Automated Feature Extraction in Satellite Imagery Using Support Vector Machines

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Problem Statement

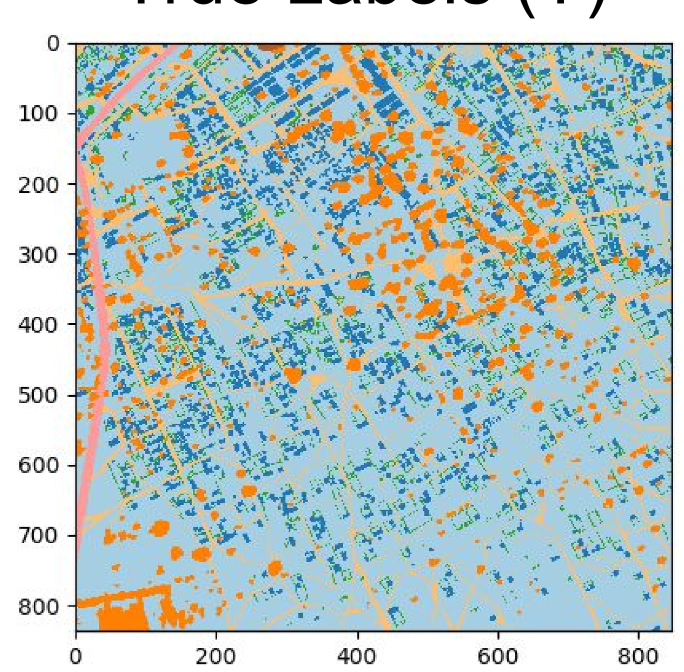
Thanks to improvements in technology, the collection and availability of satellite imagery has exploded in recent years. Fortunately, this grants us unprecedented levels of data from areas with limited ground reporting. However, the challenge exists to translate this imagery into useful demographic information (for the purposes of aid distribution, poverty identification, etc.), which is where the insights of machine learning are essential. To aid in this, one needs to recognize different features of an area indicating population characteristics, such as buildings, waterways, roads, crops, etc. As such, our goal is to generate feature masks given satellite imagery that map each pixel to a class; these masks can then be used for further analysis in a wide variety of applications.

Data

- Input data consisted of satellite imagery from Kaggle dataset "DSTL Satellite Imagery Feature Detection"
  - Landsat imagery consists of sixteen bands in the visible and infrared wavelengths, of which we are using eight
  - Input data was segmented into 1600 64x64 pixel images for training and 400 for testing
  - Image resolution varies from .31 to 7.5 meters per pixel
- True labels are in the form of WKT shapefiles that were converted to feature masks with the same size as the images

Satellite Image (X)

True Labels (Y)

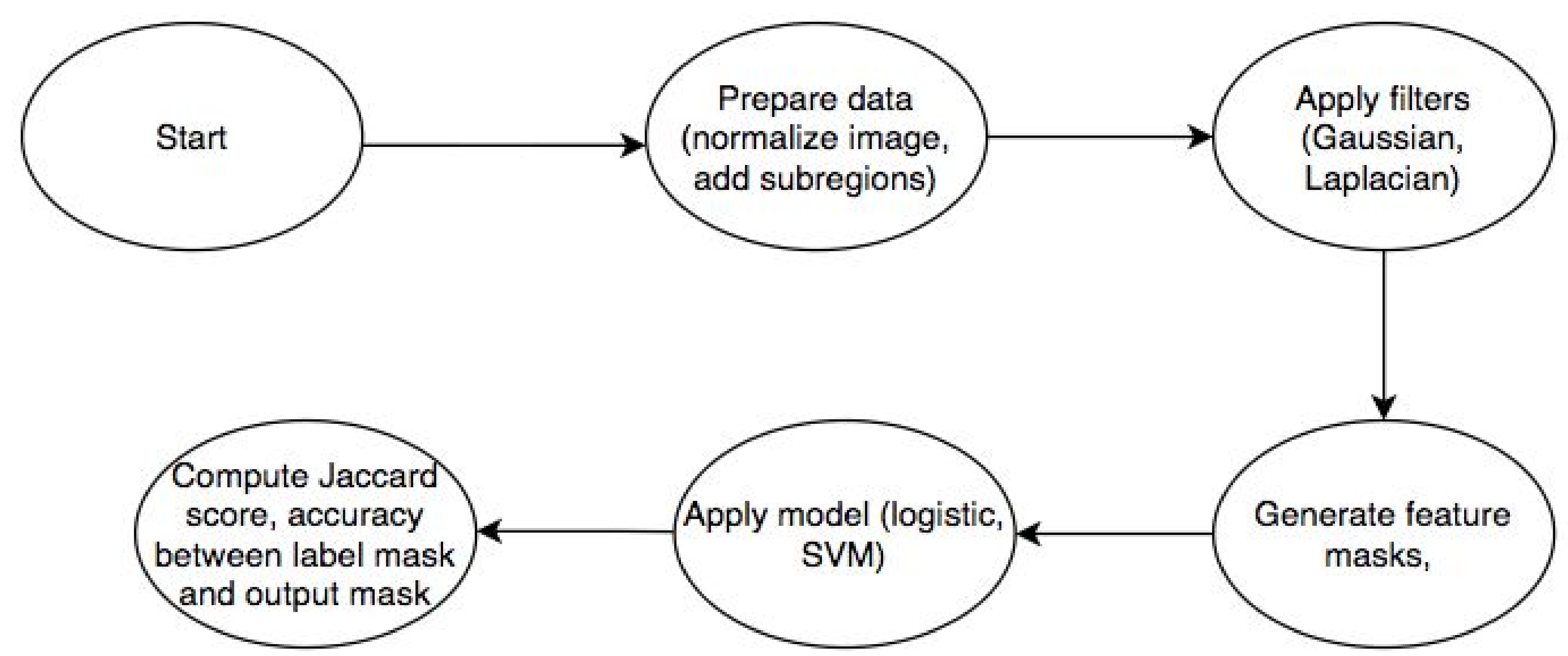


Models

- We approached this problem as a classification problem predicting the label of each pixel in a satellite image as one of eight classes
- We implemented both SVM and logistic regression models to predict class values and compared their performance
  - The sklearn library was used for logistic regression and SVM models with l2 regularization

Features

- Each satellite image contains eight bands including three in the visible spectrum in five infra-red
- We applied Gaussian and Laplacian filters to each band of the original image to increase the feature space to 24
- Each feature in the training set was normalized to have zero mean and a standard deviation of one with the same normalization applied to the test set

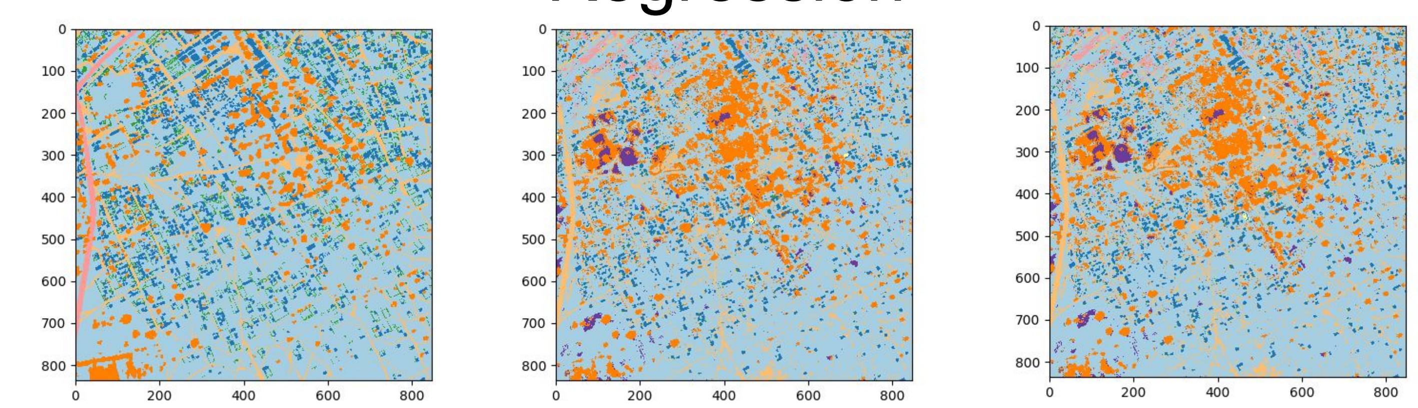


Challenges and Future Applications

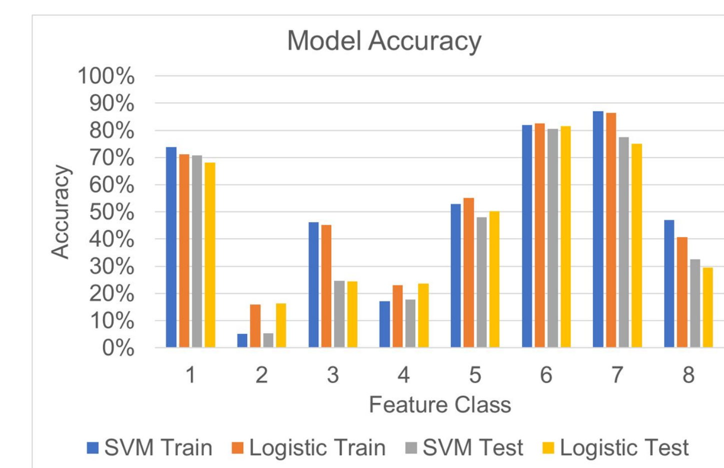
- Obtaining and creating labeled data
- Differentiating between classes with similar features (i.e. roads/tracks and waterways/standing water)
- Future work could be done in developing specialized models trained on the differences of similar classes to improve improve accuracy

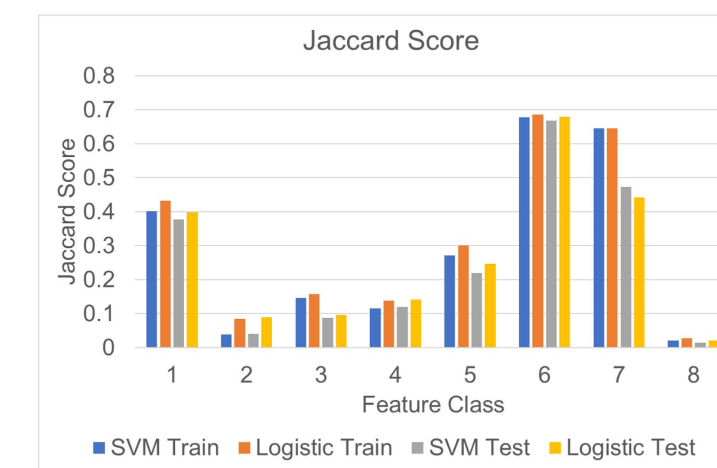
Results

True | Logistic Regression | SVM



1 – Building		5 – Trees	
2 – Man-Made Strutures		6 – Crops	
3 – Roads		7 – Waterway	
4 – Dirt Tracks		8 – Standing Water	





Results Discussion

- Logistic regression achieved superior Jaccard scores on all classes when compared to SVM
- The model with the better accuracy depended on the feature class
- Models achieved higher accuracy on feature classes with low representation by over classifying, which resulted in a lower Jaccard score (i.e. roads [3] and standing water [8])
- Feature classes 6 and 7 [crops and waterways] had both the highest model accuracy and Jaccard score, with feature class 1 [buildings] close behind.

References
Kaggle.com. (2017). Dstl Satellite Imagery Feature Detection | Kaggle. [online] Available at: https://www.kaggle.com/c/dstl-satellite-imagery-feature-detection/data [Accessed 11 Dec. 2017].
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Mitra, P., Uma Shankar, B. and Pal, S. (2017). Segmentation of multispectral remote sensing images using active support vector machines. [online] Elsevier. Available at: http://www.sciencedirect.com/science/article/pii/S0167865504000704 [Accessed 11 Dec. 2017].