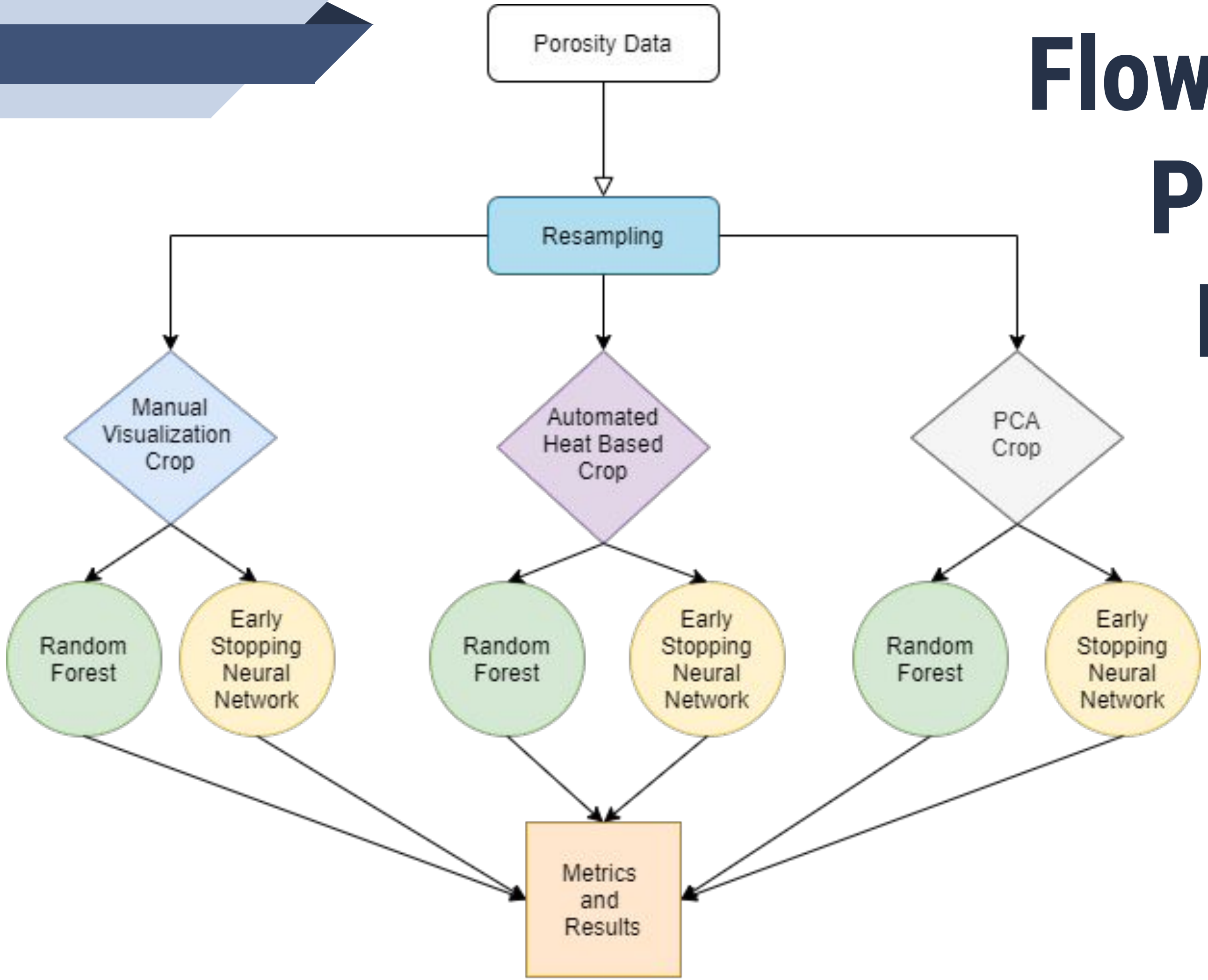
Purpose / Contribution of this Study

- Propose a consistent, accurate, and reliable way for *in-situ* for monitoring for porosity prediction in the LBAM Process

- Provide insight on which layers are more likely to produce porosity defects

- Provide methods to automatically detect melt pool in LBAM
    - Melt Pool is a signature trait of LBAM

Flowchart of the Prediction Process



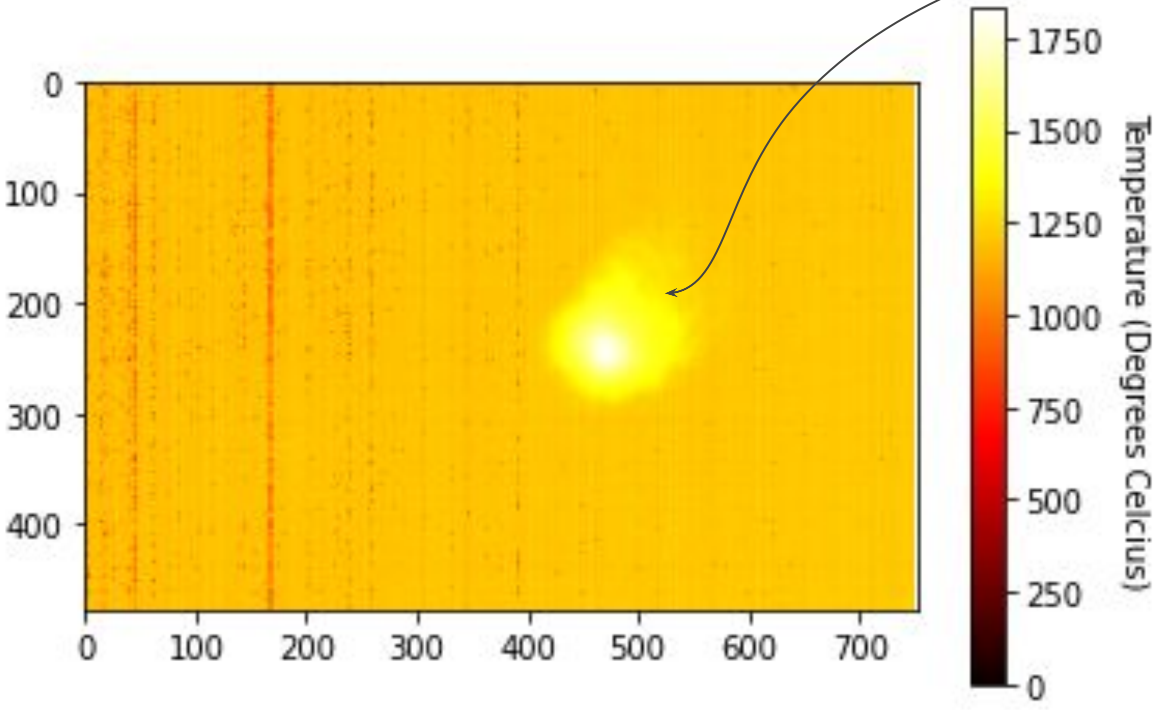
Porosity Data Set

- Data was collected from OPTOMEC LENS™750 LBAM system

- Data is described in *Data indicating temperature response of Ti−6Al−4V thin-walled structure during its additive manufacture via Laser Engineered Net Shaping* by Garrett J. Marshall, Scott M. Thompson, Nima Shamsaeia

- In total the data set consisted of 1556 csv files
  - Each data file is represented by a data matrix (479 Rows x 753 Columns)
  - Each data point in the matrix is a temperature value (°C) ranging from 0-1800
  - Each file is mapped to either a ‘0’ or a ‘1’ which represents a quality of good and bad respectively

Example Visualization of a Data File



- Example of the melt pool

Resampling the Data

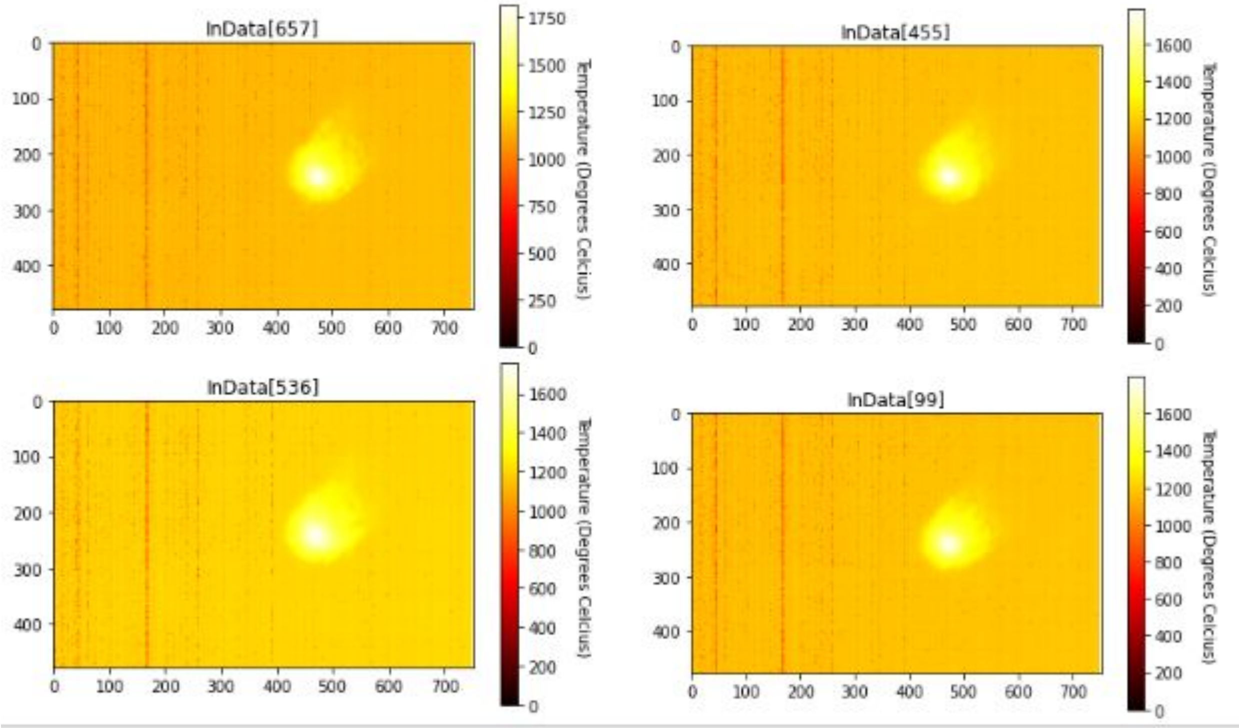
- The data set was heavily unbalanced
  - 1486 ‘Good’ or ‘0’ data files
  - 70 ‘Bad’ or ‘1’ data files
- This would be hard to train a model off of due ot the limited amount of ‘bad’ instances
- Bootstrap Resampling was used to increase the number of bad instances to 1486, which equaled the amount of good instances
- The final dataset that was used now contained 2972 data files, with an even split of ‘good’ and ‘bad’ instances

Why Crop the Datafiles?

- Reduce redundant information
  - Many data images had the same areas that had the exact same pattern, which ultimately won't contribute to a successful model

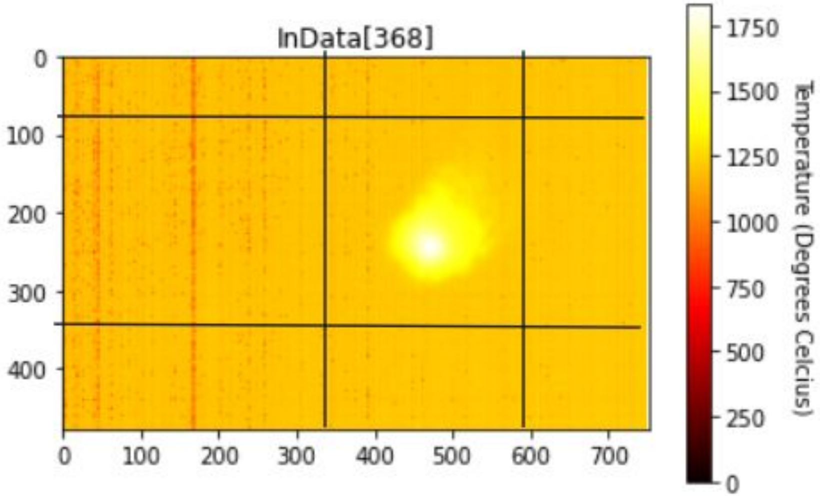
- Speed up Model Performance
  - Less data points means the model has less training, which results in faster speeds

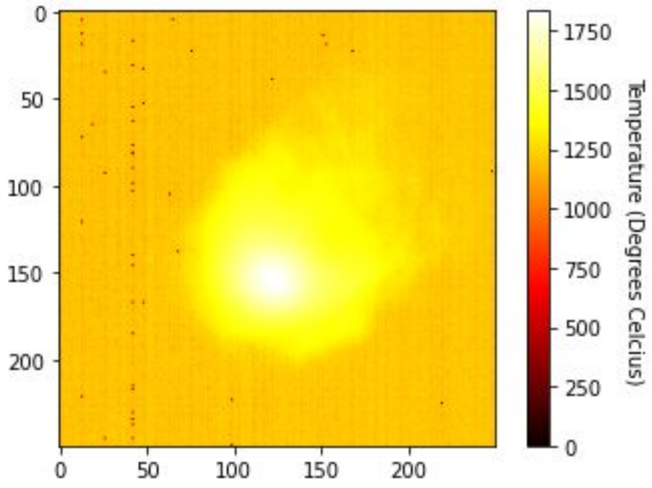
Example of Redundant Information



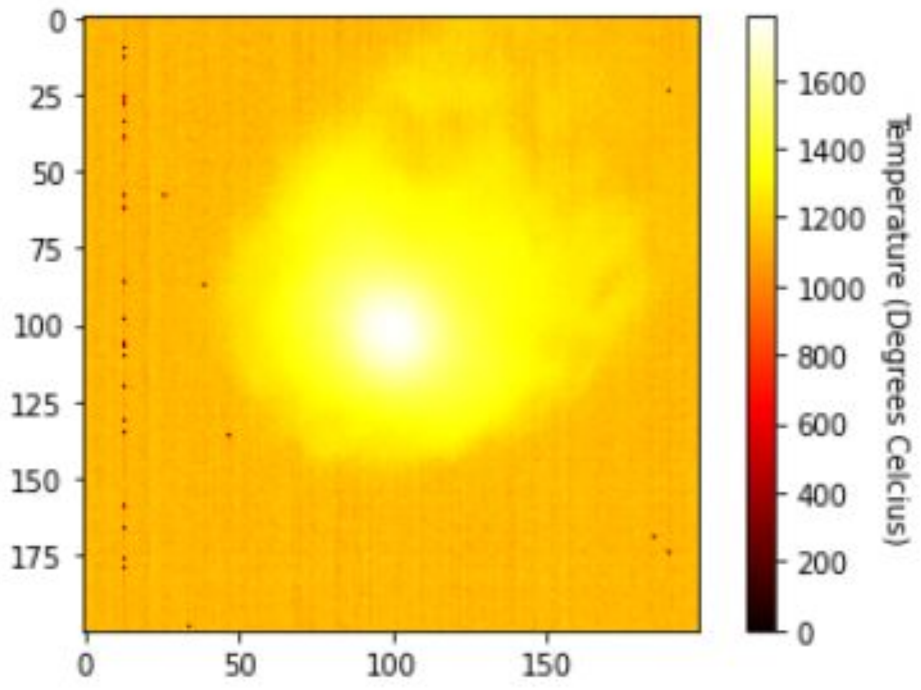
Visualization Based Crop

- By visualizing many random instances of data, a good manual based crop was determined to be $x \in [350,600]$, $y \in [90, 340]$, creating a new 250x250 matrix





Automated Heat Based Crop

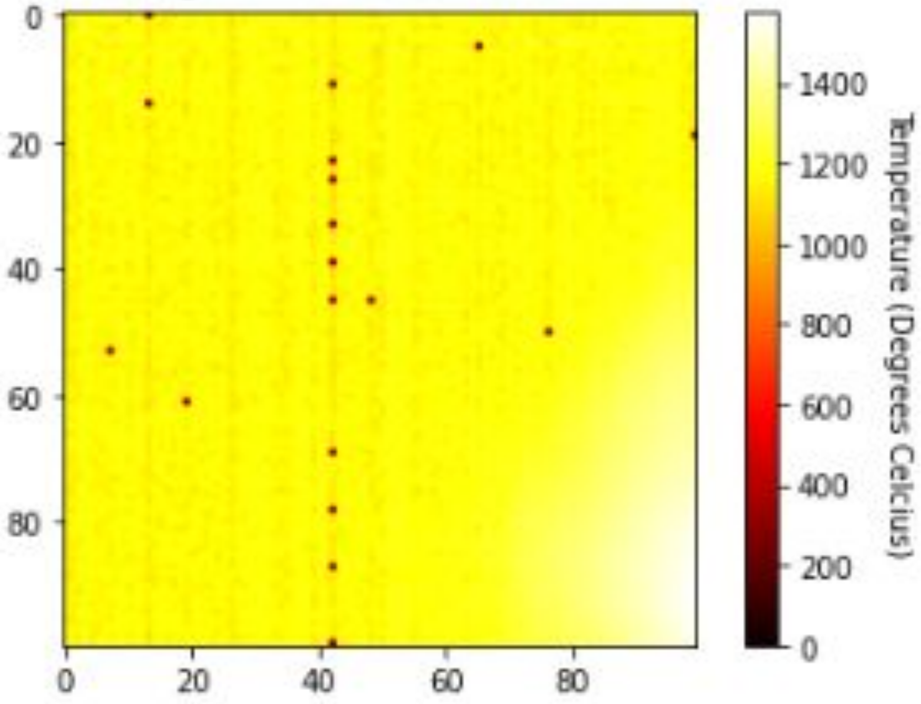


- Find hottest pixel from a linear search
  - If there is a tie, the average of their x & y coordinates are used
- Create a 200x200 box, around the hottest pixel found
- Benefit is it automatically finds the melt pool, regardless of the positioning

Principal Component Analysis (PCA) Crop

- PCA is a method to reduce the number of features in a dataset by extracting the most important features
  - These features being pixels
- Important to pick a number of components that yields a high level of variance, 40 components
  - 95% variance was chosen to be sufficient
- Each component has a list of the magnitude of each feature's (each pixel's) eigenvalue
  - The higher the magnitude the more 'importance'
- The mode for the x, y coordinates of these pixels were taken to be the center of the crop
  - If there was no mode

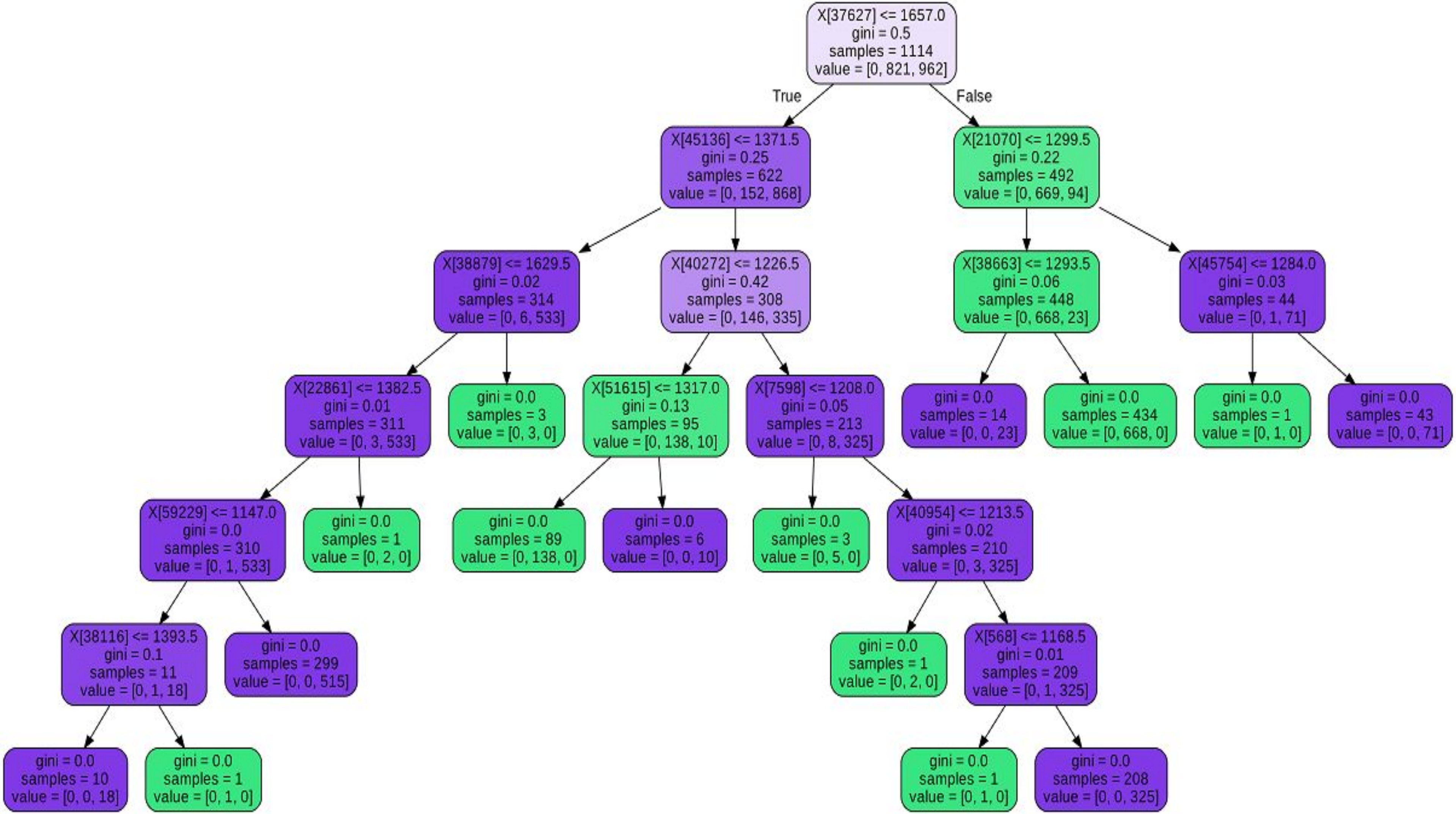
PCA Crop (cont.)



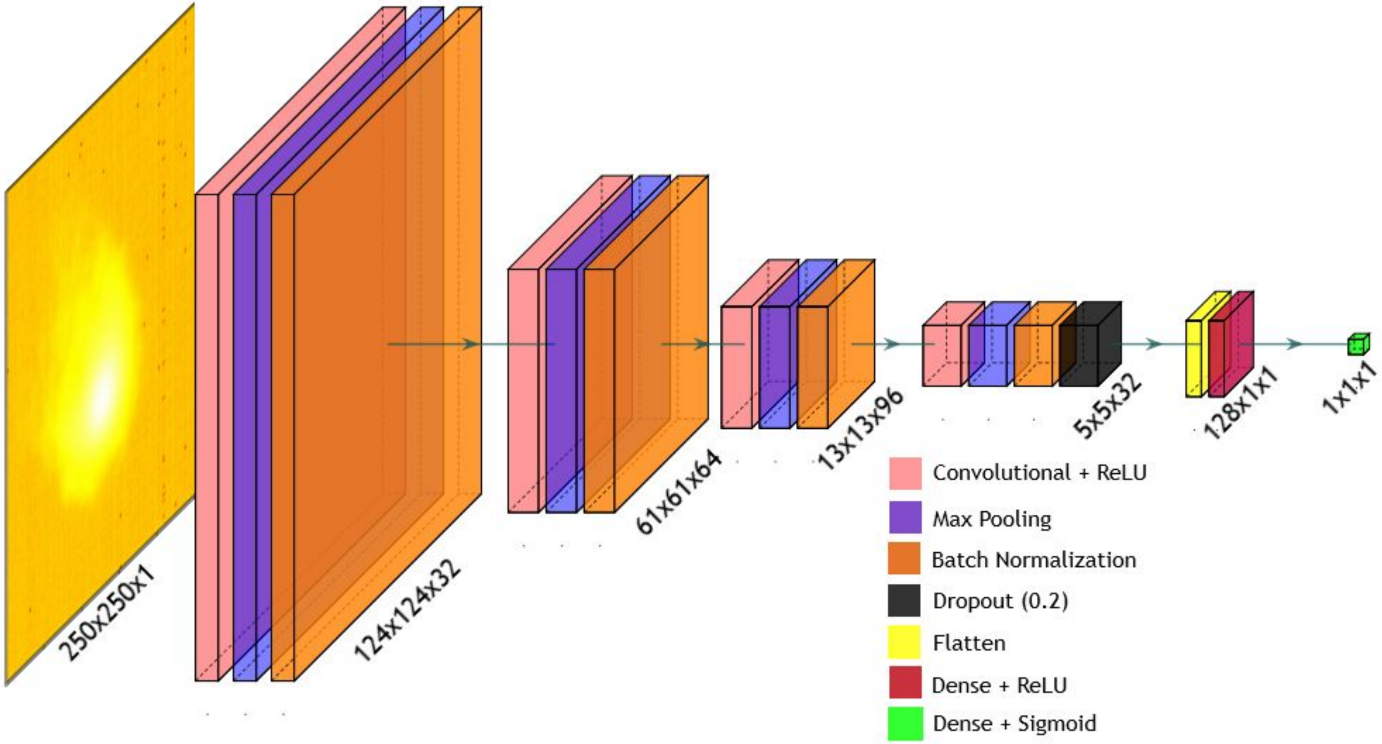
- 100x100 Grid
- From the dataset PCA determined that the x ∈ [300,400], y ∈ [148, 248] would be the new bounds with (350, 198) as the center

Random Forest Model

- Random Forest tends to be a good model in computer vision classifying tasks
  - Ex: Random Forest was used to classify human body part poses on the kinect for the xbox 360
- Data is vectorized before using the Random Forest Model
- Random Forest is built from an ensemble of decision trees
  - In our model, 10
- Using sklearn package


X[37627] <= 1657.0
gini = 0.5
samples = 1114
value = [0, 821, 962]
True
False
X[45136] <= 1371.5
gini = 0.25
samples = 622
value = [0, 152, 868]
X[21070] <= 1299.5
gini = 0.22
samples = 492
value = [0, 669, 94]
X[38879] <= 1629.5
gini = 0.02
samples = 314
value = [0, 6, 533]
X[40272] <= 1226.5
gini = 0.42
samples = 308
value = [0, 146, 335]
X[38663] <= 1293.5
gini = 0.06
samples = 448
value = [0, 668, 23]
X[45754] <= 1284.0
gini = 0.03
samples = 44
value = [0, 1, 71]
X[22861] <= 1382.5
gini = 0.01
samples = 311
value = [0, 3, 533]
gini = 0.0
samples = 3
value = [0, 3, 0]
X[51615] <= 1317.0
gini = 0.13
samples = 95
value = [0, 138, 10]
X[7598] <= 1208.0
gini = 0.05
samples = 213
value = [0, 8, 325]
gini = 0.0
samples = 14
value = [0, 0, 23]
gini = 0.0
samples = 434
value = [0, 668, 0]
gini = 0.0
samples = 1
value = [0, 1, 0]
gini = 0.0
samples = 43
value = [0, 0, 71]
X[59229] <= 1147.0
gini = 0.0
samples = 310
value = [0, 1, 533]
gini = 0.0
samples = 1
value = [0, 2, 0]
gini = 0.0
samples = 89
value = [0, 138, 0]
gini = 0.0
samples = 6
value = [0, 0, 10]
gini = 0.0
samples = 3
value = [0, 5, 0]
X[40954] <= 1213.5
gini = 0.02
samples = 210
value = [0, 3, 325]
X[38116] <= 1393.5
gini = 0.1
samples = 11
value = [0, 1, 18]
gini = 0.0
samples = 299
value = [0, 0, 515]
gini = 0.0
samples = 1
value = [0, 2, 0]
X[568] <= 1168.5
gini = 0.01
samples = 209
value = [0, 1, 325]
gini = 0.0
samples = 10
value = [0, 0, 18]
gini = 0.0
samples = 1
value = [0, 1, 0]
gini = 0.0
samples = 1
value = [0, 1, 0]
gini = 0.0
samples = 208
value = [0, 0, 325]

Early Stopping Neural Network

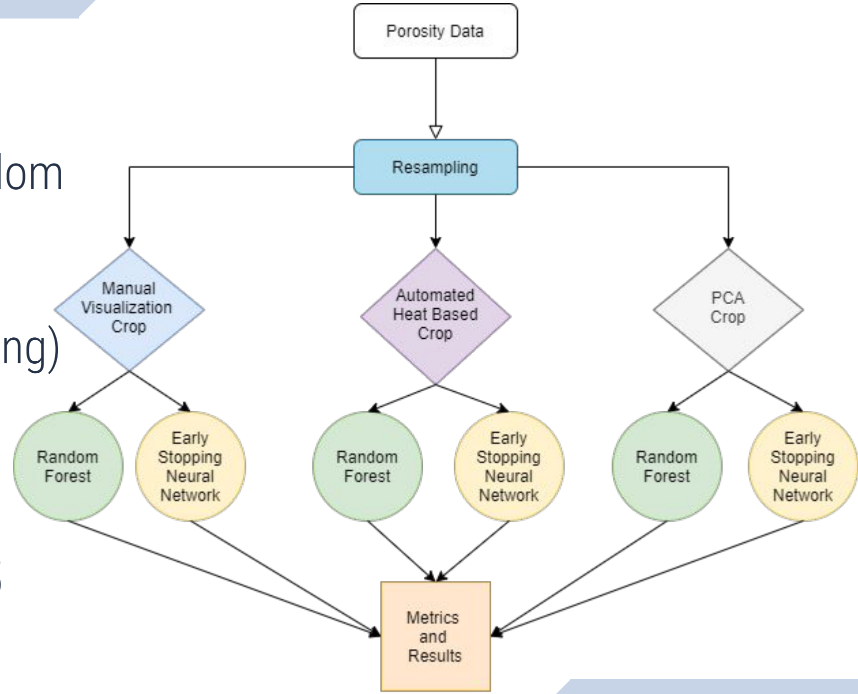


Early Stopping Neural Network (cont.)

- Throughout Training Validation Accuracy was highly related to the test accuracy on a random split
- If the validation accuracy was low on the last epoch of training the test accuracy scored at a similar level and vice-versa
- Wanted a way to ensure training stops on an epoch with a high, which was accomplish with an Early Stopping Callback Function
- The Number of Epochs were increased, to 50, and a Patience value was set
  - Patience refers to the number of epochs the model will train without an improved score in a specified metric, Validation Accuracy
  - If the patience value is reached, the model will revert back to the epoch with the highest score in the specified metric

Procedure for Obtaining Metrics

- For each cropping style (Manual, Heat-Based, PCA)
  - The cropped data was tested for both the Random Forest and Early Stopping Neural Network
  - Each set of 25 trials were don over a certain training / testing ratios (ex: 10/90 training/testing)
  - 25 trials per testing
    - Each trial had a random split
    - Testing accuracy and Time was recorded
  - Metrics were recorded as the average of the 25 trials



Results for every Cropping Style

Manual Crop

Training /Testing Split Ratio	Test Accuracy (%) Random Forest	Test Accuracy (%) Early Stopping Neural Network	Time (sec) Random Forest	Time (sec) Early Stopping Neural Network
10/90	98.45	59.83	2.49	12.02
20/80	99.26	94.66	4.30	31.58
30/70	99.67	98.19	6.18	37.02
40/60	99.68	99.18	7.82	43.39
50/50	99.57	99.00	9.56	50.98
60/40	99.82	99.69	11.37	60.78
70/30	99.79	99.50	13.07	72.20
80/20	99.75	99.90	14.66	75.84

Heat-Based

Training /Testing Split Ratio	Test Accuracy (%) Random Forest	Test Accuracy (%) Early Stopping Neural Network	Time (sec) Random Forest	Time (sec) Early Stopping Neural Network
10/90	96.48	66.23	2.20	10.12
20/80	99.14	98.56	3.95	21.89
30/70	99.58	98.08	5.71	29.14
40/60	99.84	99.01	12.17	31.69
50/50	99.46	96.29	10.09	15.21
60/40	99.64	99.49	12.00	22.18
70/30	99.78	99.72	13.80	24.05
80/20	99.90	99.53	15.55	25.63

PCA

Training /Testing Split Ratio	Test Accuracy (%) Random Forest	Test Accuracy (%) Early Stopping Neural Network	Time (sec) Random Forest	Time (sec) Early Stopping Neural Network
10/90	95.46	49.63	0.80	4.13
20/80	97.88	62.00	1.57	6.86
30/70	98.80	93.64	2.25	11.98
40/60	99.04	99.43	2.95	23.99
50/50	99.46	98.25	3.53	34.46
60/40	99.64	99.70	4.19	43.71
70/30	99.78	99.81	4.75	48.02
80/20	99.91	99.13	5.46	47.79

Misclassified Data

Over 25 trials with the Early Stopping Neural Network at the random 50/50 split

- 75 different files out of the original 1556 were misidentified
- ‘0’ status refers to a positive, while 1 refers to ‘negative’, so when they are incorrectly identified as so it refers to ‘false positive’ and ‘false negative’
    - 42 False Positives
    - 33 False Negatives
- By counting files more than once (predicted incorrectly over multiple trials)
    - 79 False Positives
    - 539 False Negatives
- 38 different layers were misidentified
    - Out of the 75 different files, Layer 1,2 & 3 constituted of 29/75
        - 12 Layer-2 Files were misidentified
        - 10 Layer 1 files were misidentified
        - 7 Layer-3 files were misidentified
        - All other files had 2 or less instances

Conclusion

- Models provided very consistent and accurate results that could be used for in-situ monitoring during the LBAM process

- Models performed well over different types of cropping methods, showing their adaptability
    - Preferring Heat-Based crop

- Future work could include trying to find out where in the image the model predicts is causing porosity defects

Acknowledgements

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References

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