



TRAFFIC SIGN CLASSIFICATION

GERARD AGADA - MARCH 31, 2022

INTRODUCTION

- BCOMP, Computer Science - University of Guelph.
- BCOMM, Accounting - University of Guelph.
- Fintech Professional - Hedge Fund Accounting, Stock Market Indices & Portfolio Optimization.
- Interested in Machine Learning, Data Science, Autonomous Vehicles & Finance.



PROJECT WORKFLOW

- Business Case
- Importing Traffic Sign Data
- Data Exploration
- Pre-Processing The Images
- Model Development
- Model Evaluation
- Testing The Model
- Potential Challenges

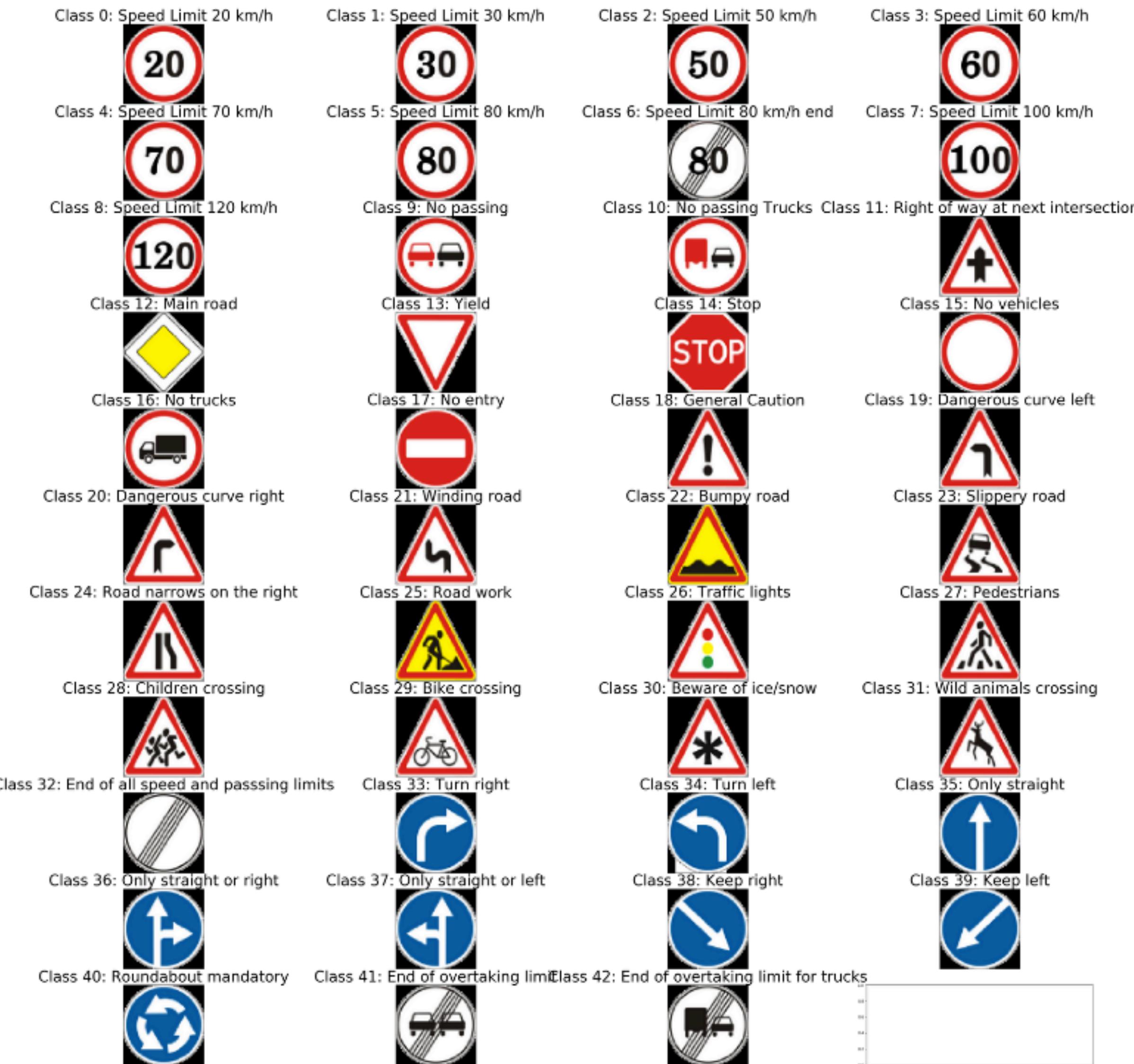


BUSINESS CASE

- Autonomous transportation usage for buses, LRT's and taxis.
- Integration into autonomous vehicles for general consumer cars.
- Potential use cases for autonomous maintenance vehicles specifically garbage collection and snow removal.
- Autonomous delivery which can be facilitated by either drones or vehicles.



TRAFFIC SIGN DATA

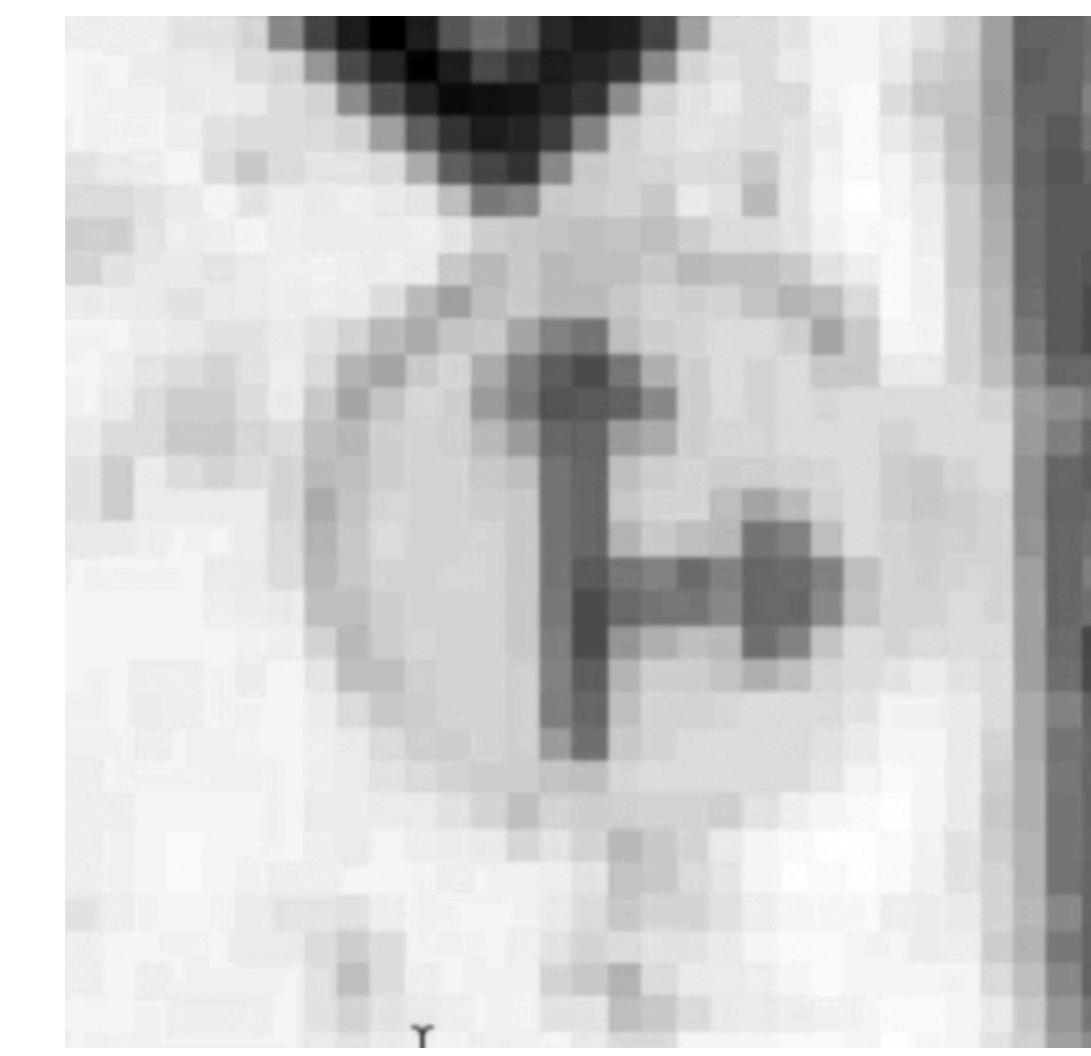
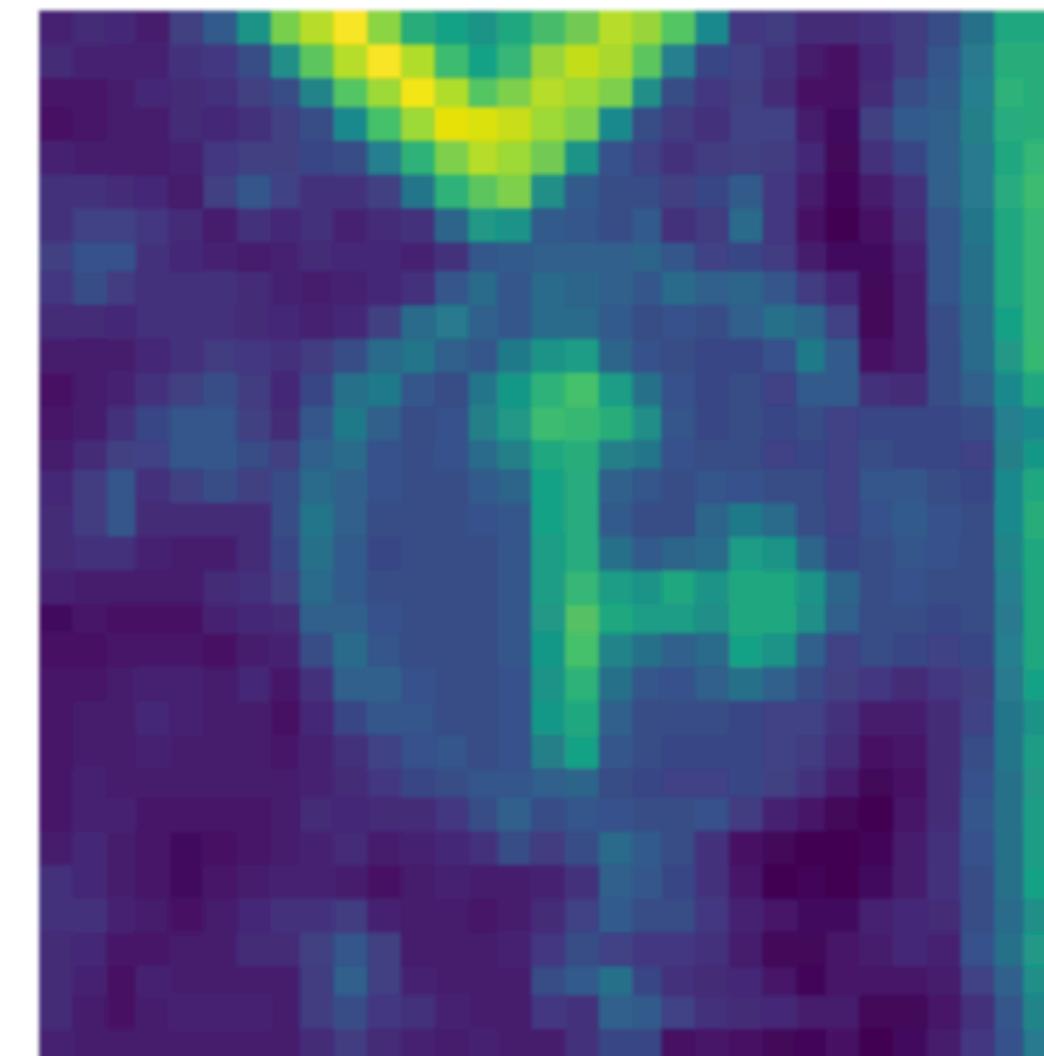
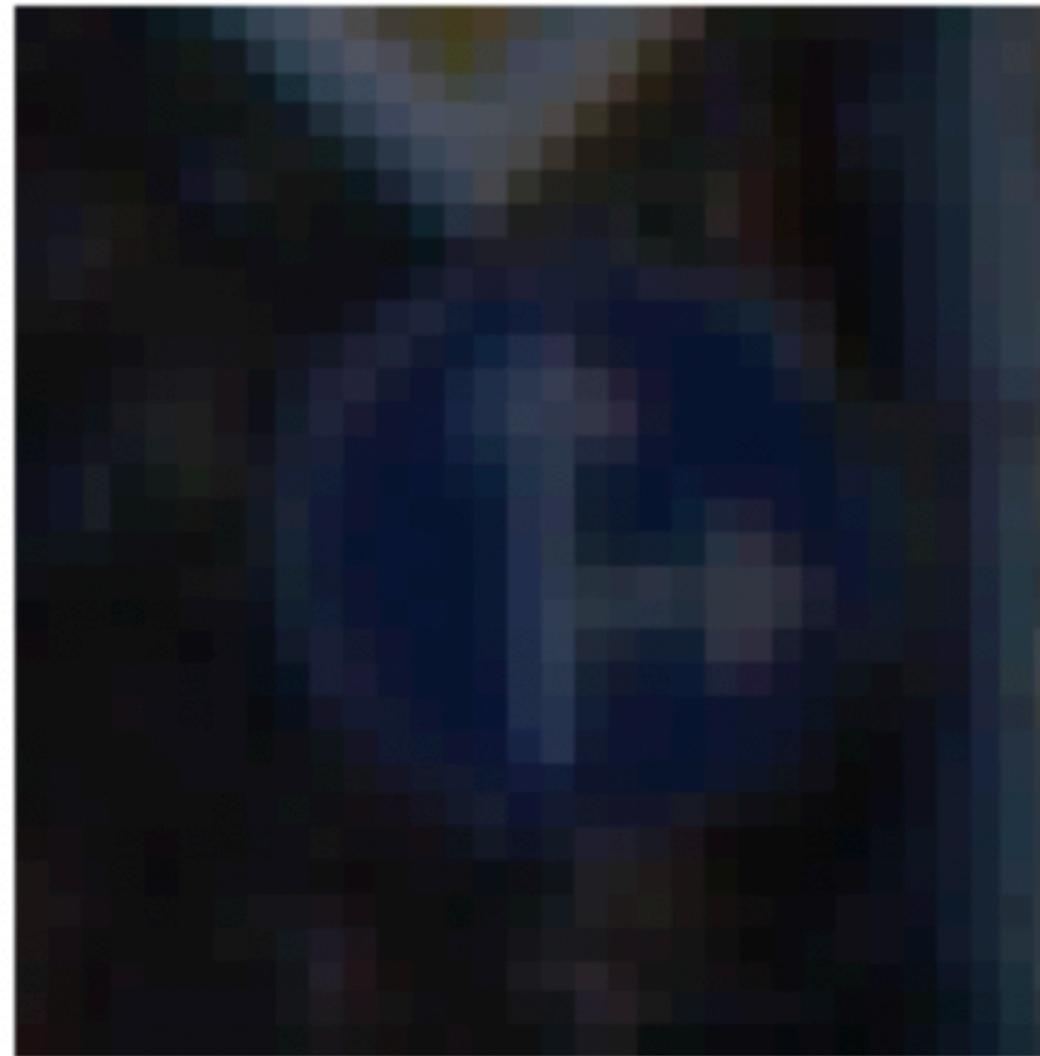


DATA EXPLORATION



IMAGE PRE-PROCESSING

- We need to reduce an RGB image which is in the 3D space to a greyscale image which is the 2D space.
- With an image that is 2D, less computing power is required and our model can classify data more efficiently.



MODEL DEVELOPMENT

Model Summary

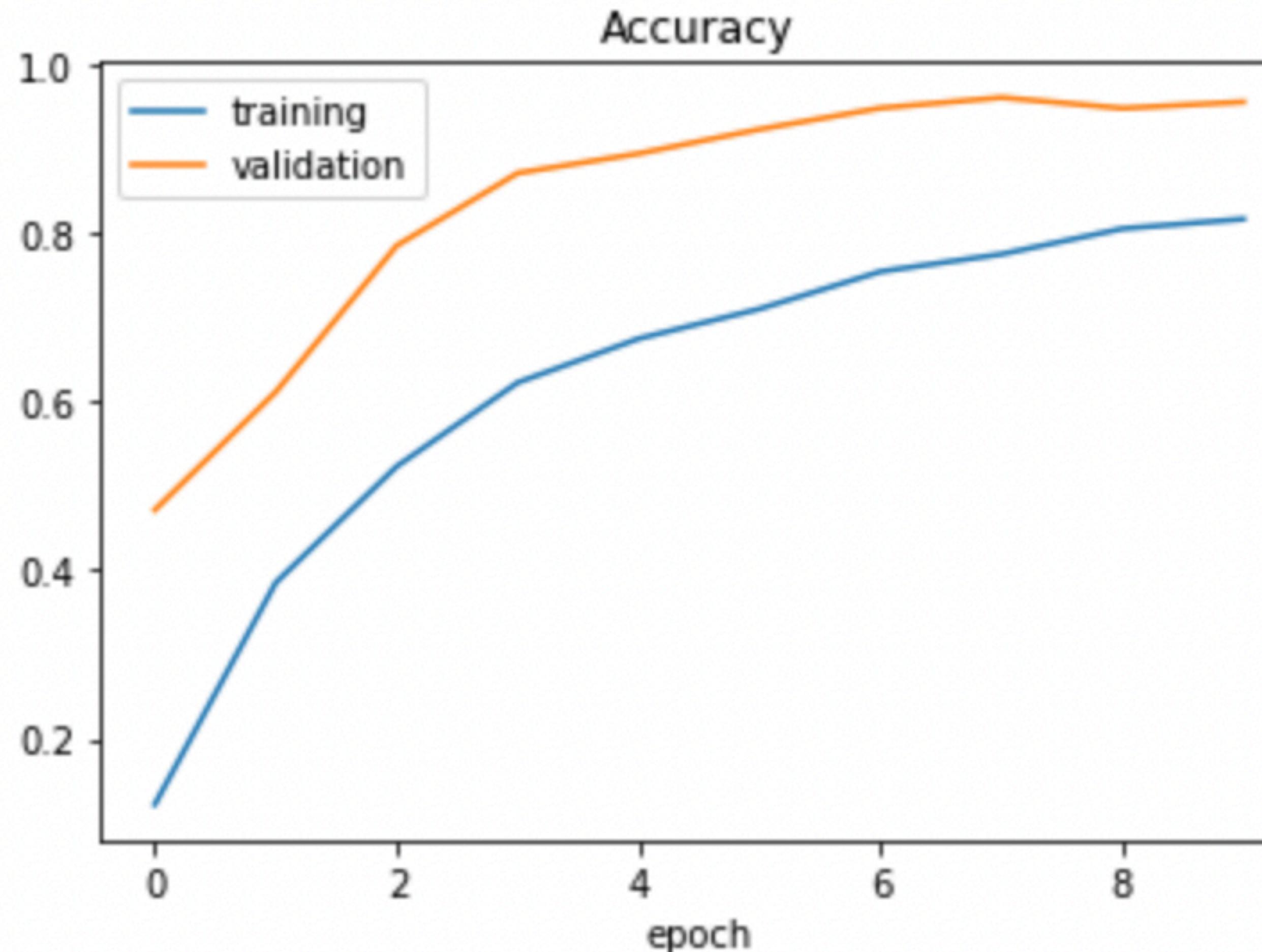
Model: "sequential"

Layer (type)	Output Shape	Param #
<hr/>		
conv2d (Conv2D)	(None, 28, 28, 60)	1560
conv2d_1 (Conv2D)	(None, 24, 24, 60)	90060
max_pooling2d (MaxPooling2D)	(None, 12, 12, 60)	0
conv2d_2 (Conv2D)	(None, 10, 10, 30)	16230
conv2d_3 (Conv2D)	(None, 8, 8, 30)	8130
max_pooling2d_1 (MaxPooling2D)	(None, 4, 4, 30)	0
dropout (Dropout)	(None, 4, 4, 30)	0
flatten (Flatten)	(None, 480)	0
dense (Dense)	(None, 500)	240500
dropout_1 (Dropout)	(None, 500)	0
dense_1 (Dense)	(None, 43)	21543
<hr/>		
Total params: 378,023		
Trainable params: 378,023		
Non-trainable params: 0		

Model Fitting & Execution

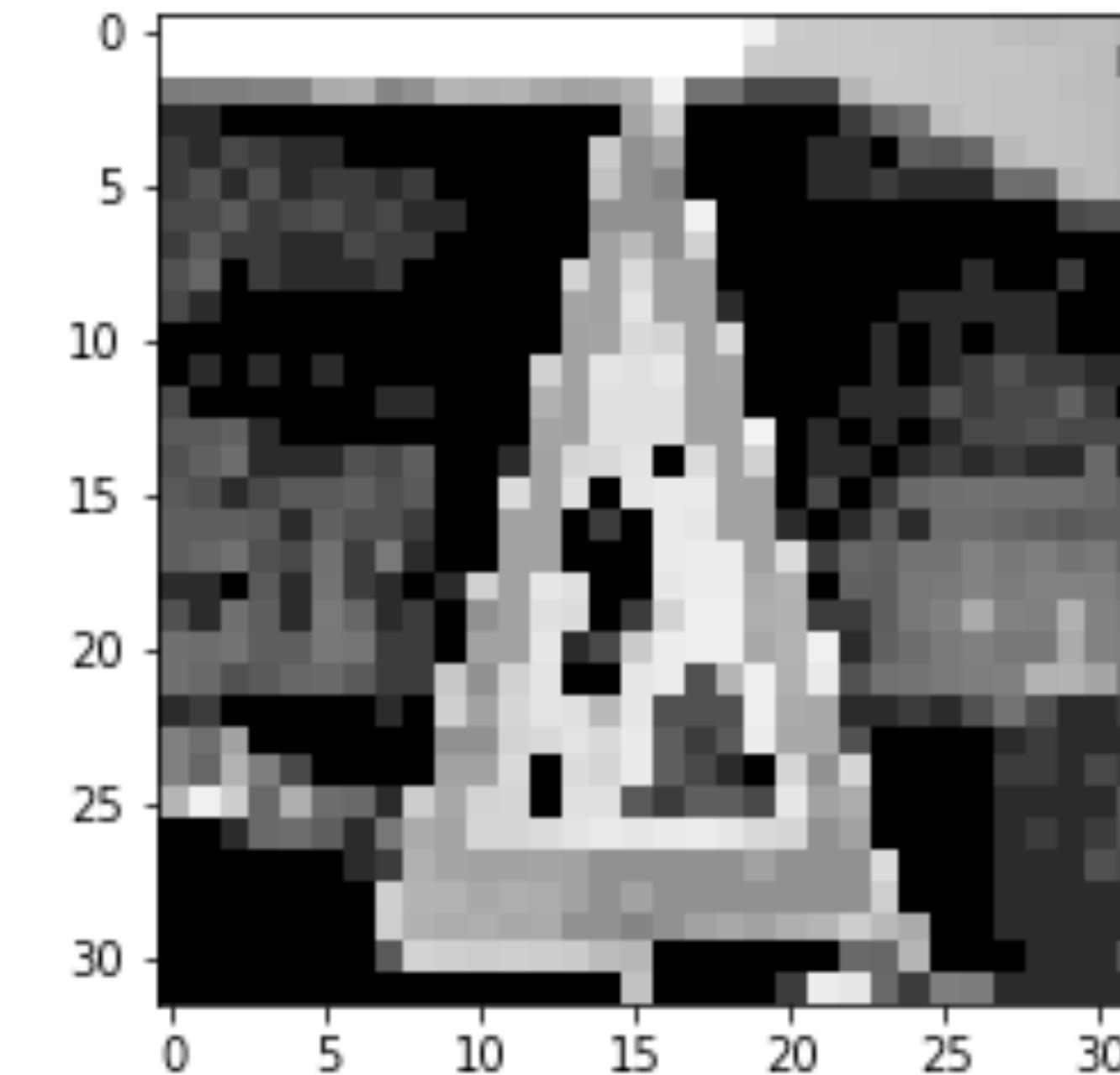
```
Epoch 1/10
200/200 [=====] - 15s 72ms/step - loss: 3.3031 - accuracy: 0.1226 - val_loss: 2.0919 - val_accuracy: 0.4717
Epoch 2/10
200/200 [=====] - 14s 72ms/step - loss: 2.1384 - accuracy: 0.3855 - val_loss: 1.2403 - val_accuracy: 0.6116
Epoch 3/10
200/200 [=====] - 15s 73ms/step - loss: 1.5678 - accuracy: 0.5234 - val_loss: 0.6830 - val_accuracy: 0.7850
Epoch 4/10
200/200 [=====] - 15s 73ms/step - loss: 1.2321 - accuracy: 0.6227 - val_loss: 0.4409 - val_accuracy: 0.8710
Epoch 5/10
200/200 [=====] - 15s 74ms/step - loss: 1.0453 - accuracy: 0.6747 - val_loss: 0.3572 - val_accuracy: 0.8941
Epoch 6/10
200/200 [=====] - 15s 75ms/step - loss: 0.9074 - accuracy: 0.7100 - val_loss: 0.2369 - val_accuracy: 0.9229
Epoch 7/10
200/200 [=====] - 15s 76ms/step - loss: 0.7977 - accuracy: 0.7543 - val_loss: 0.1972 - val_accuracy: 0.9481
Epoch 8/10
200/200 [=====] - 15s 77ms/step - loss: 0.7109 - accuracy: 0.7749 - val_loss: 0.1624 - val_accuracy: 0.9605
Epoch 9/10
200/200 [=====] - 15s 77ms/step - loss: 0.6219 - accuracy: 0.8051 - val_loss: 0.1504 - val_accuracy: 0.9478
Epoch 10/10
200/200 [=====] - 16s 79ms/step - loss: 0.5829 - accuracy: 0.8165 - val_loss: 0.1500 - val_accuracy: 0.9553
```

MODEL EVALUATION



Test Accuracy
0.9242280125617981

TESTING



```
#Test image  
print("predicted sign: "+ str(np.argmax(model.predict(img), axis ==1 )))
```

predicted sign: [25]

25_Road work



POTENTIAL BUSINESS CHALLENGES

- Dependencies on AWS, Azure, and other cloud services
- Cost of implementation
- Whether to build in the model in house or outsource
- Integration and Adoption
- Maintenance of the model (If done in house)

THE END
