Point Classification on Beach Survey LiDAR Point Clouds

Group 27:
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Background on CCIA

- One of the world’s premier coastal monitoring teams, located at Scripps
  - Use a variety of survey techniques to monitor and model coastal climates
- Truck-based mobile LiDAR (Light Detection And Ranging)
  - Beach and coastal cliff surveys
  - Supports array of research projects including beach morphology, cliff erosion, and ocean wave studies

center for Climate Change Impacts and Adaptation
at Scripps Institution of Oceanography
UC San Diego

Three Years of Field Surveys Identify Relationship between Waves and Coastal Cliff Erosion

Study shows that waves and rainfall are important parts of the erosion process, providing a new opportunity to improve forecasts Scripps Institution of Oceanography at UC San Diego researchers have ...

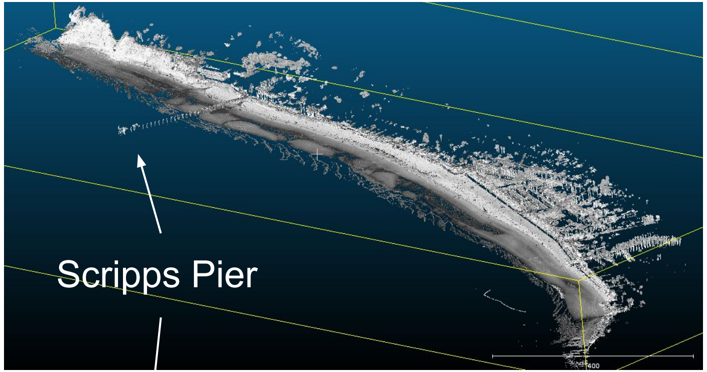
Read More

LiDAR Returns from Water

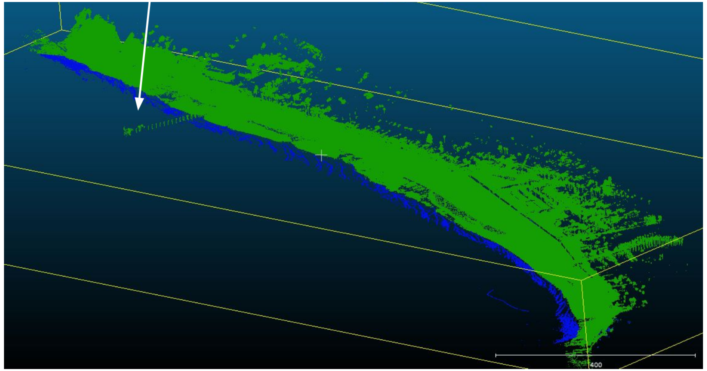
- Important to identify and label LiDAR returns from wave surfaces:
  - Complicate and confound true topological elevation measurements of beaches and cliffs
  - Can be used for wave studies of breaking waves and white water
- Currently, they are labeled by hand

- **Problem Statement:**
  - Our goal is to use machine learning to aid in these research efforts by classifying LiDAR point returns off of the wave surfaces
  - We hope we can create a framework that can be extended to classifying more specific categories (wave crests, white water, wave type)

Grayscale by intensity



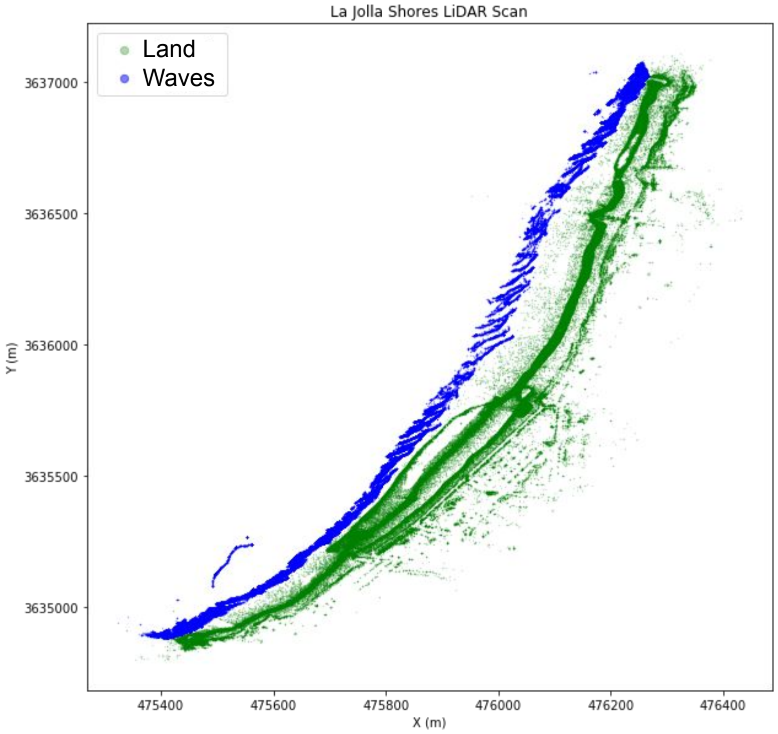
Water & Land Classification



Literature Review:

1. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation
    - Describes the design of a novel type of neural network (called PointNet) that directly uses point clouds. Its applications include (but aren't limited to): object classification, part segmentation, and scene semantic parsing.
2. Machine Learning in LiDAR 3D point clouds
    - Describes various machine learning framework implementations and experiments for irregularly distributed LiDAR point clouds
3. DANCE-NET: Density-aware convolution networks with context encoding for airborne LiDAR point cloud classification
    - Outlines using machine learning while emphasizing different characteristics of features of interest in the LiDAR point cloud such as density, curvature and roughness.
    - Inspired us to take advantage of the geometry we noticed in our data.
4. Automated Cobble Mapping of a Mixed Sand-Cobble Beach Using a Mobile LiDAR System
    - Comparison of machine learning techniques on similar coastal LiDAR dataset to identify beach cobbles
    - Co-authors provided dataset and will use successful model for future work

Dataset Description

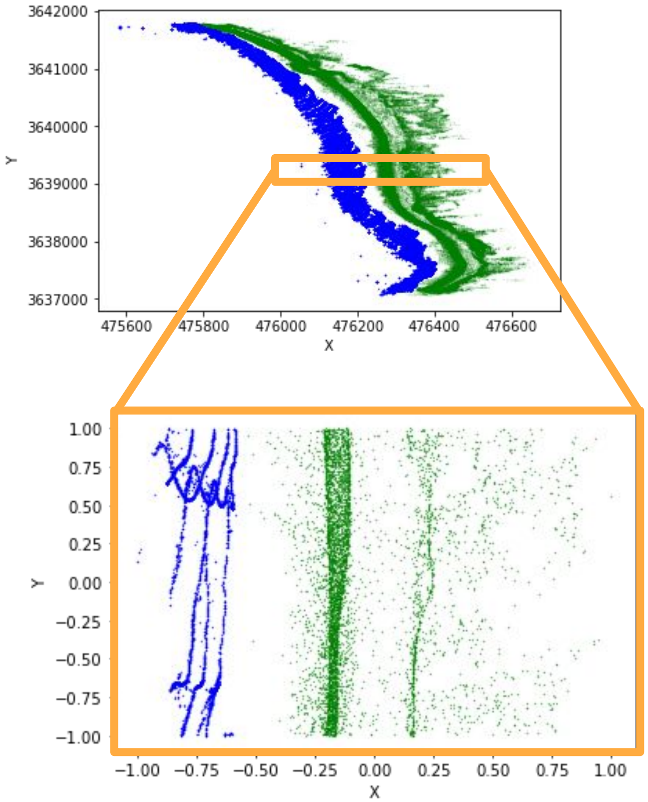


5 Southern California Beaches

- Blacks Beach, 2 x Torrey Pines, LJ shores, Del Mar
- Raw Data categorized by 4 features:
  - X, Y, Z, Intensity
- Data augmentation to reduce dependency on geometry and extend dataset
  - Flip along y axis to simulate east coast beach
  - Rotations about z axis of 90,-90 degrees to simulate north/south facing beaches
- Over 1 billion points before data augmentation (**1,006,413,610 total**)

Pre-Processing

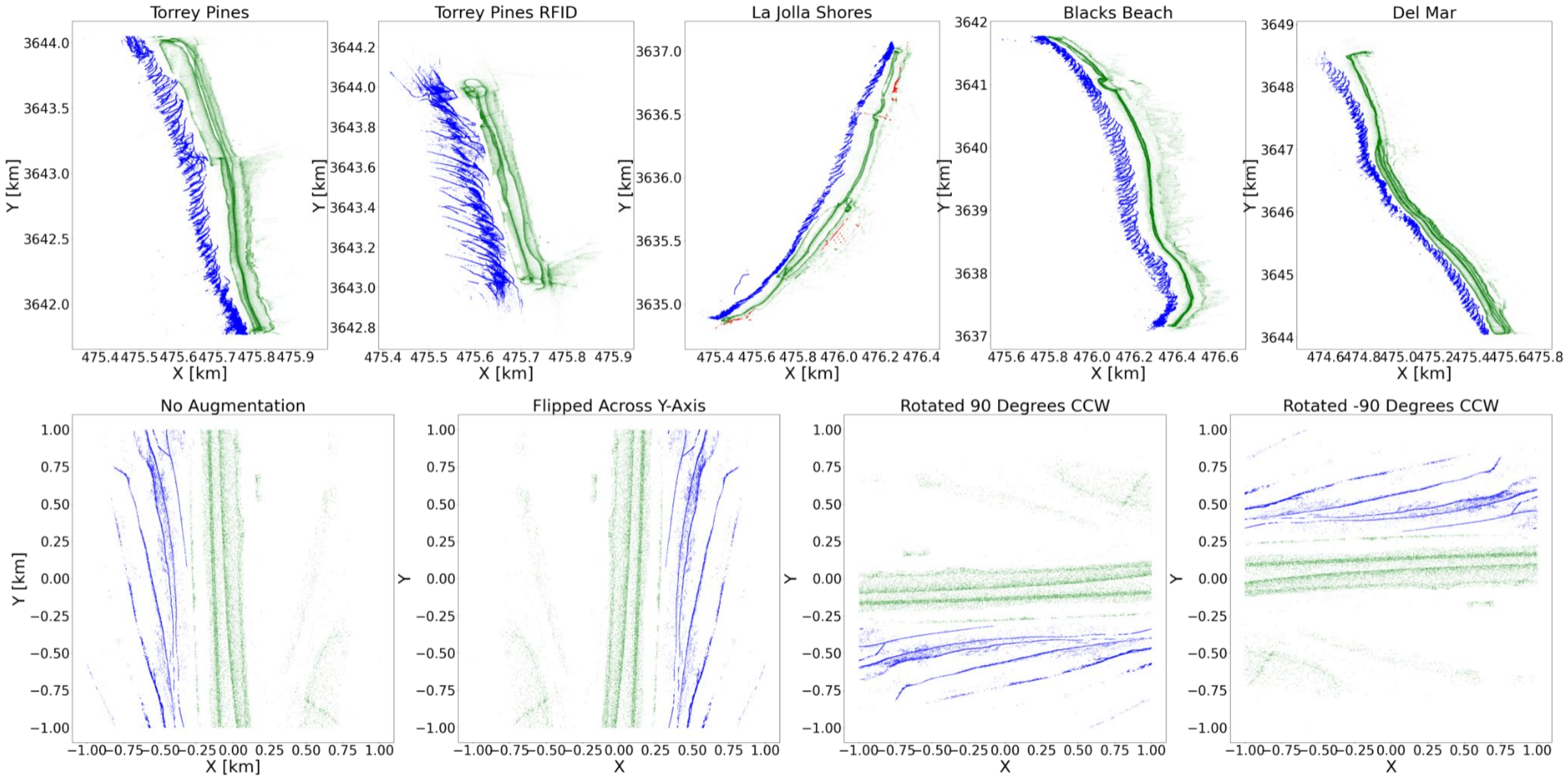
- Randomly subsample land returns to match the number of wave returns
  - Of 1 billion data points, >99% classified as land
  - Significantly increased computational efficiency
- Split Data into 100m alongshore segments
  - Reduce dependency on coastline geometry
  - 104 'segments' of beach before augmentation
- Normalization
  - XY: minmax normalization (-1 to 1)
  - Z: minmax 0 (sea level) to 1
  - Intensity:
    - nothing for RF and KNN models
    - Standard deviations above the mean for Deep Learning
- Sample weights based on inverse number of class members



Dataset Summary

All Datasets with equal land/wave points

Data Augmentations on Normalized and split data

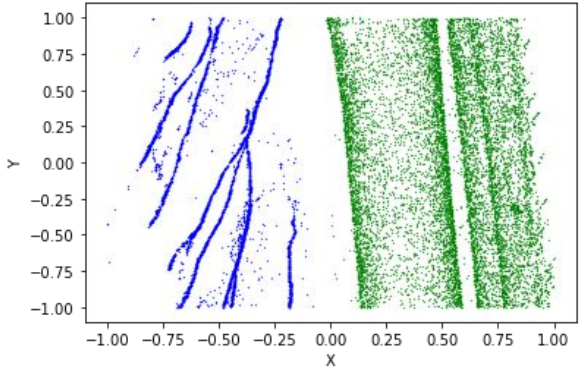


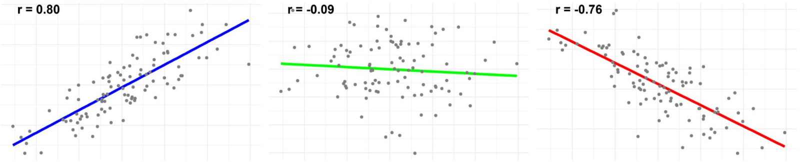
Feature Engineering

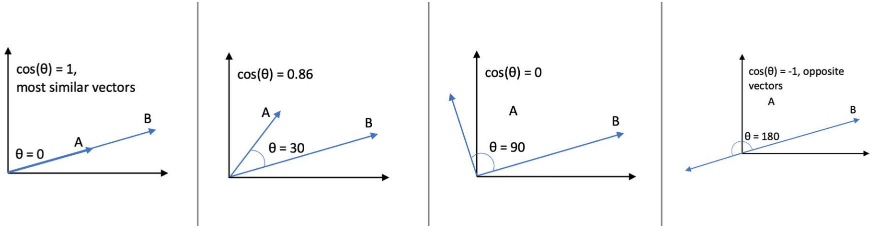
Geometrical features

- Water returns have very distinct linear features
- Land returns should be equally spaced clusters
- Leverage positional information from k=40 nearest neighbors
- R^2 value
  - Find linear fit for X,Y of nearest neighbors
  - R^2 gives approximation of how accurate the fit is, ie how linear
- Cosine Similarity
  - Sum of cosine similarity of neighbors matrices.
  - More linear matrices have higher sum than non linear points

Include intensity[3] for assistance in extracting nonlinear features



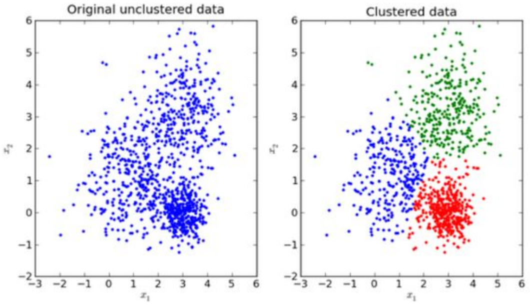




Model Details: Based on Medina et al. 2021

KNN Classifier:

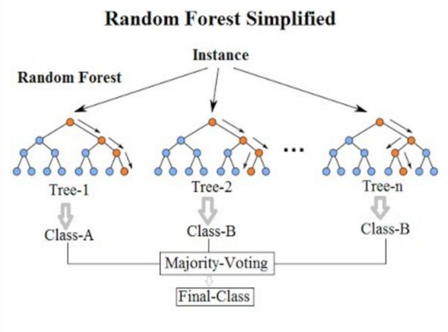
- N_neighbors = 15
- Distance Metric: Euclidean



Quora

Random Forest Classifier:

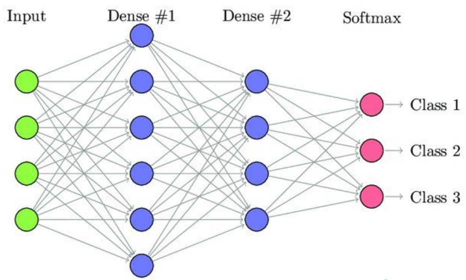
- N_estimators = 20
- Max depth = 20
- Bootstrap samples



https://en.wikipedia.org/wiki/Random_forest

Deep Learning:

- Two fully connected, dense layers:
  - 1st hidden: 20 neurons, relu activation
  - 2nd hidden: 15 neurons, relu activation
  - Output dimension: 3, softmax
- Loss: Categorical Cross Entropy
- Optimization: adam
- Epochs: 200, batch size: 1000
- Learning rate: 0.001



https://www.researchgate.net/publication/331525817_Temporal_Convolutional_Neural_Network_for_the_Classification_of_Satellite_Image_Time_Series/figures?lo=1

Result Metrics

Accuracy | Confusion Matrix | Visual Inspection

K-Nearest Neighbors / Random Forest / Deep Neural Network
Models trained on 5 datasets:

1. ‘torrey’ only
2. ‘torrey’ w/ geometrical augmentations
3. ‘torrey’ + ‘blacks’ + ‘delmar’ + ‘LJshores’ w/ geometrical augmentations
4. ‘torrey’ w/ feature engineering
5. ‘torrey’ w/ feature engineering and geometrical augmentations

Tested twice:

- 20% Random Test Data
  - Accuracy
  - Confusion Matrix
- Entire Additional Survey (‘torreyRFID8’ dataset)
  - Accuracy
  - Confusion Matrix

Results

Accuracy | Confusion Matrix | Visual Inspection

- Random Forest performs best most often
- Trained models perform best on same beach
- Feature engineering increases model prediction accuracy nearly across the board

	Training Dataset(s)	Augmentation	Testing	K-Nearest Neighbors (KNN)	Random Forest (RF)	Deep Neural Network (DNN)
Model	torrey	NA	20% of dataset	accuracy: 0.9029968787799328 confusion matrix: [51799 6158] [5310 54956]	accuracy: 0.9963135199120656 confusion matrix: [57806 145] [291 60028]	accuracy: 0.9772 confusion matrix: [57270 832] [1869 58245]
			torreyRFID	accuracy: 0.8953210995990746 confusion matrix: [186559 22294] [21413 187268]	accuracy:0.8120210727969349 confusion matrix: [196640 12287] [66213 142460]	accuracy: 0.6771507397845549 confusion matrix: [186145 22891] [111916 96602]
	torrey	flipY, rot 90, rot -90	20% of dataset	accuracy: 0.8539621181202434 confusion matrix: [197328 34779] [34281 206503]	accuracy: 0.9791261520250275 confusion matrix: [229006 2755] [7120 234199]	accuracy: 0.9291 confusion matrix: [219878 12539] [20982 219465]
			torreyRFID	accuracy: 0.7994534576824881 confusion matrix: [165129 43724] [40011 168670]	accuracy: 0.7485632183908046 confusion matrix: [180061 28866] [76134 132539]	accuracy: 0.510621380707645 confusion matrix: [138219 70817] [133525 74993]
	torrey, LJshores, blacks, delmar	flipY, rot 90, rot -90	20% of dataset	accuracy: 0.8263269645028746 confusion matrix: [528382 122553] [95469 620460]	accuracy: 0.8306001431418722 confusion matrix: [522853 121343] [93451 623190]	accuracy: 0.8747 confusion matrix: [597203 52233] [80463 645950]
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Accuracy

Confusion Matrix

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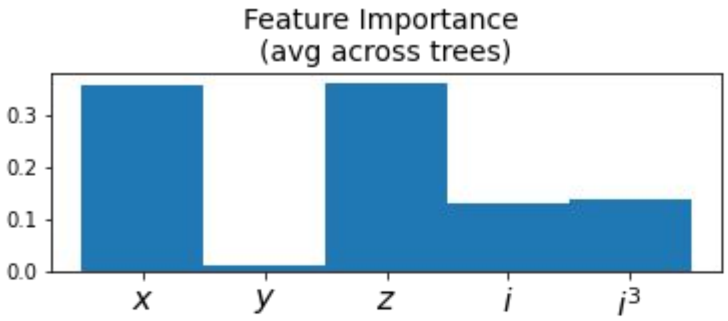
[True land | Land classified as waves]
[Waves classified as land | True waves]

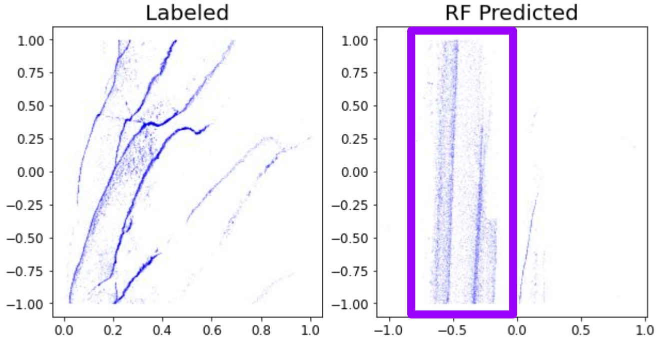
Data Augmentation Increases Model Robustness

Accuracy | Confusion Matrix | Visual Inspection

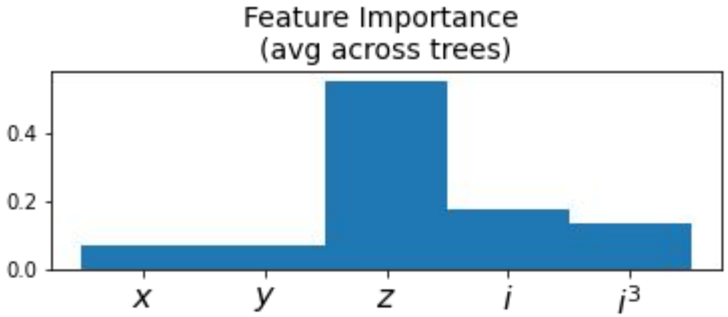
Simple RF: 1 Training Beach, No augmentation



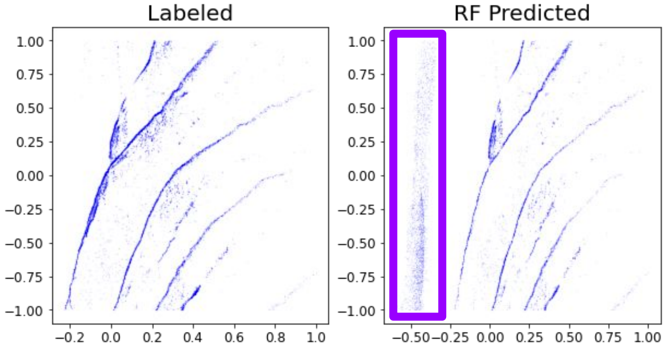
Failure to classify on ‘East Coast’: ~25% accuracy



Data augmentation reduces dependency on X (East-West) which helps resolve ‘flipped’ classification issue



Increase accuracy on ‘East Coast’: ~80% accuracy



Land misclassified as waves

Future Work

- Explore hyperparameter space
- Further expand training data with full datasets & additional surveys
  - Confusion matrices will be best measure of model accuracy because of class imbalance
  - Investigate how wave conditions impact model performance
- Compare methods for normalization (e.g. min/max scaling vs. mean/std)
- Explore more robust error metrics for classification
  (i.e. Precision, Recall, AUC curve etc.)

Future Work (beyond class report)

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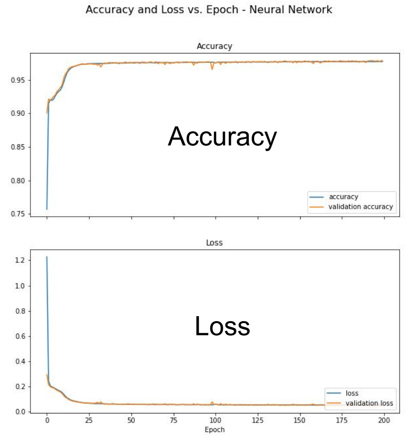
  - Investigate how wave conditions impact model performance
- Compare methods for normalization (e.g. min/max scaling vs. mean/std)
- Explore more robust error metrics for classification (i.e. Precision, Recall, AUC curve etc.)
- Modify deep learning model
  - Implement early stopping
  - Smooth out accuracy and loss curves



CCCIA field crew will decide on best model

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