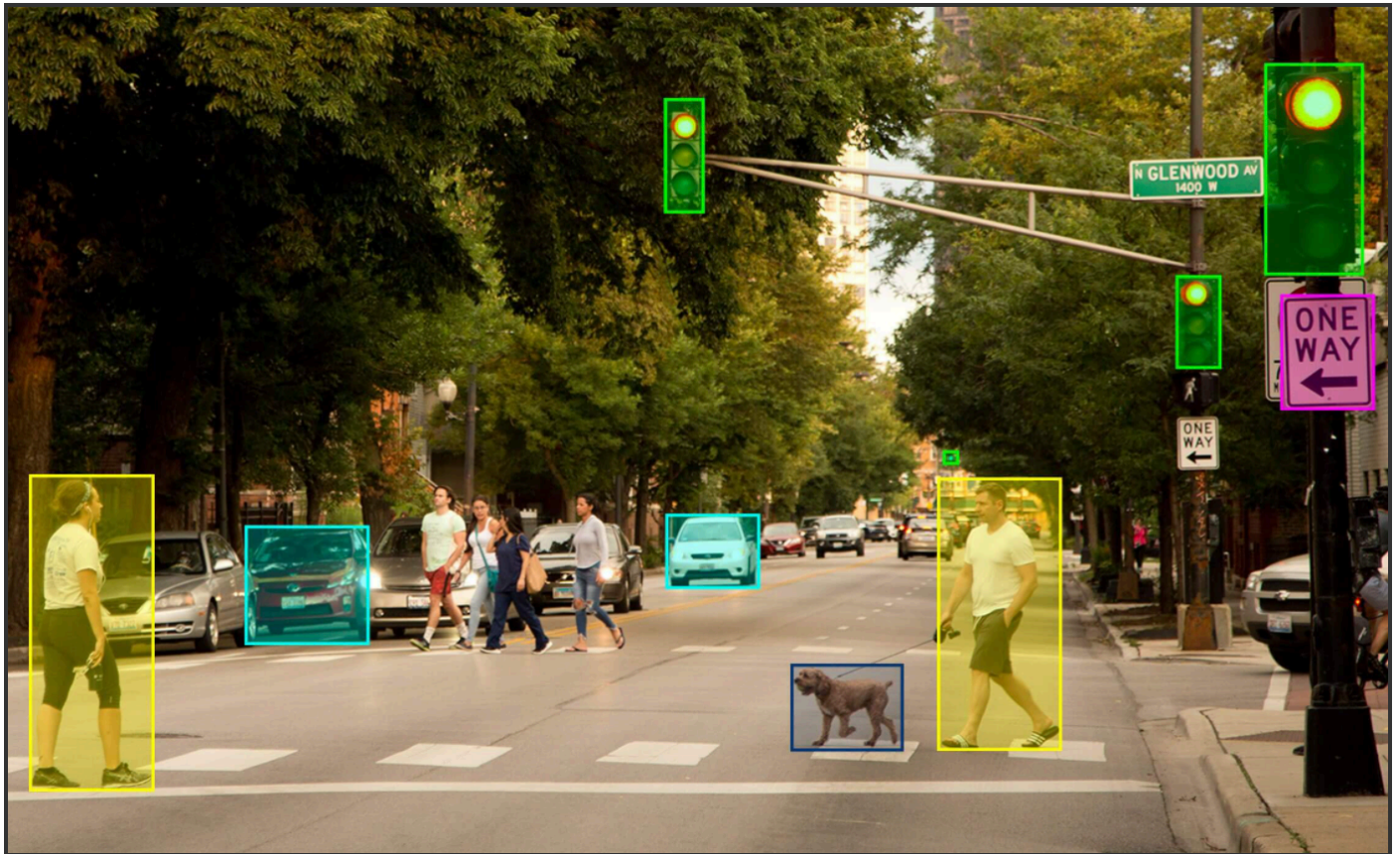

IMAGE RECOGNITION WITH DRIVERLESS-VEHICLES



Minimum Viable Product

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EXECUTIVE SUMMARY

An initial proposal was made to aid the auto-industry in realizing the long sought after goal of producing fully autonomous vehicles. Key to this endeavor is the ability of driverless software applications to accurately classify commonly and uncommonly encountered objects during drives. The idea behind the project was to illustrate the various methodologies and models available within the realm of deep learning that can enhance these applications. Uniformly distributed target classes allowed for the use of *accuracy* as metric to evaluate the overall model.

Variations of two models thus far have been evaluated. The best variation of each type of model will be illustrated.

Model 1: Baseline

The first model was a simple baseline built from the ground-up using a sequential architecture. The table below provides a summary of the sequence of layers along with the number of parameters used in the model.

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 30, 30, 45)	1260
max_pooling2d_4 (MaxPooling2D)	(None, 15, 15, 45)	0
conv2d_5 (Conv2D)	(None, 13, 13, 70)	28420
max_pooling2d_5 (MaxPooling2D)	(None, 6, 6, 70)	0
flatten_2 (Flatten)	(None, 2520)	0
dense_6 (Dense)	(None, 3000)	7563000
dense_7 (Dense)	(None, 1000)	3001000
dense_8 (Dense)	(None, 10)	10010
Total params: 10,603,690		
Trainable params: 10,603,690		
Non-trainable params: 0		

The model produced an accuracy of **0.689**, which will serve as a baseline metric for comparison to all other models.

Model 2: Transfer Learning

This model made use of a commonly used methodology in deep learning named *transfer learning*, which uses pre-trained models. The convolutional bases of these pre-trained models are used in conjunction with customizable fully connected dense layers of neurons. The generalized pre-extraction of features allows for quicker training time and more accurate predictions with respect to specialized tasks. In this instance the *MobileNet* base model was used. The table below provides a summary of the sequence of layers along with the number of parameters used in the model.

Layer (type)	Output Shape	Param #
mobilenetv2_1.00_224 (Function)	(None, 1, 1, 1280)	2257984
dropout_26 (Dropout)	(None, 1, 1, 1280)	0
flatten_33 (Flatten)	(None, 1280)	0
dense_99 (Dense)	(None, 1000)	1281000
dense_100 (Dense)	(None, 750)	750750
dropout_27 (Dropout)	(None, 750)	0
dense_101 (Dense)	(None, 500)	375500
dropout_28 (Dropout)	(None, 500)	0
dense_102 (Dense)	(None, 250)	125250
dropout_29 (Dropout)	(None, 250)	0
dense_103 (Dense)	(None, 125)	31375
dropout_30 (Dropout)	(None, 125)	0
dense_104 (Dense)	(None, 10)	1260
Total params: 4,823,119		
Trainable params: 4,789,007		
Non-trainable params: 34,112		

The model produced an accuracy of **0.737** versus 0.689 for the base model.

Further Work

- The transfer learning model was prone to overfitting therefore certain steps will be taken to reduce complexity. This will include reductions in the number of neural layers and nodes, adjustment of dropout rates and recalibration of other parameters.
- A 10 x 10 confusion matrix will be produced that will enable us to judge the model's performance according to each individual class across a spectrum of metrics. In addition to the overall assessment of the model it is important to judge its efficacy with respect each class. Each object type will require its own metric to fully appreciate the impact of the model. For example, whilst *accuracy* may prove to be fine with the 'bird' object, *recall* will be more appropriate for larger objects such as trucks.