Introduction

With automation becoming increasingly common, machine models being able understand traffic signs is key for self-driving cars and other forms of transport to ensure safety. As such, I wanted to incorporate deep learning into this and see how a machine learning model would respond to identifying various traffic signs.

The goal of this investigation is to see if, using a pertained model, I could get a model that is able to accurately classify traffic signs.

Setting Up

First, we need to set up the general base for a machine learning model.

```
# loading general packages and libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
import os
import cv2
import random
from PIL import Image

# loading tensor flow libraries needed
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense
from keras.layers import Dropout, Flatten,
MaxPool2D,BatchNormalization
from keras.preprocessing import image
from tensorflow.keras.optimizers import Adam,SGD
import keras
from keras.preprocessing import image

seed=1
np.random.seed(seed)
tf.random.set_seed(seed)
```

```
2024-03-11 15:54:20.784320: E
external/local_xla/xla/stream_executor/cuda/cuda_dnn.cc:9261] Unable
to register cuDNN factory: Attempting to register factory for plugin
cuDNN when one has already been registered
```

```
2024-03-11 15:54:20.784454: E
external/local_xla/xla/stream_executor/cuda/cuda_fft.cc:607] Unable to
register cuFFT factory: Attempting to register factory for plugin
cuFFT when one has already been registered
2024-03-11 15:54:21.072771: E
external/local_xla/xla/stream_executor/cuda/cuda_blas.cc:1515] Unable
to register cuBLAS factory: Attempting to register factory for plugin
cuBLAS when one has already been registered
```

Gather and Explore the Data

For this investigation, I will be using a dataset I found on Kaggle. The data consists of images of traffic signs which have been automatically registered so that the sign is centred and occupies around the same space in each image.

The are around 58 classes and each class has around 120 images. Since this dataset has not been cleaned and organised completely, we first need to ensure there is an adequete amount of photos in each class and that they are correctly categorised.

```python
# importing images
train_dir =
"/kaggle/input/traffic-sign-dataset-classification/traffic_Data/DATA/"


# reading the csv file
labels = pd.read_csv("/kaggle/input/traffic-sign-dataset-
classification/labels.csv")
labels
```

	ClassId	Name
0	0	Speed limit (5km/h)
1	1	Speed limit (15km/h)
2	2	Speed limit (30km/h)
3	3	Speed limit (40km/h)
4	4	Speed limit (50km/h)
5	5	Speed limit (60km/h)
6	6	Speed limit (70km/h)
7	7	speed limit (80km/h)
8	8	Dont Go straight or left
9	9	Dont Go straight or Right
10	10	Dont Go straight
11	11	Dont Go Left
12	12	Dont Go Left or Right
13	13	Dont Go Right
14	14	Dont overtake from Left
15	15	No Uturn
16	16	No Car
17	17	No horn
18	18	Speed limit (40km/h)

```
19        19          Speed limit (50km/h)
20        20          Go straight or right
21        21                   Go straight
22        22                       Go Left
23        23              Go Left or right
24        24                      Go Right
25        25                     keep Left
26        26                    keep Right
27        27          Roundabout mandatory
28        28            watch out for cars
29        29                          Horn
30        30             Bicycles crossing
31        31                         Uturn
32        32                  Road Divider
33        33               Traffic signals
34        34                  Danger Ahead
35        35                Zebra Crossing
36        36             Bicycles crossing
37        37             Children crossing
38        38   Dangerous curve to the left
39        39  Dangerous curve to the right
40        40                      Unknown1
41        41                      Unknown2
42        42                      Unknown3
43        43          Go right or straight
44        44           Go left or straight
45        45                      Unknown4
46        46                  ZigZag Curve
47        47                Train Crossing
48        48            Under Construction
49        49                      Unknown5
50        50                        Fences
51        51       Heavy Vehicle Accidents
52        52                      Unknown6
53        53                      Give Way
54        54                   No stopping
55        55                      No entry
56        56                      Unknown7
57        57                      Unknown8
```

```python
# no. of images per label
lst = []
for i in labels.index:
    lst.append(len(os.listdir(train_dir + str(i))))
labels['count'] = lst
labels['count'].describe()
```

```
count     58.000000
mean      71.896552
std       83.818034
```

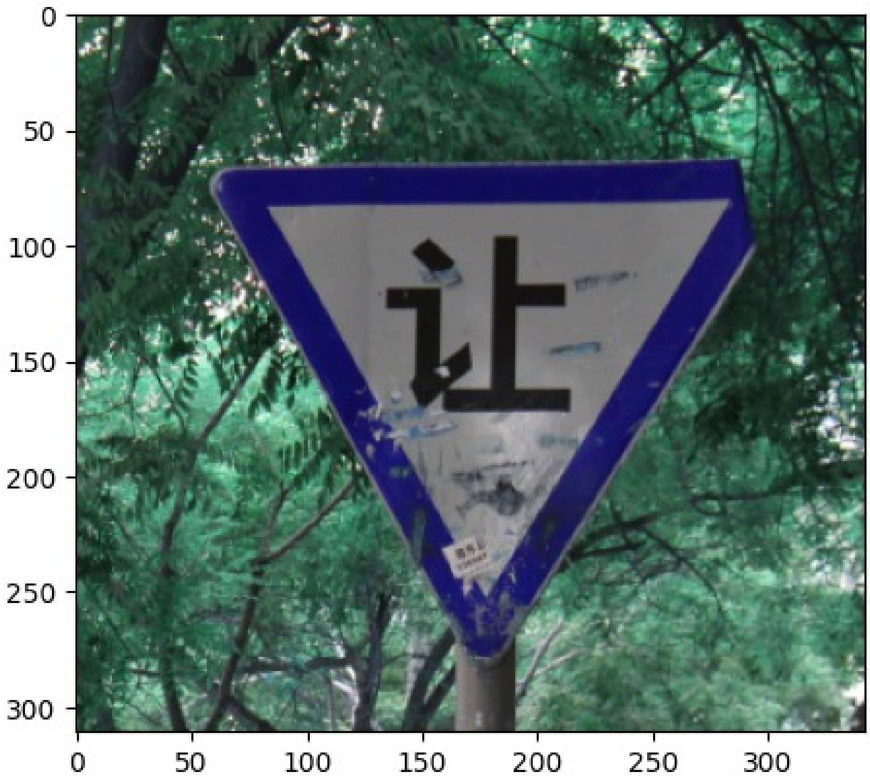
```
min        2.000000
25%       18.000000
50%       38.000000
75%      107.500000
max      446.000000
Name: count, dtype: float64
```

```
# only keep those with enough images in each label
labels = labels[labels['count'] >= 107.5]
labels
```

	ClassId	Name	count
0	0	Speed limit (5km/h)	118
3	3	Speed limit (40km/h)	260
5	5	Speed limit (60km/h)	194
7	7	speed limit (80km/h)	152
11	11	Dont Go Left	138
14	14	Dont overtake from Left	128
16	16	No Car	142
17	17	No horn	130
26	26	keep Right	126
28	28	watch out for cars	446
30	30	Bicycles crossing	150
35	35	Zebra Crossing	156
54	54	No stopping	324
55	55	No entry	162
56	56	Unknown7	110

```
# finding the unknown image
fnames = os.listdir(train_dir + '56')
img = cv2.imread(train_dir + '56/' + fnames[3])
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x787859a72530>
```




```
# renaming
labels.loc[56, "Name"] = "Yield"

labels["Name"] = ["Speed Limit 5", "Speed Limit 40",
       "Speed Limit 60", "Speed Limit 80", "No Left",
       "No Overtake from Left", "No Cars", "No Horn", "Keep Right",
       "Watch for Cars", "Bicycle Crossing", "Zebra Crossing",
       "No Stopping", "No Entry", "Yield"]
```

```
/tmp/ipykernel_26/733333294.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  labels["Name"] = ["Speed Limit 5", "Speed Limit 40",
```

Now that we have cleaned the data, we can load the libraries.

```
# set the image size
image_size = 128

# input and data augmentation
train_datagen = ImageDataGenerator(
```

```
        rescale = 1 / 255.,
        rotation_range=10,
        zoom_range=0.2,
        width_shift_range=0.1,
        height_shift_range=0.1,
        fill_mode="nearest",
        validation_split=0.25,
    )

train_generator = train_datagen.flow_from_directory(
    directory = train_dir,
    target_size = (image_size, image_size),
    batch_size = 28,
    shuffle=True,
    class_mode = "categorical",
    subset = "training"
)

validation_generator = train_datagen.flow_from_directory(
    directory = train_dir,
    target_size = (image_size, image_size),
    batch_size = 28,
    class_mode = "categorical",
    subset = "validation"
)
```

```
Found 3144 images belonging to 58 classes.
Found 1026 images belonging to 58 classes.
```

Transfer Learning

Since the data is ready, it is time to train the model using the pretrained ResNet50 model. This is already done through transfer learning, which takes a pretrained model, removes the final layer, and replaces that last layer with the relevant output.

ResNet50 is quite a popular model and accurate for this project since it is commonly used for traffic sign analysis.

Below, is the first model (removing the final layer of the ResNet50 model and replacing it with a Dense final layer with the number of nodes being the number of outputs).

Model 1

```
# set classes to number of categories and input weight paths
num_classes = 58
resnet_weights_path =
'../input/resnet50/resnet50_weights_tf_dim_ordering_tf_kernels_notop.h
5'

# defining the model
```

```
model = Sequential()
model.trainable = True

model.add(ResNet50(include_top=False, pooling='avg', weights=
resnet_weights_path))
model.add(BatchNormalization())
model.add(Dense(48, activation='relu'))
model.add(Dropout(0.25))
model.add(BatchNormalization())
model.add(Dense(128, activation='relu'))
model.add(Dense(num_classes, activation='softmax'))

model.summary()
```

```
Model: "sequential"
```

```
┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━
━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━
━━━━━┩
│ resnet50 (Functional)            │ ?                      │
23,587,712 │
├──────────────────────────────────┼────────────────────────┼─────────
─────┤
│ batch_normalization              │ ?                      │   0
(unbuilt) │
│ (BatchNormalization)             │                        │
│
├──────────────────────────────────┼────────────────────────┼─────────
─────┤
│ dense (Dense)                    │ ?                      │   0
(unbuilt) │
├──────────────────────────────────┼────────────────────────┼─────────
─────┤
│ dropout (Dropout)                │ ?                      │
0 │
├──────────────────────────────────┼────────────────────────┼─────────
─────┤
│ batch_normalization_1            │ ?                      │   0
(unbuilt) │
│ (BatchNormalization)             │                        │
│
├──────────────────────────────────┼────────────────────────┼─────────
─────┤
│ dense_1 (Dense)                  │ ?                      │   0
(unbuilt) │
├──────────────────────────────────┼────────────────────────┼─────────
─────┤
```

```
│ dense_2 (Dense)                  │ ?                        │    0
(unbuilt) │
└──────────────────────────────────┴──────────────────────────┴──────────
──────┘

 Total params: 23,587,712 (89.98 MB)

 Trainable params: 23,534,592 (89.78 MB)

 Non-trainable params: 53,120 (207.50 KB)
```

Now, we need to compile the final layer of the network using categorical_crossentropy as the loss function and the stochastic gradient descent (as the optimizer) to minimize the categorical cross-entropy loss.

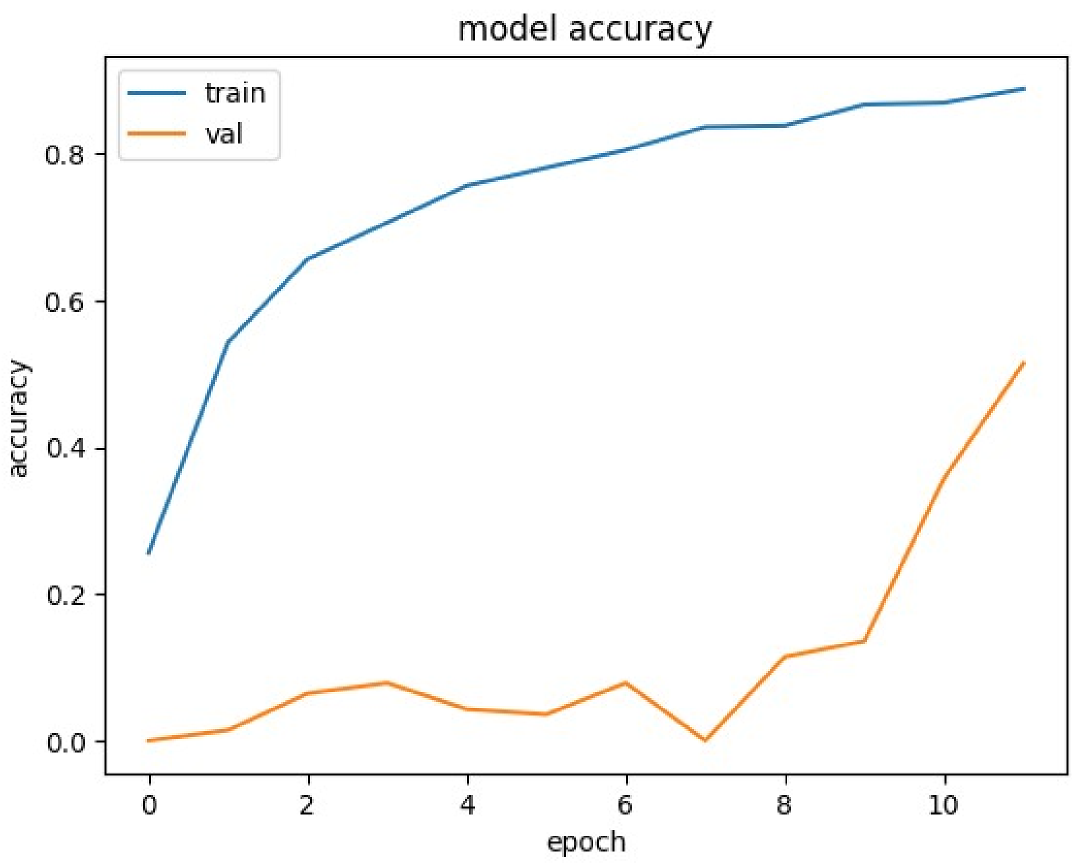
```
model.compile(optimizer="sgd", loss='categorical_crossentropy',
metrics=['accuracy'])
```

Now we fit the model for training and validation using 12 epochs and 60 steps per epoch.

```
history = model.fit(
        train_generator,
        steps_per_epoch= 60,
        epochs = 12,
        validation_data=validation_generator,
        validation_steps=5)

Epoch 1/12

/opt/conda/lib/python3.10/site-packages/keras/src/trainers/
data_adapters/py_dataset_adapter.py:122: UserWarning: Your `PyDataset`
class should call `super().__init__(**kwargs)` in its constructor.
`**kwargs` can include `workers`, `use_multiprocessing`,
`max_queue_size`. Do not pass these arguments to `fit()`, as they will
be ignored.
  self._warn_if_super_not_called()

 1/60 ━━━━━━━━━━━━━━━━━━━━ 43:29 44s/step - accuracy: 0.0000e+00 -
loss: 4.1371

WARNING: All log messages before absl::InitializeLog() is called are
written to STDERR
I0000 00:00:1710172528.620729      93 device_compiler.h:186] Compiled
cluster using XLA!  This line is logged at most once for the lifetime
of the process.
W0000 00:00:1710172528.693876      93 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

31/60 ━━━━━━━━━━━━━━━━━━━━ 31s 1s/step - accuracy: 0.0546 - loss:
3.9831
```

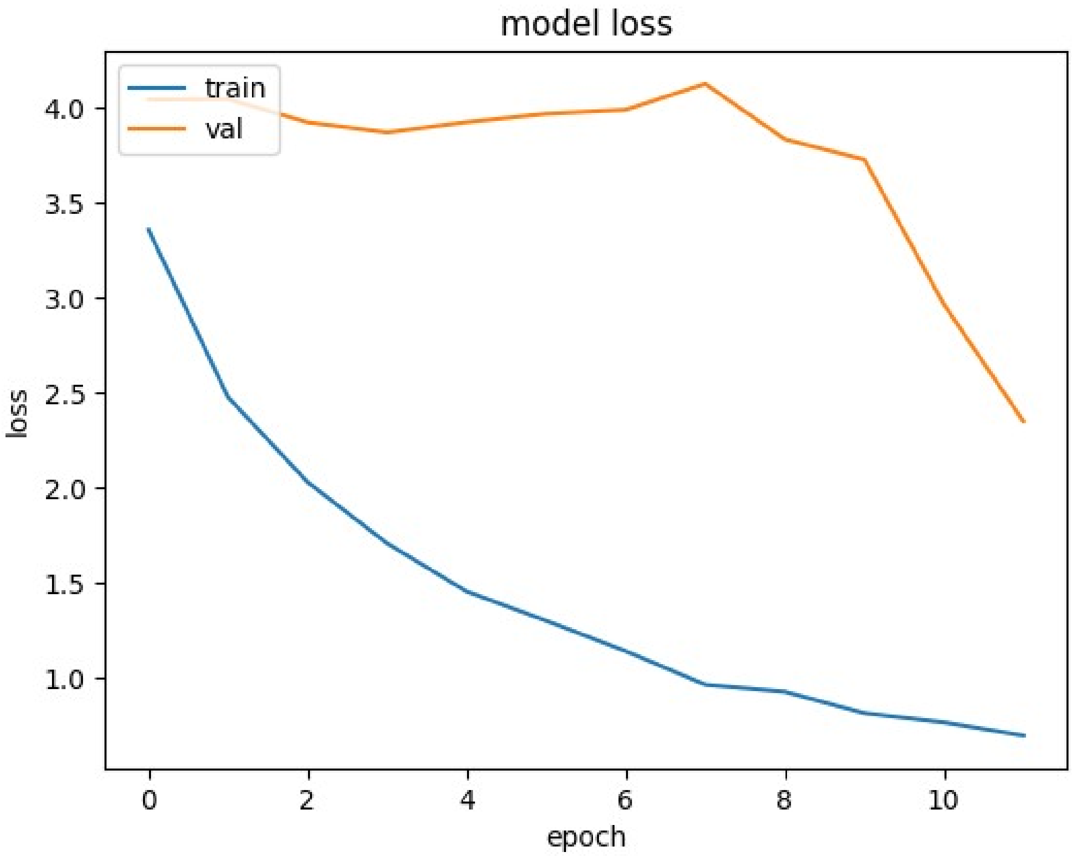
```
W0000 00:00:1710172561.473679      91 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 0s 743ms/step - accuracy: 0.1246 - loss:
3.7589

W0000 00:00:1710172577.659930      92 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 94s 849ms/step - accuracy: 0.1268 - loss:
3.7523 - val_accuracy: 0.0000e+00 - val_loss: 4.0423
Epoch 2/12
53/60 ━━━━━━━━━━━━━━━━━━━━ 1s 223ms/step - accuracy: 0.4956 - loss:
2.6119

/opt/conda/lib/python3.10/contextlib.py:153: UserWarning: Your input
ran out of data; interrupting training. Make sure that your dataset or
generator can generate at least `steps_per_epoch * epochs` batches.
You may need to use the `.repeat()` function when building your
dataset.
  self.gen.throw(typ, value, traceback)

60/60 ━━━━━━━━━━━━━━━━━━━━ 13s 217ms/step - accuracy: 0.5012 - loss:
2.5960 - val_accuracy: 0.0143 - val_loss: 4.0449
Epoch 3/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 16s 237ms/step - accuracy: 0.6566 - loss:
2.0942 - val_accuracy: 0.0643 - val_loss: 3.9227
Epoch 4/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 10s 171ms/step - accuracy: 0.7097 - loss:
1.7188 - val_accuracy: 0.0786 - val_loss: 3.8691
Epoch 5/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 14s 205ms/step - accuracy: 0.7460 - loss:
1.4982 - val_accuracy: 0.0429 - val_loss: 3.9235
Epoch 6/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 10s 163ms/step - accuracy: 0.7774 - loss:
1.3368 - val_accuracy: 0.0357 - val_loss: 3.9676
Epoch 7/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 177ms/step - accuracy: 0.7898 - loss:
1.1872 - val_accuracy: 0.0786 - val_loss: 3.9890
Epoch 8/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 13s 226ms/step - accuracy: 0.8263 - loss:
1.0238 - val_accuracy: 0.0000e+00 - val_loss: 4.1249
Epoch 9/12

W0000 00:00:1710172666.946222      93 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 13s 190ms/step - accuracy: 0.8502 - loss:
0.9415 - val_accuracy: 0.1143 - val_loss: 3.8336
Epoch 10/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 158ms/step - accuracy: 0.8572 - loss:
```

```
0.8670 - val_accuracy: 0.1357 - val_loss: 3.7268
Epoch 11/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 178ms/step - accuracy: 0.8522 - loss:
0.8374 - val_accuracy: 0.3571 - val_loss: 2.9649
Epoch 12/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 143ms/step - accuracy: 0.8848 - loss:
0.7143 - val_accuracy: 0.5143 - val_loss: 2.3493

plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```




```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
```

```
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



This wasn't bad at all for a first model! We got a accuracy score of 88% and a validation accuracy of 52%. Let's see if it can be improved with a different optimiser called adam and changing a few parameters.

Model 2

```
# define the model (add layers)
model2 = Sequential()
model2.trainable = True

model2.add(ResNet50(include_top=False, pooling='avg', weights=
resnet_weights_path))
model2.add(BatchNormalization())
model2.add(Dense(48, activation='relu'))
model2.add(BatchNormalization())
model2.add(Dense(256, activation='relu'))
model2.add(Dropout(0.25))
model2.add(Dense(128, activation='relu'))
model2.add(Dense(num_classes, activation='softmax'))
```

```
model2.summary()

Model: "sequential_1"

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━━━━━┓
┃ Layer (type)                      ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━
━━━━━┩
│ resnet50 (Functional)             │ ?                      │
23,587,712 │
├───────────────────────────────────┼────────────────────────┼──────────
─────┤
│ batch_normalization_2             │ ?                      │   0
(unbuilt) │
│ (BatchNormalization)              │                        │
│
├───────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_3 (Dense)                   │ ?                      │   0
(unbuilt) │
├───────────────────────────────────┼────────────────────────┼──────────
─────┤
│ batch_normalization_3             │ ?                      │   0
(unbuilt) │
│ (BatchNormalization)              │                        │
│
├───────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_4 (Dense)                   │ ?                      │   0
(unbuilt) │
├───────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dropout_1 (Dropout)               │ ?                      │
0 │
├───────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_5 (Dense)                   │ ?                      │   0
(unbuilt) │
├───────────────────────────────────┼────────────────────────┼──────────
─────┤
│ dense_6 (Dense)                   │ ?                      │   0
(unbuilt) │
└───────────────────────────────────┴────────────────────────┴──────────
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 Total params: 23,587,712 (89.98 MB)
```
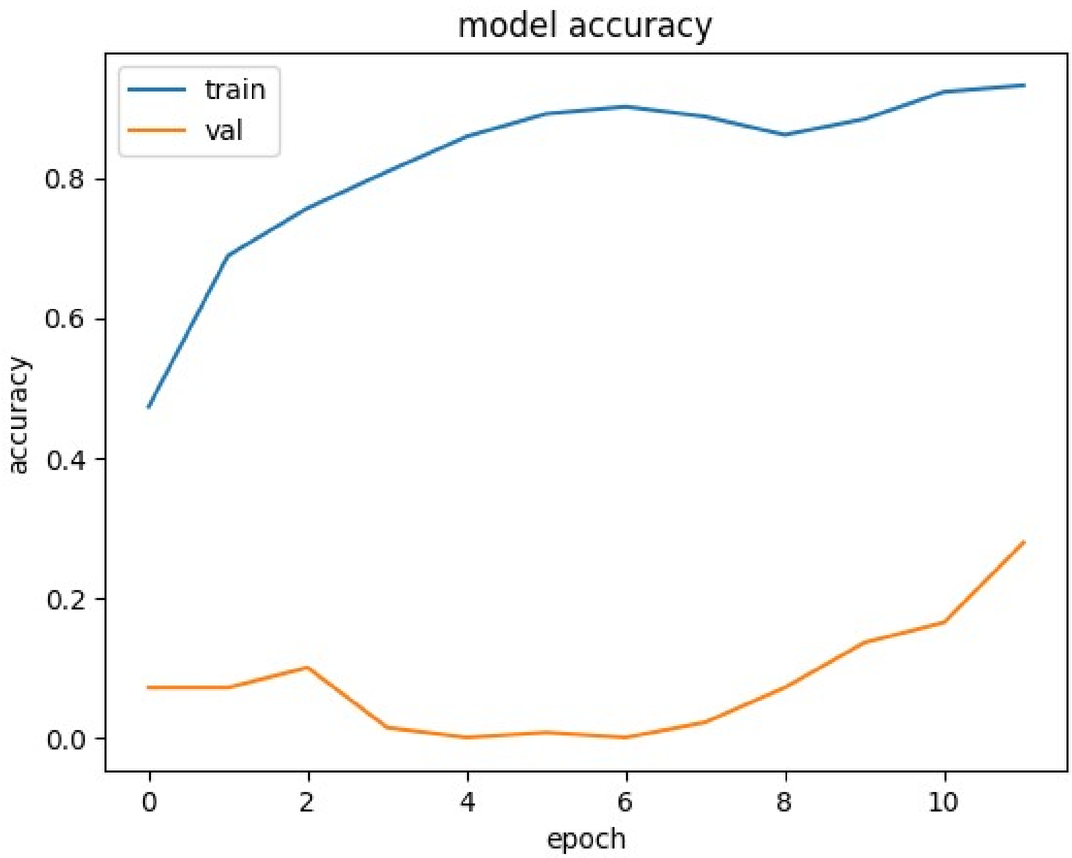

```
 Trainable params: 23,534,592 (89.78 MB)

 Non-trainable params: 53,120 (207.50 KB)

model2.compile(optimizer="adam", loss='categorical_crossentropy',
metrics=['accuracy'])

history2 = model2.fit(
        train_generator,
        steps_per_epoch= 60,
        epochs = 12,
        validation_data=validation_generator,
        validation_steps=5)

Epoch 1/12
 1/60 ━━━━━━━━━━━━━━━━━━━━ 59:11 60s/step - accuracy: 0.0000e+00 -
loss: 4.3901

W0000 00:00:1710172774.212604      93 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

 2/60 ━━━━━━━━━━━━━━━━━━━━ 26:23 27s/step - accuracy: 0.0000e+00 -
loss: 4.3513

W0000 00:00:1710172801.463471      93 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 0s 641ms/step - accuracy: 0.3012 - loss:
3.1742

W0000 00:00:1710172816.729791      91 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 103s 733ms/step - accuracy: 0.3040 - loss:
3.1618 - val_accuracy: 0.0714 - val_loss: 3.9114
Epoch 2/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 10s 163ms/step - accuracy: 0.6645 - loss:
1.4237 - val_accuracy: 0.0714 - val_loss: 3.7693
Epoch 3/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 179ms/step - accuracy: 0.7652 - loss:
0.9614 - val_accuracy: 0.1000 - val_loss: 4.1421
Epoch 4/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 154ms/step - accuracy: 0.7863 - loss:
0.8261 - val_accuracy: 0.0143 - val_loss: 4.1909
Epoch 5/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 174ms/step - accuracy: 0.8484 - loss:
0.5489 - val_accuracy: 0.0000e+00 - val_loss: 4.5445
Epoch 6/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 155ms/step - accuracy: 0.8872 - loss:
0.3861 - val_accuracy: 0.0071 - val_loss: 4.3466
Epoch 7/12
```

```
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 185ms/step - accuracy: 0.9118 - loss:
0.3289 - val_accuracy: 0.0000e+00 - val_loss: 8.6772
Epoch 8/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 10s 176ms/step - accuracy: 0.8663 - loss:
0.4509 - val_accuracy: 0.0217 - val_loss: 6.3532
Epoch 9/12

W0000 00:00:1710172892.620914      92 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 13s 197ms/step - accuracy: 0.8727 - loss:
0.5293 - val_accuracy: 0.0714 - val_loss: 6.0716
Epoch 10/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 151ms/step - accuracy: 0.8762 - loss:
0.4240 - val_accuracy: 0.1357 - val_loss: 7.5043
Epoch 11/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 180ms/step - accuracy: 0.9347 - loss:
0.2367 - val_accuracy: 0.1643 - val_loss: 5.4562
Epoch 12/12
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 156ms/step - accuracy: 0.9193 - loss:
0.2759 - val_accuracy: 0.2786 - val_loss: 3.9369
```

```
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



This model is slightly better! With an accuracy score of 89%, this was improved however the validation accuracy was only 10%. Using this as the base, lets tune the parameters to see if we can improve the validation accuracy score.

Model 3

```
# define the model
model3 = Sequential()
model3.trainable = True

model3.add(ResNet50(include_top=False, pooling='avg', weights=
resnet_weights_path))
model3.add(BatchNormalization())
model3.add(Dense(48, activation='relu'))
model3.add(BatchNormalization())
model3.add(Dense(256, activation='relu'))
model3.add(Dropout(0.25))
model3.add(Dense(128, activation='relu'))
model3.add(Dense(num_classes, activation='softmax'))

model3.summary()

Model: "sequential_2"
```

Layer (type)	Output Shape	Param #
resnet50 (Functional)	?	23,587,712
batch_normalization_4 (BatchNormalization)	?	0 (unbuilt)
dense_7 (Dense)	?	0 (unbuilt)
batch_normalization_5 (BatchNormalization)	?	0 (unbuilt)
dense_8 (Dense)	?	0 (unbuilt)
dropout_2 (Dropout)	?	0
dense_9 (Dense)	?	0 (unbuilt)
dense_10 (Dense)	?	0 (unbuilt)

Total params: 23,587,712 (89.98 MB)

Trainable params: 23,534,592 (89.78 MB)

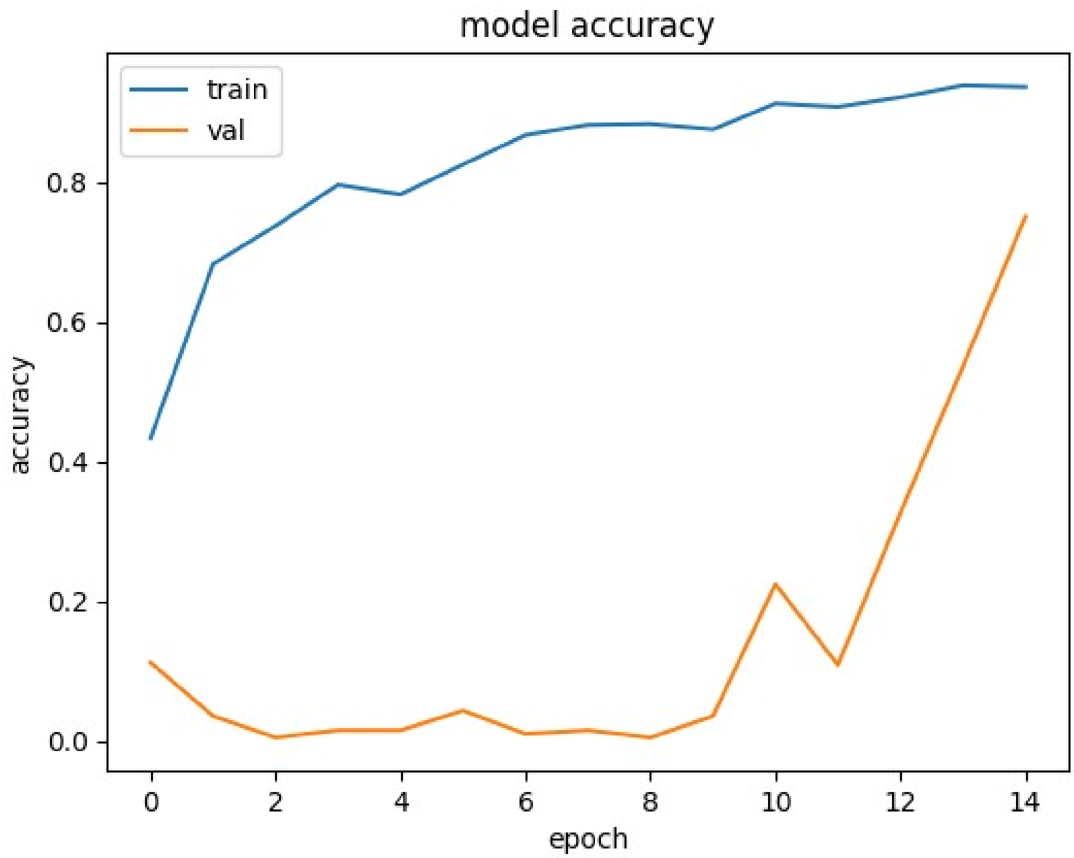
Non-trainable params: 53,120 (207.50 KB)

```python
model3.compile(optimizer="adam", loss='categorical_crossentropy',
metrics=['accuracy'])

# tuning to try to improve the score
history3 = model3.fit(
        train_generator,
        steps_per_epoch= 60,
        epochs = 15,
        validation_data=validation_generator,
        validation_steps=7)
```

```
Epoch 1/15
 1/60 ━━━━━━━━━━━━━━━━━━━━ 58:34 60s/step - accuracy: 0.0000e+00 -
loss: 4.2561

W0000 00:00:1710173000.081032      91 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 0s 176ms/step - accuracy: 0.2940 - loss:
3.1609

W0000 00:00:1710173014.831014      92 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 75s 264ms/step - accuracy: 0.2963 - loss:
3.1499 - val_accuracy: 0.1122 - val_loss: 26.0758
Epoch 2/15
18/60 ━━━━━━━━━━━━━━━━━━━━ 57s 1s/step - accuracy: 0.6512 - loss:
1.4993

W0000 00:00:1710173039.138016      93 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update

60/60 ━━━━━━━━━━━━━━━━━━━━ 30s 501ms/step - accuracy: 0.6648 - loss:
1.4168 - val_accuracy: 0.0357 - val_loss: 8.4326
Epoch 3/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 13s 189ms/step - accuracy: 0.7455 - loss:
0.9719 - val_accuracy: 0.0051 - val_loss: 4.2894
Epoch 4/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 159ms/step - accuracy: 0.7723 - loss:
0.8509 - val_accuracy: 0.0153 - val_loss: 4.3103
Epoch 5/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 179ms/step - accuracy: 0.7780 - loss:
0.8527 - val_accuracy: 0.0153 - val_loss: 4.4693
Epoch 6/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 10s 176ms/step - accuracy: 0.8208 - loss:
0.5962 - val_accuracy: 0.0435 - val_loss: 6.2045
Epoch 7/15

W0000 00:00:1710173090.281853      92 graph_launch.cc:671] Fallback to
op-by-op mode because memset node breaks graph update
```

```
60/60 ━━━━━━━━━━━━━━━━━━━━ 13s 199ms/step - accuracy: 0.8661 - loss:
0.4977 - val_accuracy: 0.0102 - val_loss: 6.7922
Epoch 8/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 10s 162ms/step - accuracy: 0.8829 - loss:
0.3841 - val_accuracy: 0.0153 - val_loss: 9.3577
Epoch 9/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 184ms/step - accuracy: 0.8959 - loss:
0.3400 - val_accuracy: 0.0051 - val_loss: 10.8075
Epoch 10/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 152ms/step - accuracy: 0.8582 - loss:
0.4715 - val_accuracy: 0.0357 - val_loss: 9.4032
Epoch 11/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 12s 180ms/step - accuracy: 0.9136 - loss:
0.2878 - val_accuracy: 0.2245 - val_loss: 4.1916
Epoch 12/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 8s 141ms/step - accuracy: 0.9025 - loss:
0.3427 - val_accuracy: 0.1087 - val_loss: 4.9673
Epoch 13/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 14s 206ms/step - accuracy: 0.9314 - loss:
0.2633 - val_accuracy: 0.3265 - val_loss: 3.9551
Epoch 14/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 9s 159ms/step - accuracy: 0.9361 - loss:
0.1991 - val_accuracy: 0.5357 - val_loss: 2.6390
Epoch 15/15
60/60 ━━━━━━━━━━━━━━━━━━━━ 13s 188ms/step - accuracy: 0.9460 - loss:
0.1866 - val_accuracy: 0.7500 - val_loss: 1.0308
```

```python
plt.plot(history3.history['accuracy'])
plt.plot(history3.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



This was much better! It seems Model 3 resulted in the best scores with an accuracy score of 92% and a validation score of 68%.

Prediction

Let's use an image from the testing data to see the accuracy of the model.

```
label = {0:"Speed Limit 5", 1:"Speed Limit 15", 2:"Speed Limit 30",
         3:"Speed Limit 40", 4:"Speed Limit 50", 5:"Speed Limit 60",
         6:"Speed Limit 70", 7:"Speed Limit 80", 8:"Don't go straight
or left",
         9:"Don't go straight or right", 10:"Don't go straight",
11:"No Left",
         12:"Don't go right or left", 13:"Don't go right", 14:"No
Overtake from Left",
         15:"No U-turn", 16:"No Cars", 17:"No Horn", 18:"Speed Limit
(40km/h)",
         19:"Speed Limit (50km/h)", 20:"Go straight or right",
21:"Watch out for cars",
         22:"Go left", 23:"Go left or right", 24:"Go right", 25:"Keep
Left",
         26:"Keep Right", 27:"Roundabout mandatory", 28:"Go Straight",
         29:"Horn", 30:"Bicycle Crossing", 31:"U-turn", 32:"Road
```

```
Divider",
         33:"Traffic Signals", 34:"Danger ahead", 35:"Zebra Crossing",
         36:"Bicycle Crossing", 37:"Children Crossing", 38:"Dangerous
curve to the left",
         39:"Dangerous curve to the right", 40:"Unknown 1",
41:"Unknown 2", 42:"Unknown 3",
         43:"Go right or straight", 44:"Go left or straight",
45:"Unknown 4",
         46:"Zigzag curve", 47:"Train Crossing", 48:"Under
construction", 49:"Unknown 5",
         50:"Fences", 51:"Heavy Vehicle Accidents", 52:"Unknown 6",
53:"Give way",
         54:"No Stopping", 55:"No Entry", 56:"Yield", 57:"Unknown 8"}

img_directory =
"/kaggle/input/traffic-sign-dataset-classification/traffic_Data/TEST/
021_1_0008.png"
test_image = image.load_img(img_directory, target_size=(128, 128))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis=0)
test_image

result = model3.predict(test_image)

img = mpimg.imread(img_directory)
imgplot = plt.imshow(img)
plt.show()

print(f"Predicted class: {label[np.argmax(result)]}")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 5s 5s/step
```


```
Predicted class: Don't go right or left
```

As you can see, the predicticted class matches what the image is saying showing that our model works well!

Conclusion

Through this investigation, I feel that we were able to be pretty successful in my goal. I found a model using a pretrained one that was able to fairly accurately predict and determine common traffic signs.

However, I think the data I used was quite standardised, so I'm not sure if this accuracy would be the same for photos where there is more background noise or it is further away. A major challenge was trying to make sure that the model was not overfit to the data as certain classes did not have many images and some images were in mutiple classes as well.

Nonetheless, I think this model is very applicable to the real world with further steps. It can be used for automation in transport or to help the visually impaired with road safety.

Future Work

What are the next steps?

1. Having live image detection so cars can respond in real time
2. Converting it to speech for audio aid

3. Adding a wider variety of road signs / altering based on country

References

1. Transfer learning example notebook (goes with the video demonstration)- https://www.kaggle.com/dansbecker/transfer-learning/
2. Kaggle Computer Vision course final notebook on Data Augmentation- https://www.kaggle.com/ryanholbrook/data-augmentation
3. Traffic Sign Dataset https://www.kaggle.com/datasets/ahemateja19bec1025/traffic-sign-dataset-classification