

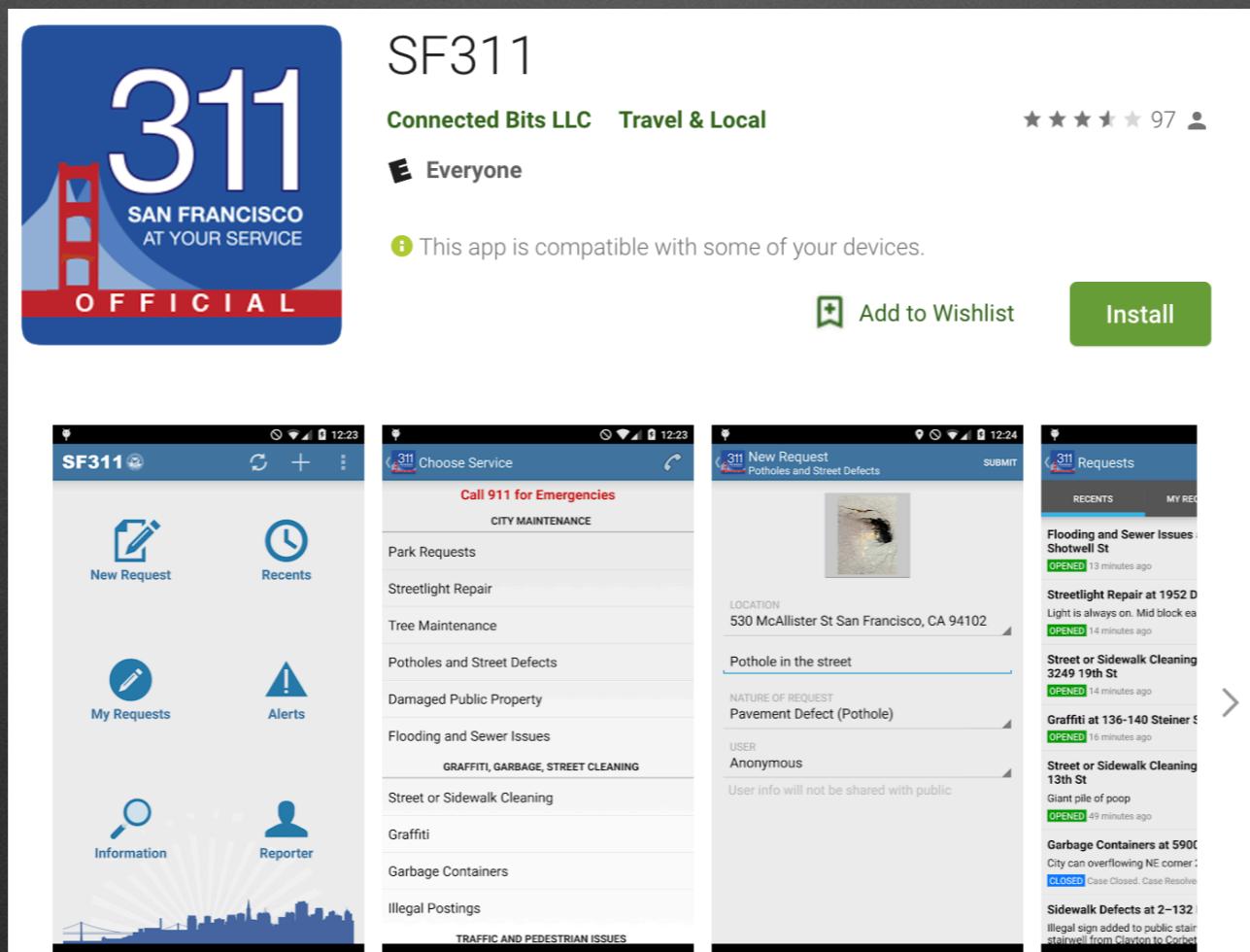


San Francisco 311 Reports Neural Network Image Classification

Crystal Bevis

San Francisco 311Cases

- 311 Reports - Non-emergency reports requesting city service
 - Example: Trash, graffiti, damaged roads
- Primarily created by mobile app
- Open data - images and categorical data about cases available



Objective

- Determine the type of case by using the images, location, and date data.
- Motivation:
 - Make it easier to submit cases
 - Audit cases - can predict which forms may need human review
 - Accessibility - all languages, vision impaired
 - Better allocate city resources



311 - Data

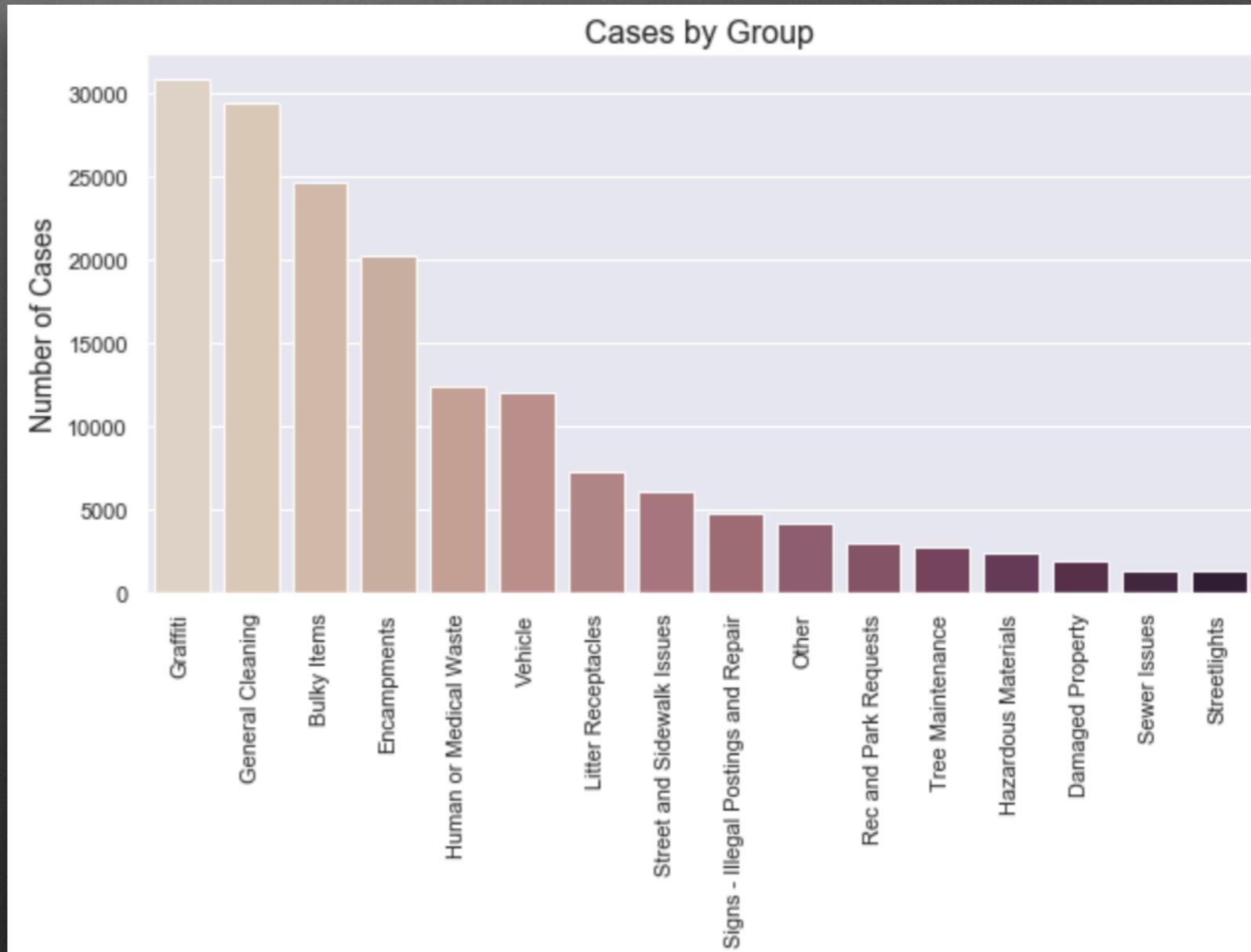
SF Open Data: <https://data.sfgov.org/City-Infrastructure/311-Cases/vw6y-z8j6>

- Large dataset
 - 3.48M samples
 - 20 features
- Selected a subset
 - Samples with valid image URLs
 - 2017-2018
 - Approximately 160,000 images
- Cropped edges, resize, grayscale, and save as 128x128 images on download



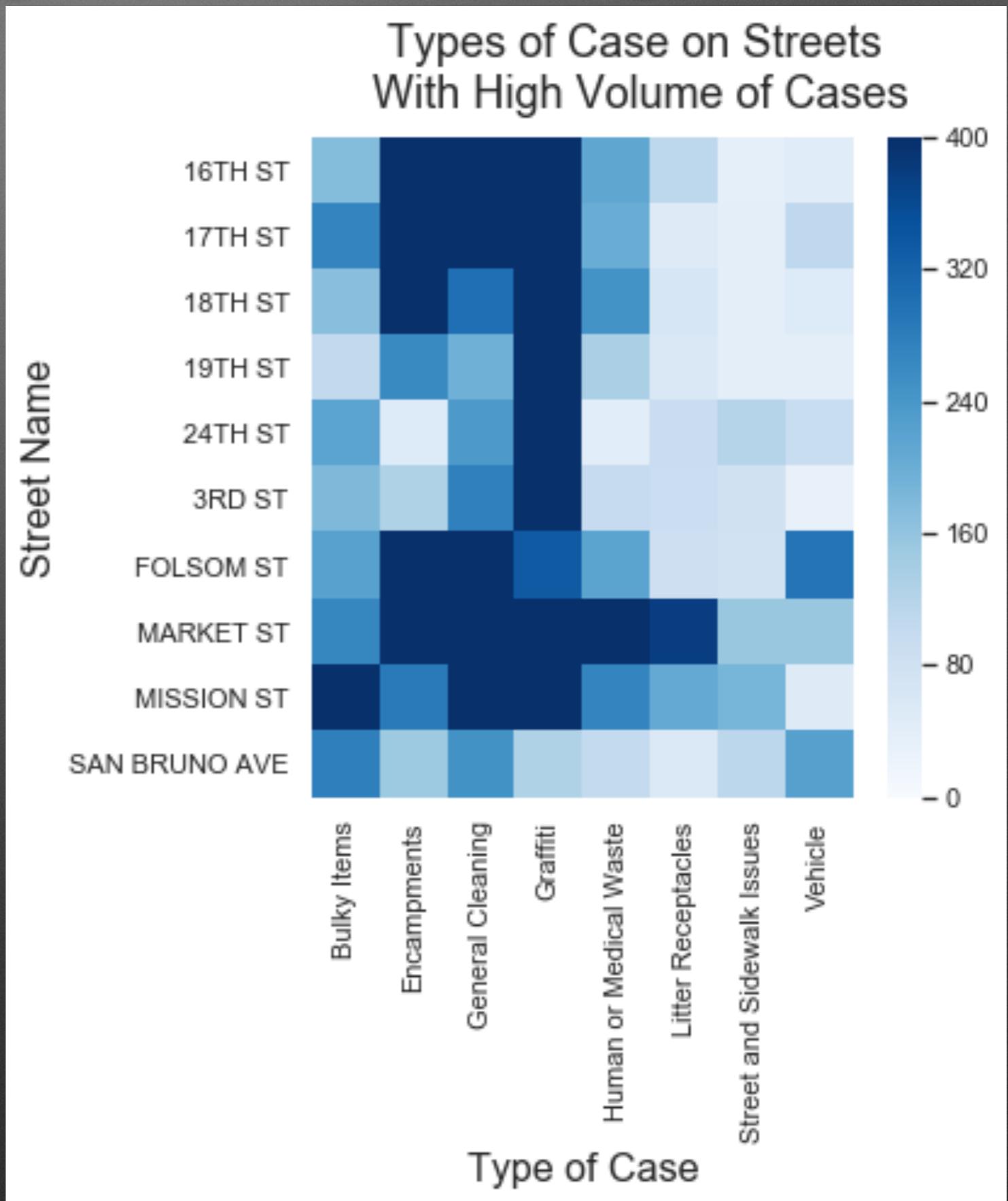
311 Data - Labels

- Which labels?
 - Category - 31 unique labels, ~50% in one class
 - Request Type - 119 unique labels
- Combined small categories
- Split large category
- Example:
 - Parking enforcement, abandoned vehicles -> Vehicles
- 16 Groups



Exploratory Data Analysis

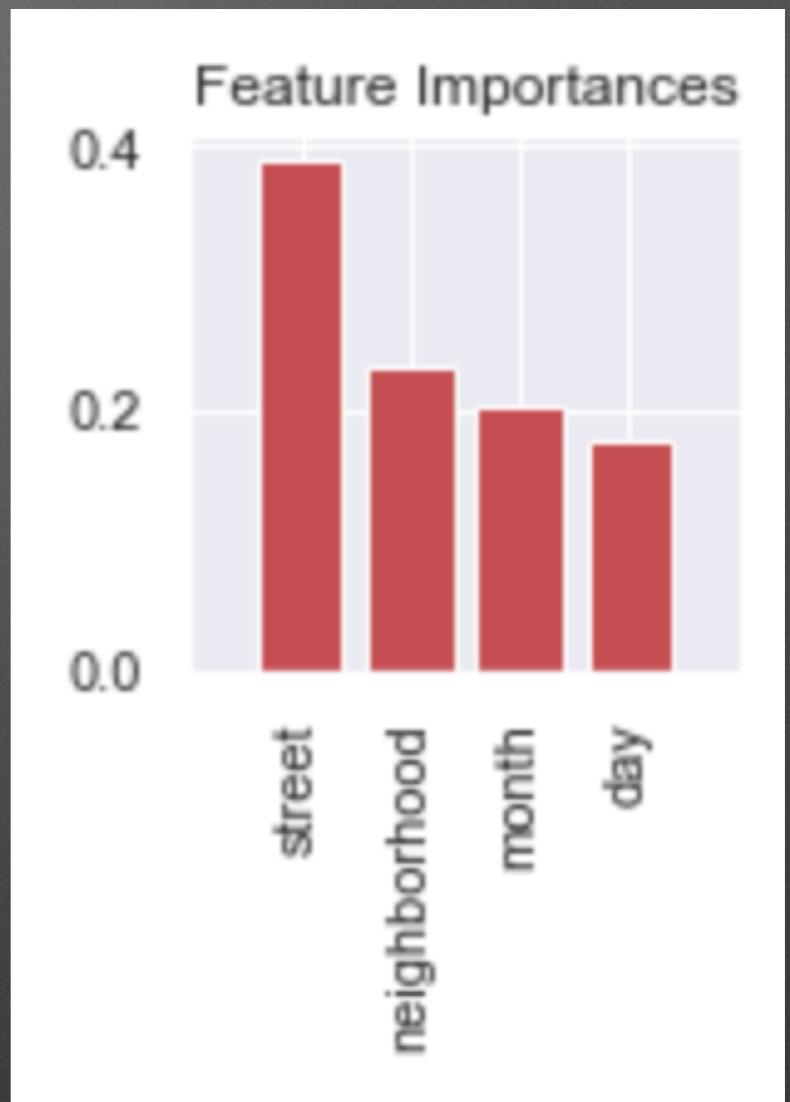
- Categorical features
 - Street
 - Neighborhood
 - Date
- Split date
 - Month
 - Day of the week
- Scale on heat map shown set to maximum of 400 to better see the distribution



Categorical Data Modeling

Random Forest

- Feature importances
- Handle categorical data
- Determine a baseline for MLP model
- Train accuracy: 38%
- Test accuracy: 32%



Multilayer Perceptron

- One hot encoded categorical features
- Applied variance threshold
 - ~ 400 features remaining
- Dense 128, activation Relu
- Dropout
- Dense 64, activation Relu
- Dropout
- Dense, activation Softmax

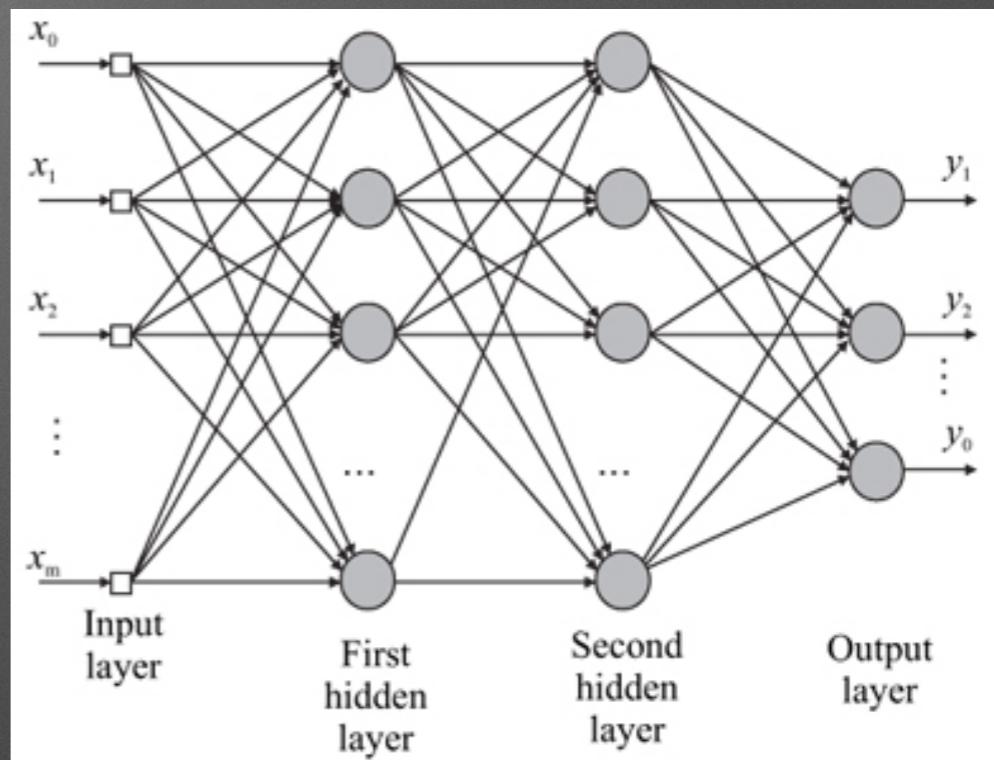


Image Source: [http://www.scielo.br/scielo.php?
script=sci_arttext&pid=S0104-77602013000200012](http://www.scielo.br/scielo.php?script=sci_arttext&pid=S0104-77602013000200012)

Multilayer Perceptron

- Training Accuracy: 0.34
- Test Accuracy: 0.32
- Top AUC:
 - 9: Parks and Recreation (0.95)
 - 15: Vehicles (0.81)
 - 2: Encampments (0.80)
- Bottom AUC:
 - 5: Hazardous Materials (0.61)

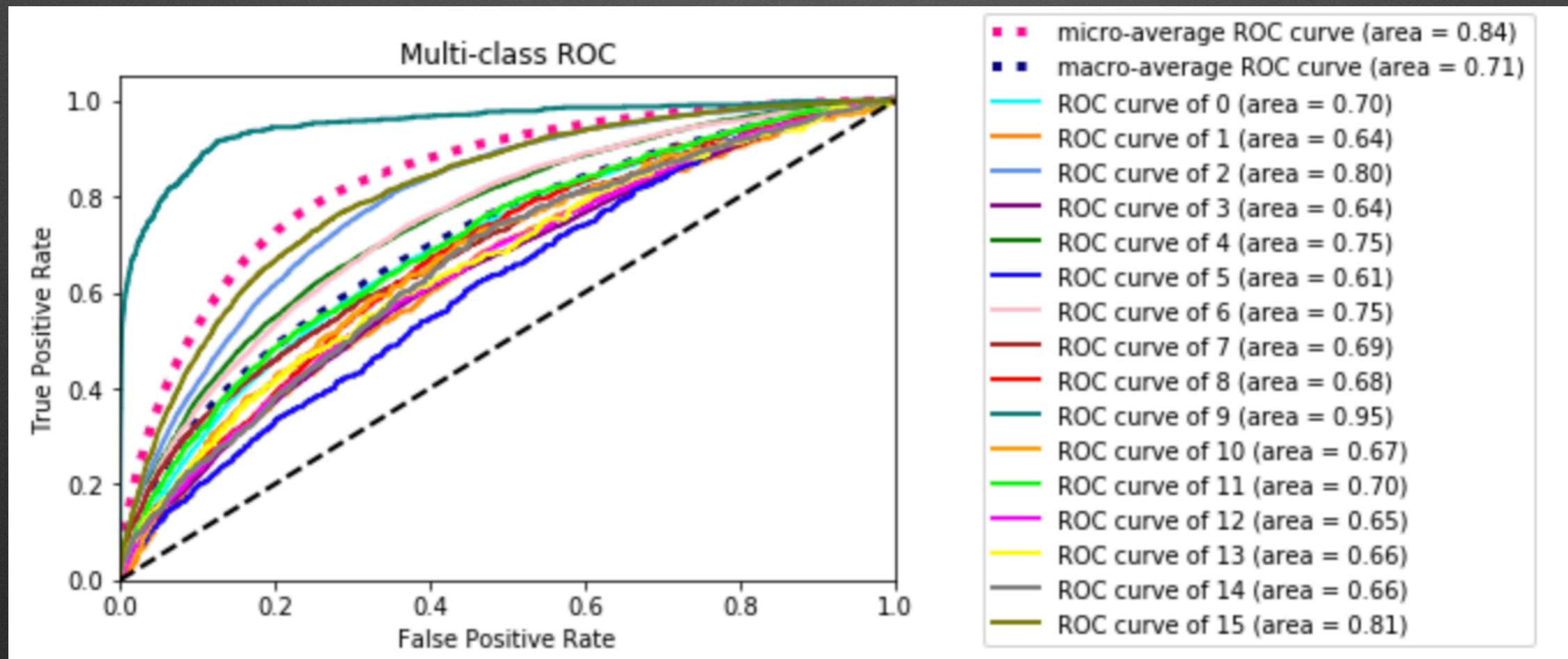


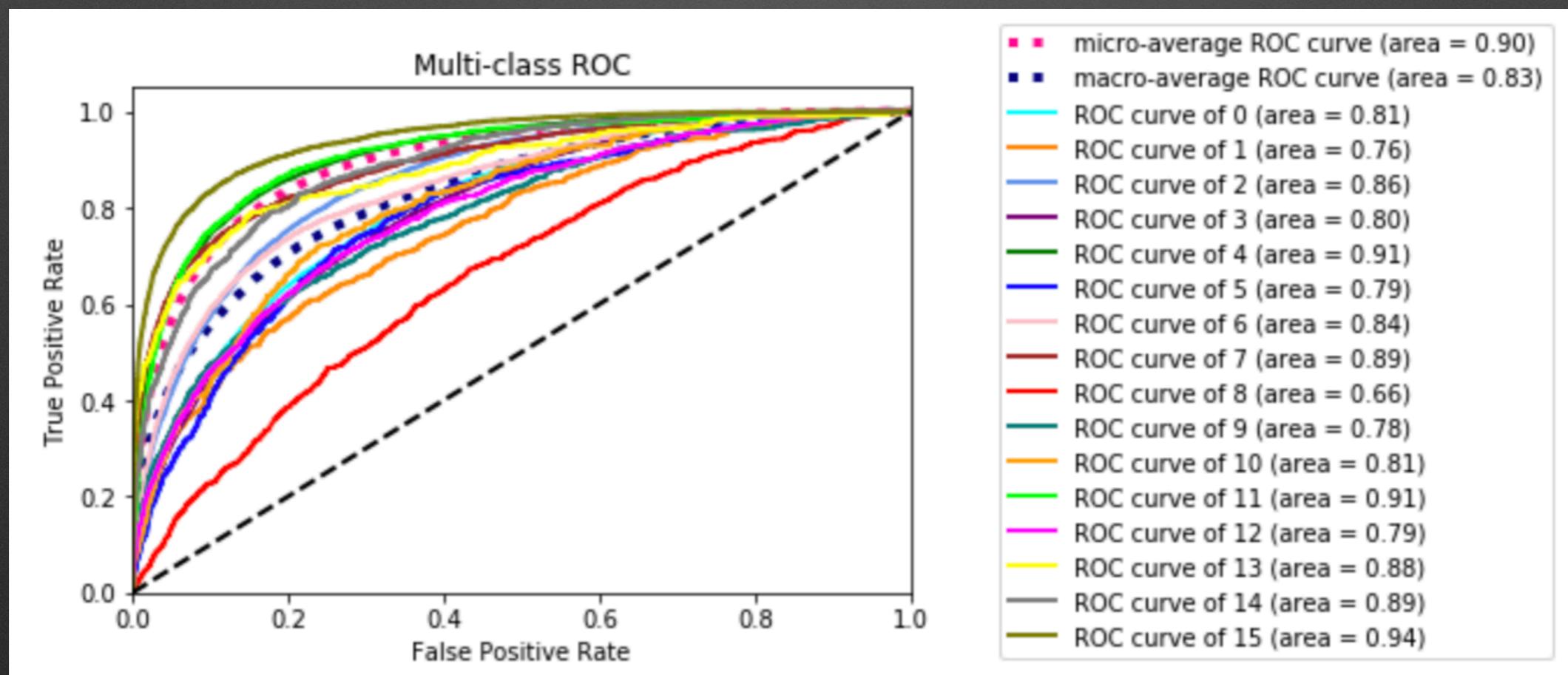
Image Data Modeling

Convolutional Neural Network

- Moved from local machine to Google Colab (14 hrs -> 15 min)
 - 40,000 data points, basic version of model
- 6 Convolutional 2D layers
 - Kernel sizes (3 x 3)
 - ReLu activation
- Model overfits - used several techniques to reduce this
 - Batch normalization
 - Drop out
 - Max Pooling

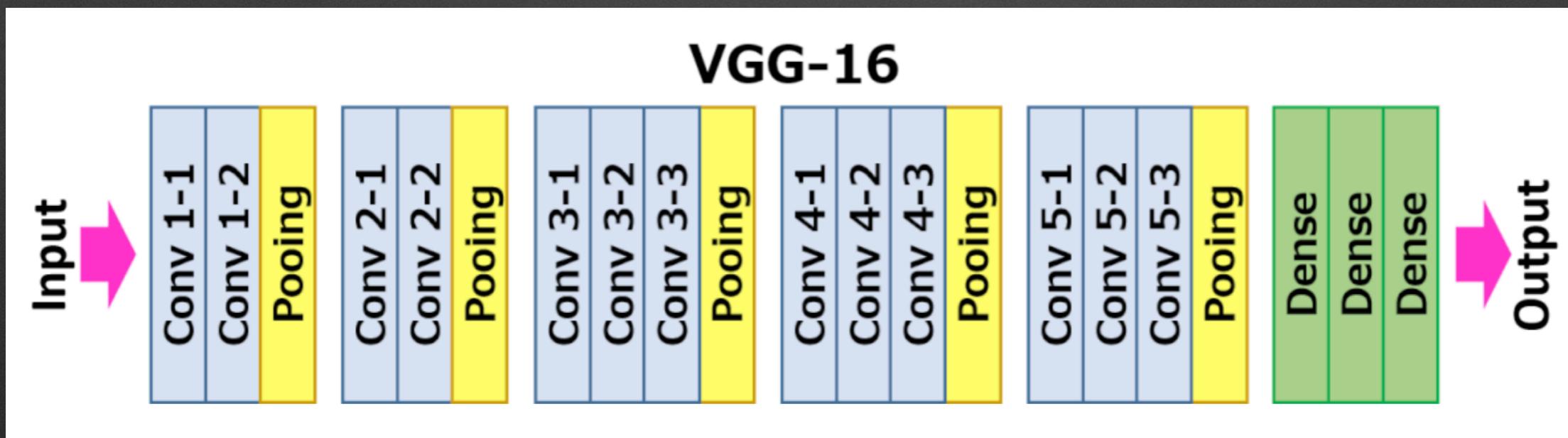
Convolutional Neural Network

- Training Accuracy: 0.54
- Test Accuracy: 0.48
- Top 3 AUC:
 - 15: Vehicles (0.94)
 - 11: Signs - Illegal Postings and Repairs (0.91)
 - 4: Graffiti (0.91)
- Bottom AUC:
 - 8: Other (0.66)



VGG 16

- Developed and trained by the Visual Geometry Group (VGG) at Oxford
- Very Deep Convolutional Network for Large-Scale Image Classification
- Pre-trained on ImageNet
 - Recognize 1,000 different object categories
- Easy to implement - included in Keras
- Large - over 533MB



VGG 16

Modify to
128x128
Grayscale x 3

The diagram depicted below is VGG16.

$224 \times 224 \times 64$

$112 \times 112 \times 128$

$56 \times 56 \times 256$

$28 \times 28 \times 512$

$14 \times 14 \times 512$

$7 \times 7 \times 512$

\downarrow

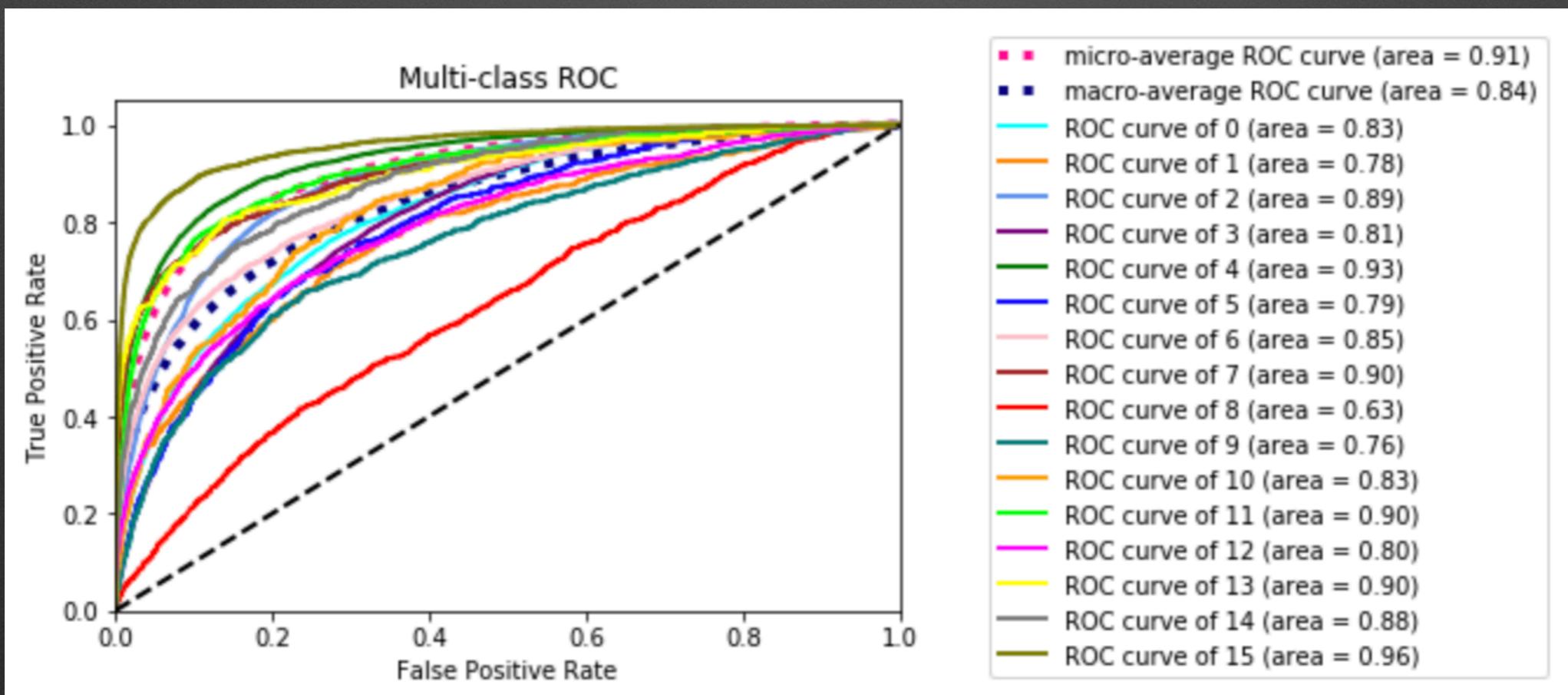
Unfreeze

- convolution+ReLU
- max pooling
- fully connected+ReLU
- softmax

Dropout
Flatten
Dense
(Softmax, 16 classes)

VGG 16 Results

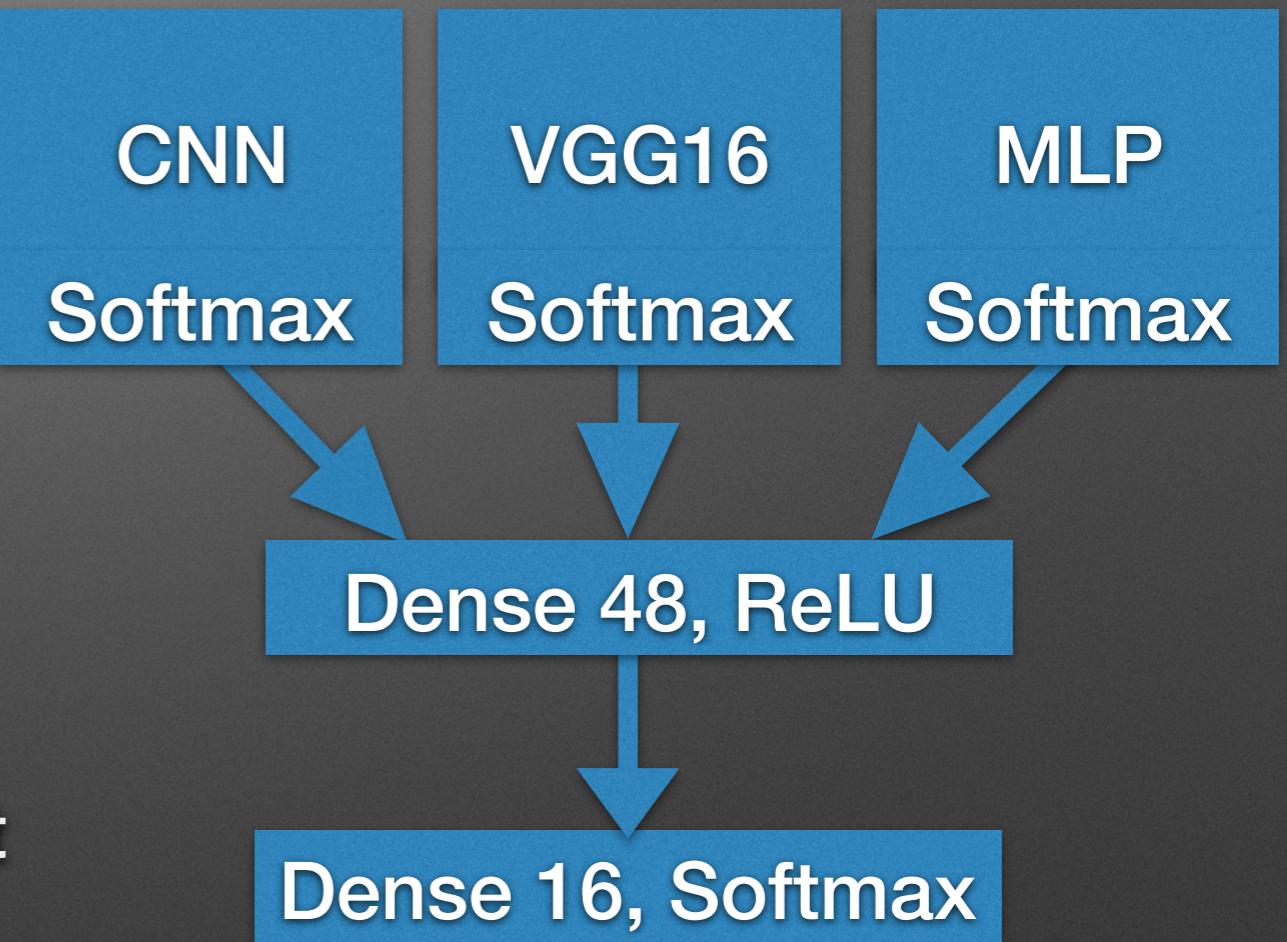
- Training Accuracy: 0.78
- Testing Accuracy: 0.53
- Top 3 AUC:
 - 15: Vehicles (0.96)
 - 4: Graffiti (0.93)
 - 7: Litter Receptacles, 11: Signs - Illegal Postings and Repairs, 13: Streetlights (0.90)
- Bottom AUC:
 - 8: Other (0.63)



Combining Mixed Data Types

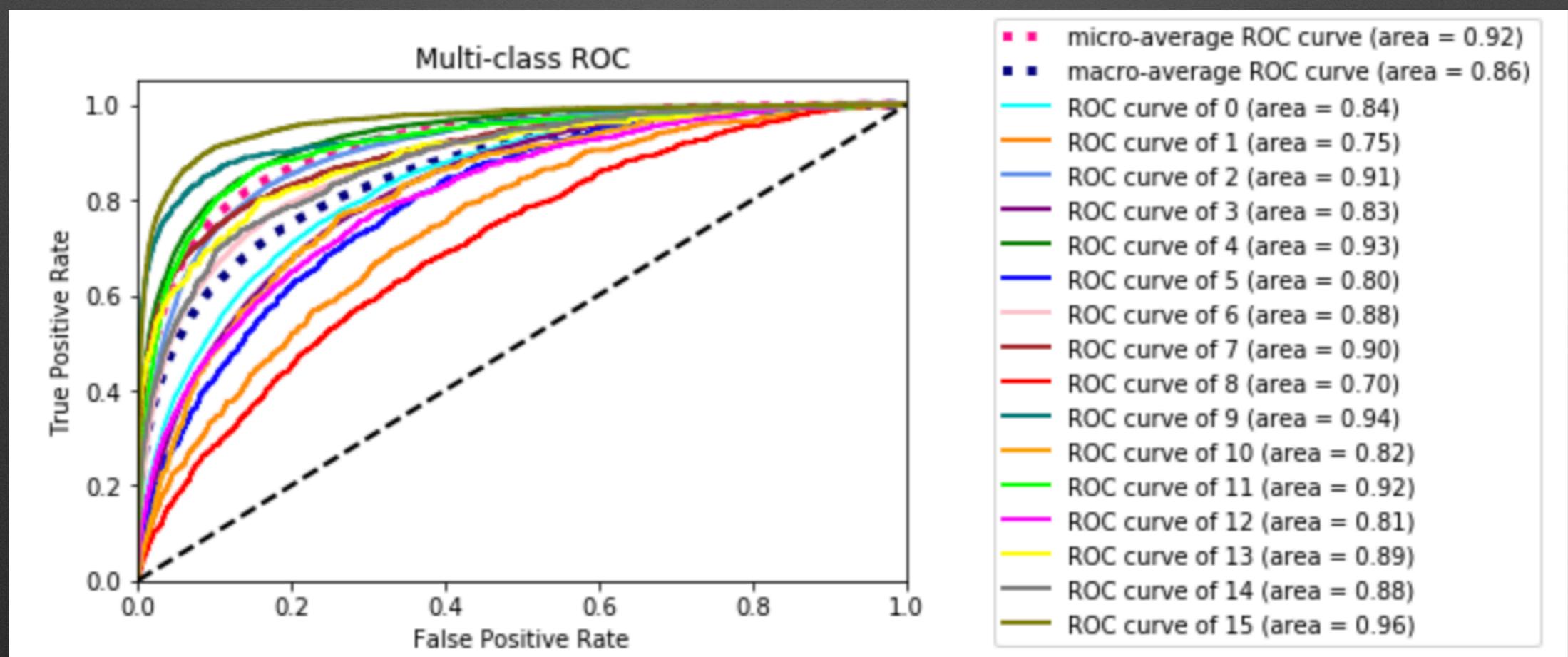
Multiple Data Types Model

- Train accuracy: 62%
- Test accuracy: 54%
- Using 2 models would max at 32%
- Overtraining, but adding dropout hurt the test performance



Multiple Data Types Model

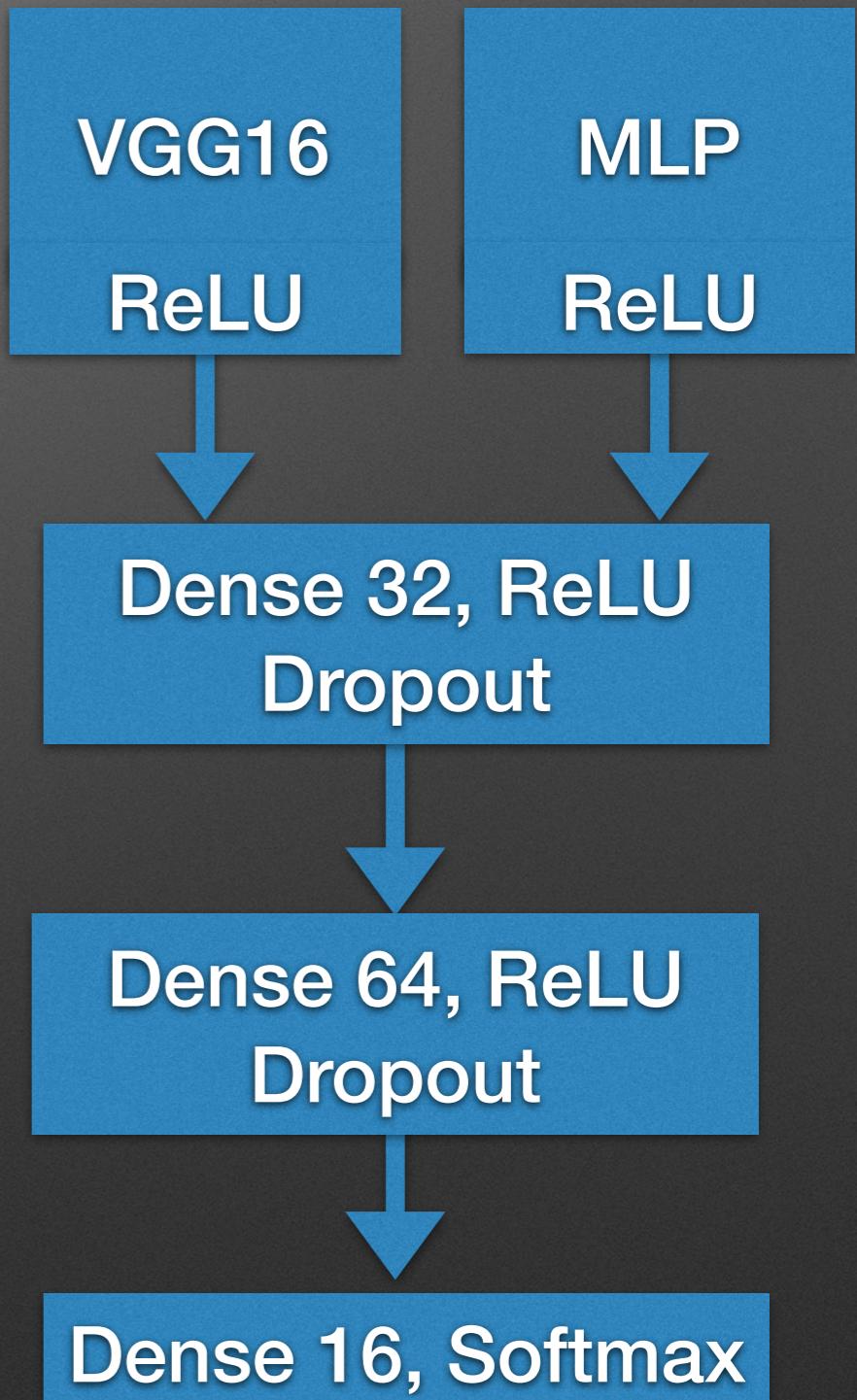
- Train accuracy: 62%
- Test accuracy: 54%
- Best AUC:
 - 15: Vehicles (0.96)
 - 9: Parks and Recreation (0.94)
 - 4: Graffiti (0.93)
- Worst AUC:
 - 8: Other (0.70)
 - 1: Property Damage (0.75)
- Overall accuracy not much higher than VGG16 alone, but it correctly classifies parks and recreation



Multiple Data Types VGG 16 and MLP

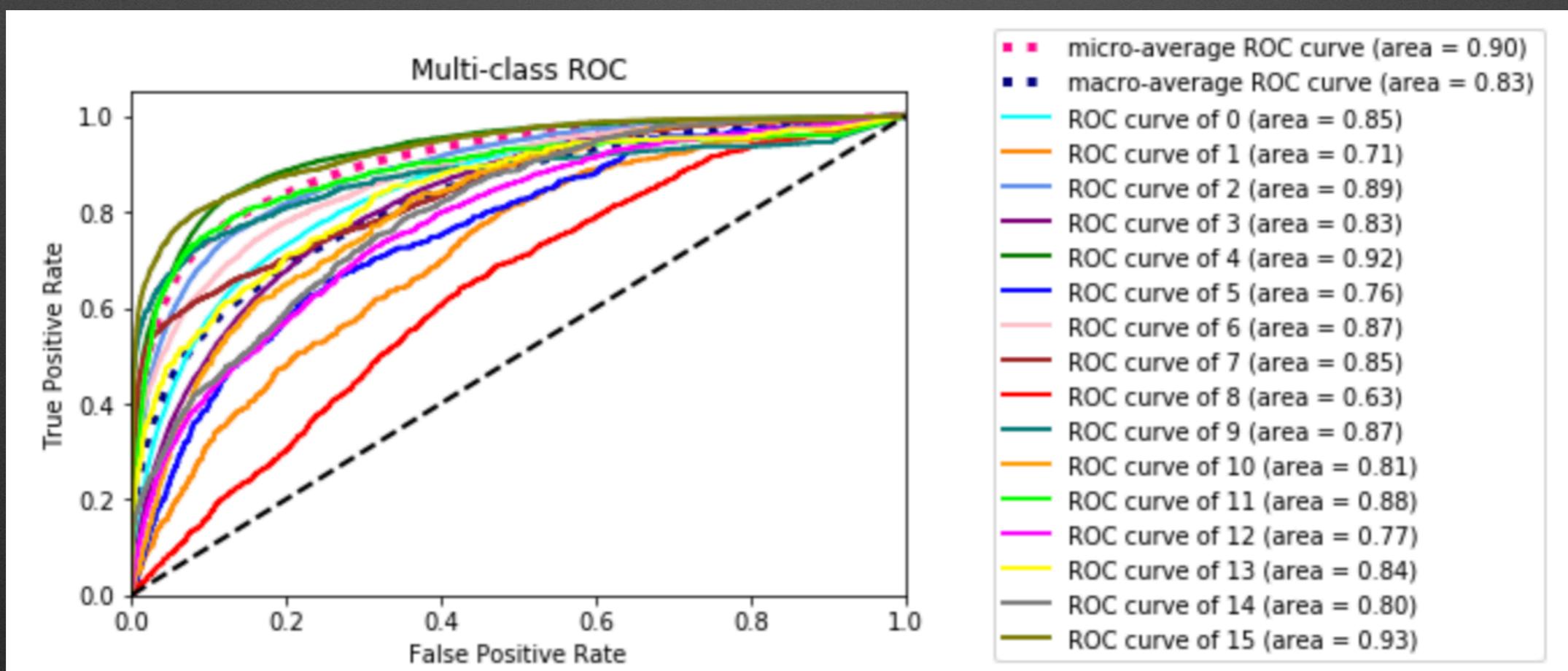
- Reinitialize models before training
- Changed outputs of individual models to ReLU
- No Softmax until the end

- Train Accuracy: 0.54
- Test Accuracy: 0.54



Multiple Data Types VGG 16 and MLP

- Best AUC:
 - 15: Vehicles (0.93)
 - 4: Graffiti (0.92)
 - 2: Encampments (0.89)
- Bottom:
 - 8: Other (0.63)
- Less overtraining
- Less complex - less memory involved per batch
- Slightly lower AUC scores than 3 model combo



Example 1

Graffiti (2%)



Predictions

- General Cleaning (33.4%)
- Bulky Item (32.9%)

Example 2

Vehicle



Prediction

- Vehicle (99%)

Example 3

Bulky Item



Predictions

- Bulky Item (58%)
- General Cleaning (17%)

Example 4

Signs - Illegal Postings and Repair (5.9%)



Predictions

- Graffiti (93.6%)
- Signs - Illegal Postings and Repair (5.9%)

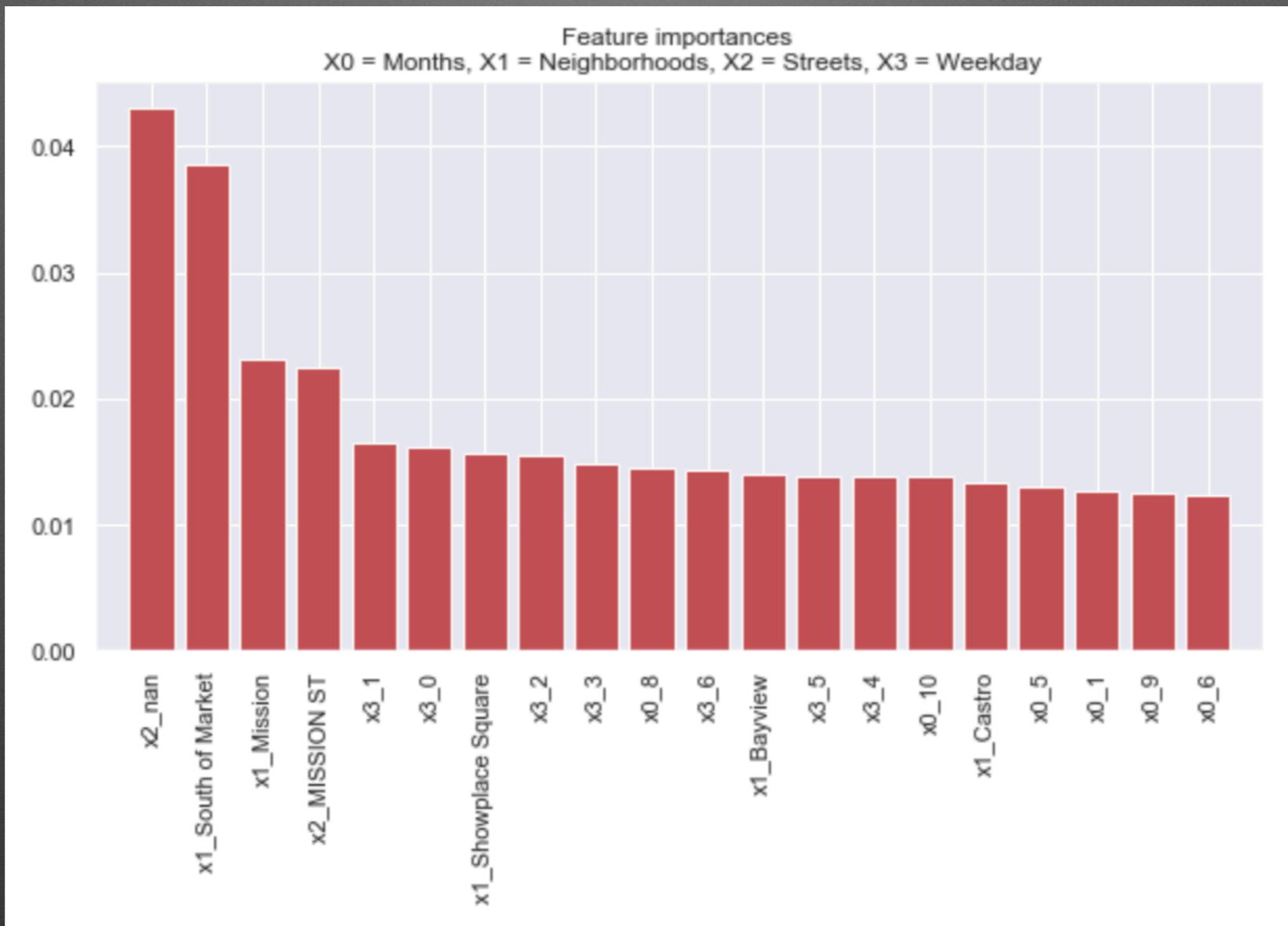
Future Work

- Expand to include time series information across years: 2013-2019
 - Are types of cases increasing or decreasing over time?
- Include more images or more pixels
- Use RGB images
- Include image rotation
- Refine groupings

Conclusion

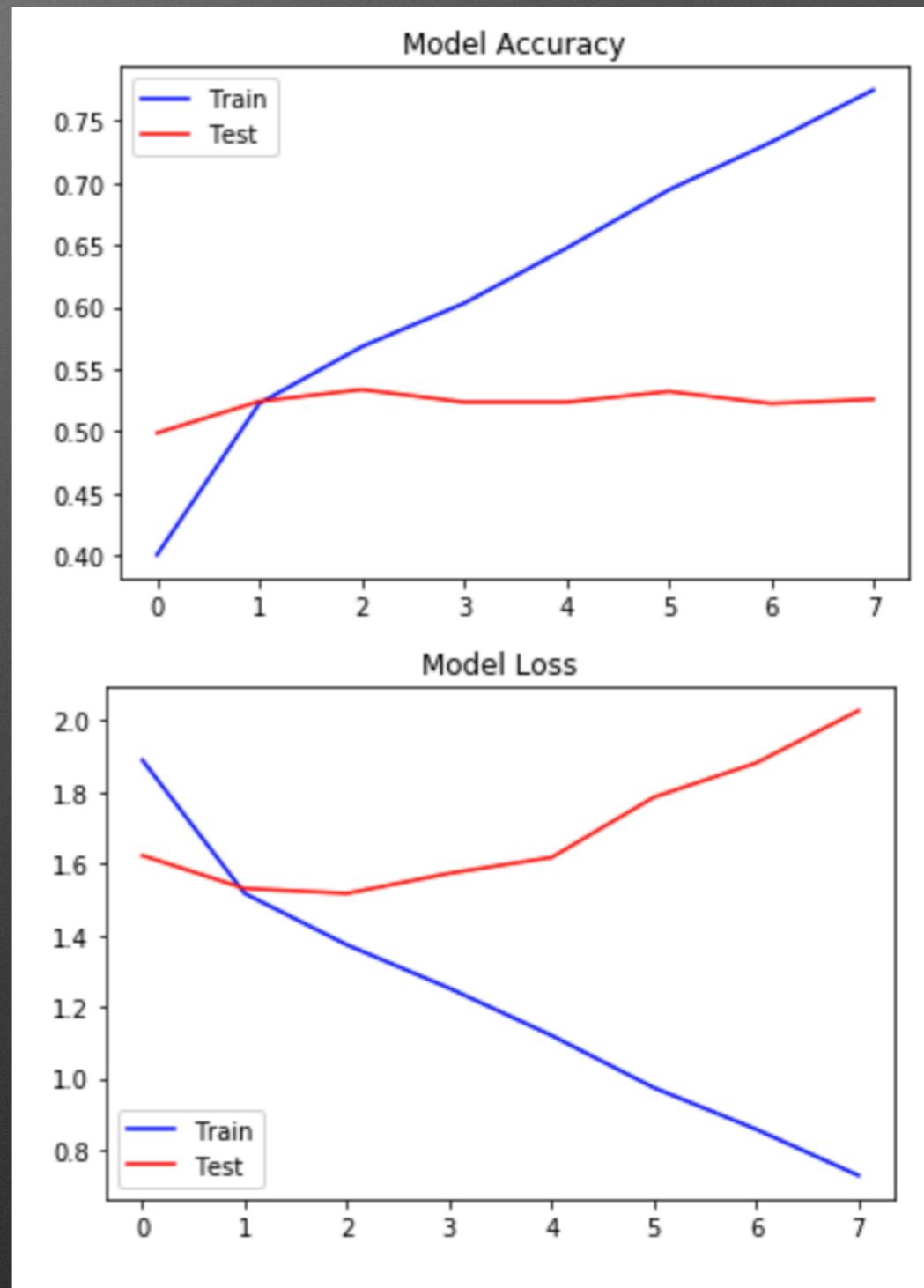
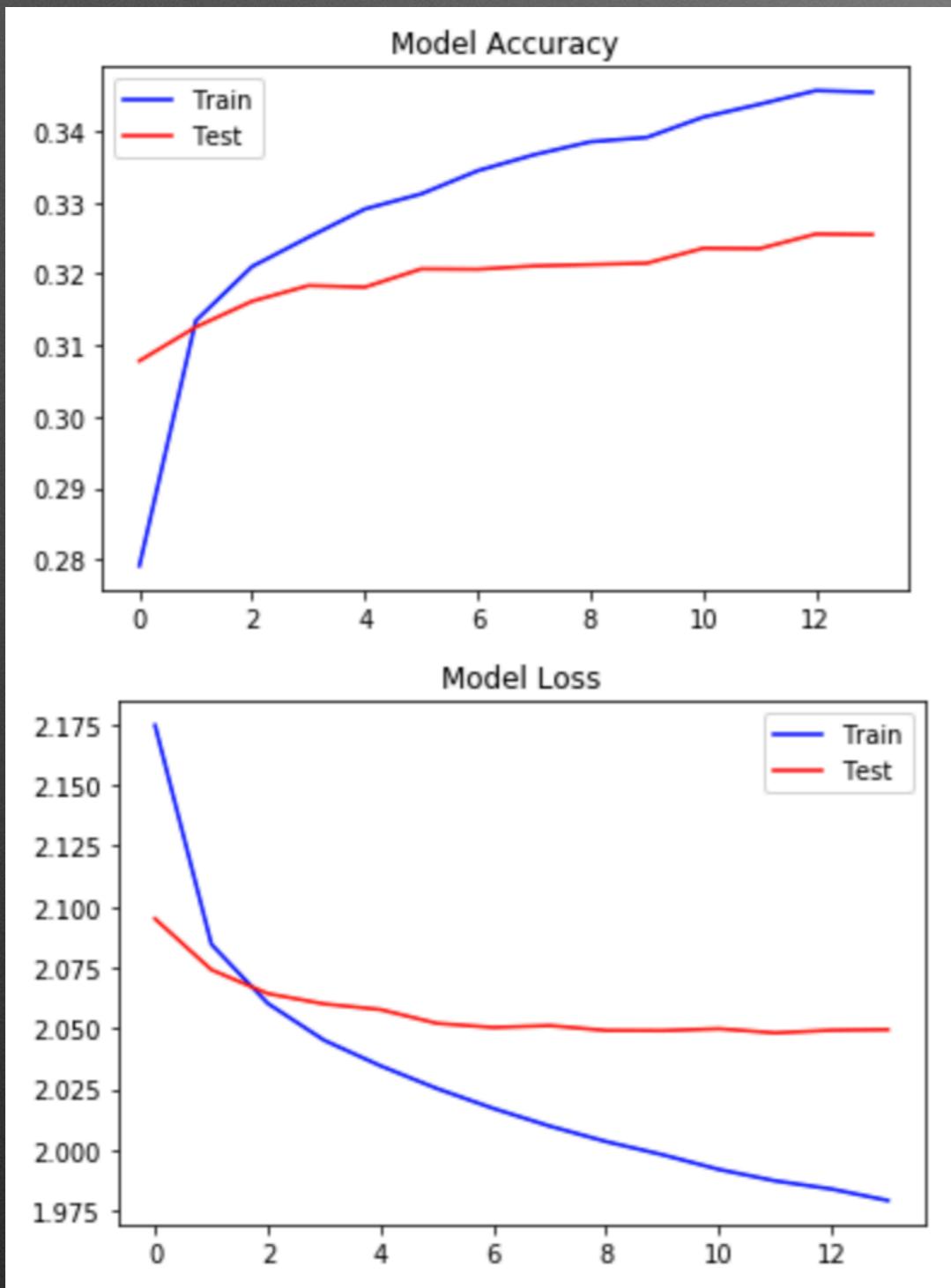
- Small accuracy gain using mixed data types over images alone (1% gain)
- Biggest increase in AUC in a couple of smaller groups
- Preferred model
 - VGG 16 and MLP combined
 - Small drop in AUC scores for less complexity and less memory intensive

Thank you!



MLP

VGG 16



CNN

