# Recognizing Traffic Signs

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# Problem


The goal of this project is to build a model capable of determining the type of traffic sign that is displayed in an image captured under different real-life conditions and showing obstructions, poor lighting, or even the sign being far away from the camera.

32x32 images

43 labels

34,799 train, 4,410 validation, 12,630 test ~ 67-9-24 %

51,839 total

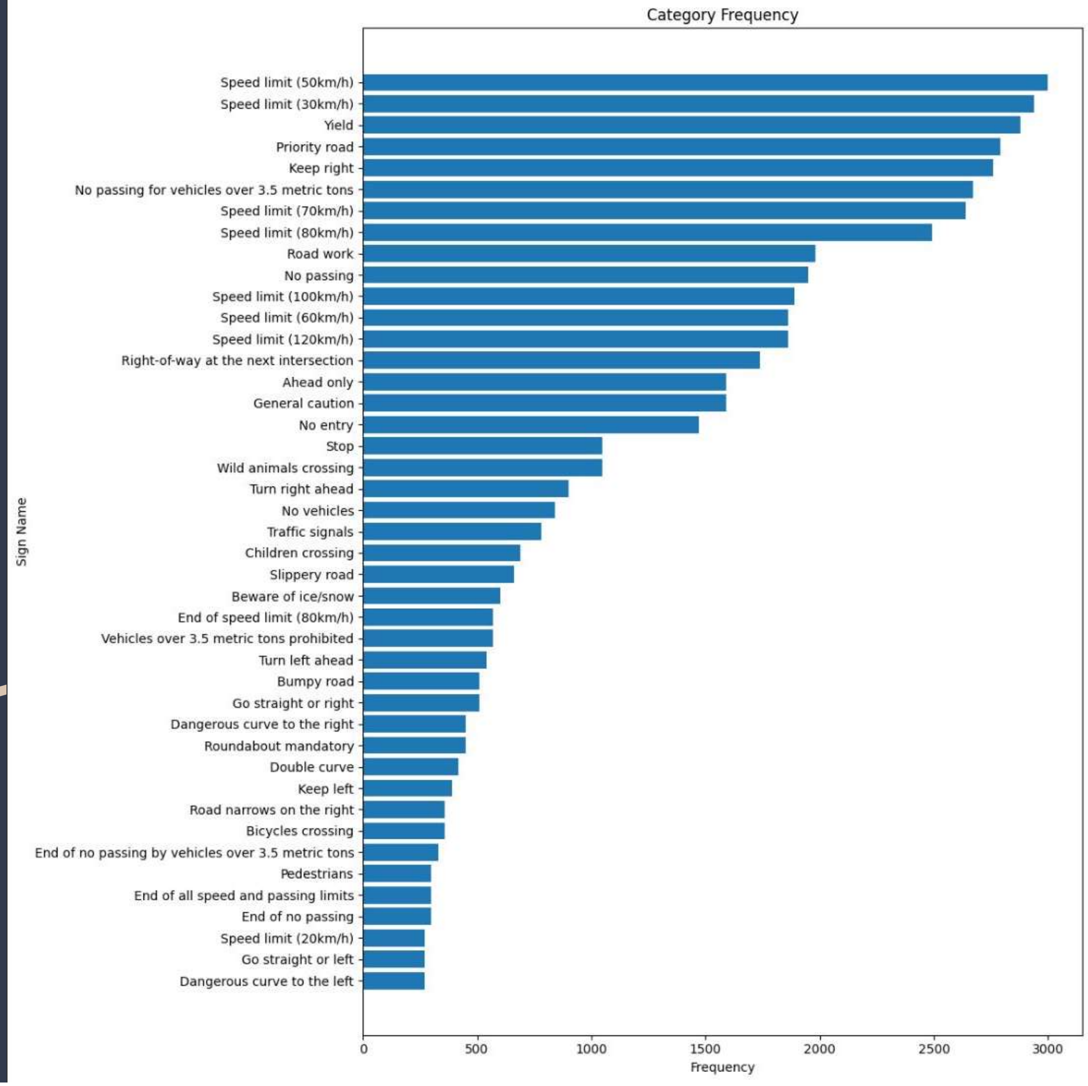
Dataset itself is clean

# Data distribution

Looks somewhat unbalanced

Largest category ~5.8%

Smallest category ~0.5%



# Model Preparation

**Available models**

| Model | Size (MB) | Top-1 Accuracy | Top-5 Accuracy | Parameters | Depth | Time (ms) per inference step (CPU) | Time (ms) per inference step (GPU) |
|---|---|---|---|---|---|---|---|
| Xception | 88 | 79.0% | 94.5% | 22.9M | 81 | 109.4 | 8.1 |
| VGG16 | 528 | 71.3% | 90.1% | 138.4M | 16 | 69.5 | 4.2 |
| VGG19 | 549 | 71.3% | 90.0% | 143.7M | 19 | 84.8 | 4.4 |
| ResNet50 | 98 | 74.9% | 92.1% | 25.6M | 107 | 58.2 | 4.6 |
| [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] | [illegible] |

Images needed to be upscaled in order to be fed into pre-trained models - 128x128

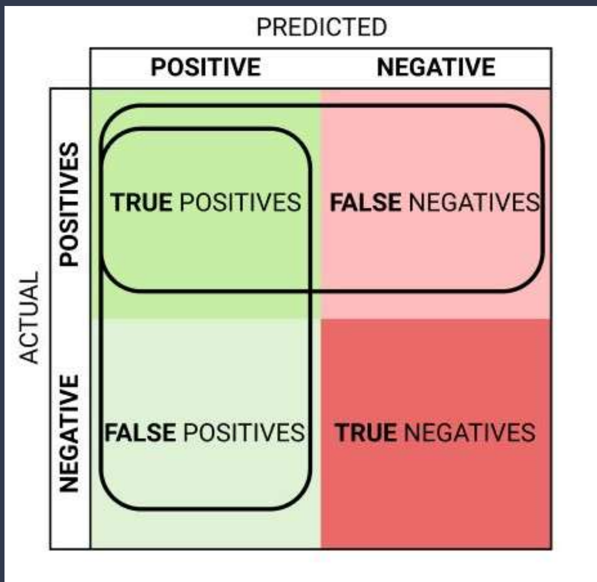
One-hot encode labels

In order to form a baseline and choose pre-trained model, trained several different pre-trained models with only a softmax activation layer added (no custom layers)

Pre-trained models selected from [https://keras.io/api/applications/](https://keras.io/api/applications/) with imagenet weights

EfficientNetB0 performed the best

# Metrics




Recall
TP/(TP+FN)

Precision
TP/(TP+FP)

Because dataset is unbalanced, accuracy can be misleading. Favors more frequent categories.

Recall and Precision are better in this case.

In a multi-class scenario, generate Confusion Matrix for each class. Binary "Class X / Not Class X"

**Confusion Matrix for "Stop sign" class**

| | Predicted: Stop sign | Predicted: Speed limit 100 | Predicted: Yield sign |
|---|---|---|---|
| Actual: Stop sign | TP | FN | FN |
| Actual: Speed limit 100 | FP | TN | TN |
| Actual: Yield sign | FP | TN | TN |

Recall minimize false-negatives
Precision minimize false-positives
F1 score is the harmonic mean of both.

$$\text{Recall} = \frac{TP_A + TP_B + \dots TP_N}{TP_A + FN_A + TP_B + FN_B + \dots TP_N + FN_N}$$

*Micro-average*

# Model tuning

Baseline validation recall: 71.70%
Baseline validation accuracy: 72.04%

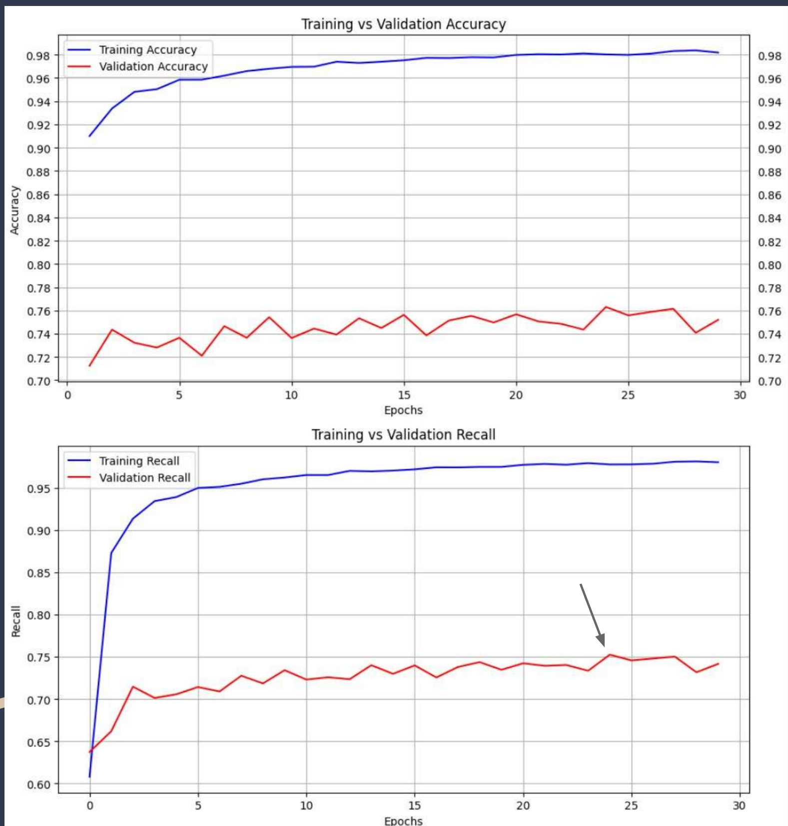
Performed a Grid Search for neurons & dropout of custom Dense layer

Overfitting was an early problem. Addressed by trying: Early Stopping, Data Augmentation, L2 Regularization, Batch Normalization

Tried different hyperparameters: optimizer, number of neurons, more training time (epochs & patience)

Decaying Learning Rate

# Results




Final model used:
Data Augmentation on 4x upscaled images
EfficientNetB0 pre-trained model as base
Batch Normalization
Custom 32-neuron Dense layer with 0.2 Dropout
Adam optimizer

97.78% training recall
98.01% training accuracy

75.24% validation recall
76.30% validation accuracy

60.11% test recall
61.05% test accuracy