# Dog vs Cat Classification

August 23, 2023

## 1 Dog vs Cat Classification

### 1.1 Introduction

Kaggle competition: https://www.kaggle.com/competitions/dog-vs-cat-classification/

In this competition, the competitor is tasked with writing a script to classify whether an image contains a dog or a cat. I have chosen to approach this challenge using a CNN, which is a reliable deep learning algorithm used for image classification.

### 1.2 Setup

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import math
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, BatchNormalization,␣
↪Activation, Conv2D, MaxPooling2D, MaxPool2D
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import plot_model
from glob import glob
from PIL import Image
import pydot
import graphviz
import os
```

[2]:
```
path = "/Users/clairerobbins/Documents/MS-DS CU Boulder/Introduction to Deep␣
↪Learning/Final Project/dog-vs-cat-classification/"
cat_path = path + 'train/cats'
dog_path = path + 'train/dogs'
test_path = path + 'test/test'
```

### 1.3 Data Preprocessing & EDA

[3]:
```
cats = pd.DataFrame({'path': glob(os.path.join(cat_path,'*.jpg'))})
cats['id'] = [os.path.basename(i) for i in cats['path']]
cat_labels = [0 for i in range(len(cats))]
cats['label'] = cat_labels
cats.head(5)
```

[3]:

| | path | id | label |
|---|---|---|---|
| 0 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.5077.jpg | 0 |
| 1 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.2718.jpg | 0 |
| 2 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.10151.jpg | 0 |
| 3 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.3406.jpg | 0 |
| 4 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.4369.jpg | 0 |

[4]:
```
dogs = pd.DataFrame({'path': glob(os.path.join(dog_path,'*.jpg'))})
dogs['id'] = [os.path.basename(i) for i in dogs['path']]
dog_labels = [1 for i in range(len(dogs))]
dogs['label'] = dog_labels
dogs.head(5)
```

[4]:

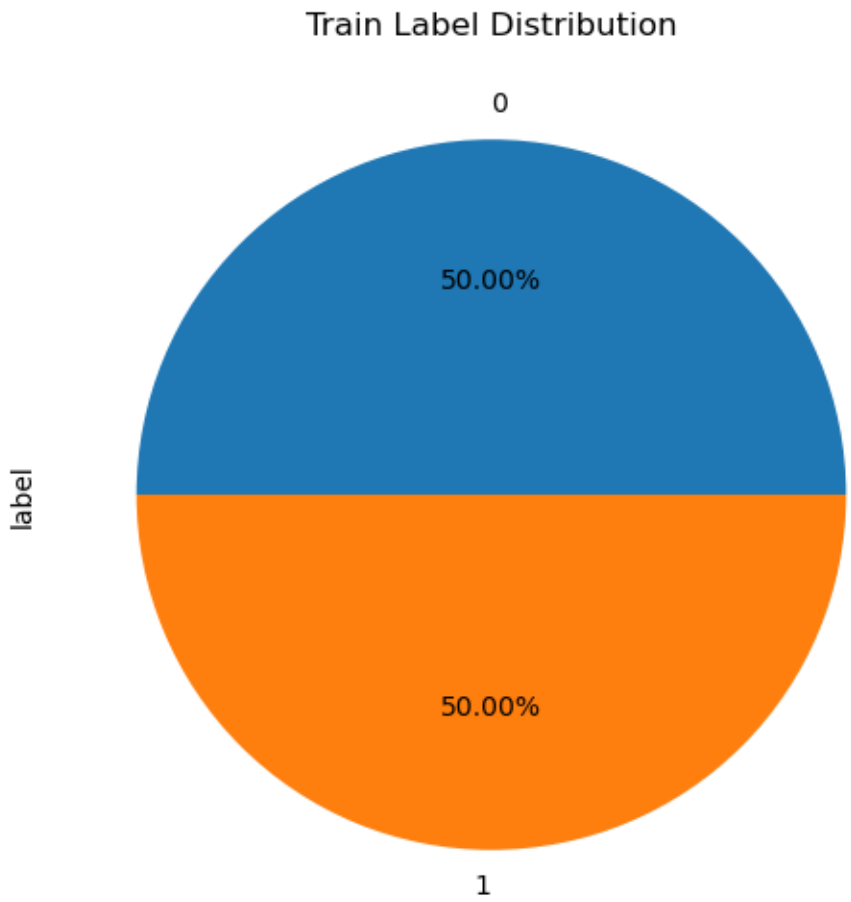
| | path | id | label |
|---|---|---|---|
| 0 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | dog.8011.jpg | 1 |
| 1 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | dog.7322.jpg | 1 |
| 2 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | dog.1753.jpg | 1 |
| 3 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | dog.5535.jpg | 1 |
| 4 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | dog.3144.jpg | 1 |

[5]:
```
dfs = [cats, dogs]
train = pd.concat(dfs)
train.head(5)
```

[5]:

| | path | id | label |
|---|---|---|---|
| 0 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.5077.jpg | 0 |
| 1 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.2718.jpg | 0 |
| 2 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.10151.jpg | 0 |
| 3 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.3406.jpg | 0 |
| 4 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | cat.4369.jpg | 0 |

[6]:
```
train['label'].value_counts().plot(figsize=(6,6),kind='pie',autopct='%.2f%%')
plt.title('Train Label Distribution')
plt.show()
```




[7]:
```
test = pd.DataFrame({'path': glob(os.path.join(test_path,'*.jpg'))})
test['id'] = [os.path.basename(i) for i in test['path']]
test['label'] = [None for i in range(len(test))]
test
```

[7]:

| | path | id | label |
|---|---|---|---|
| 0 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 003301.jpg | None |
| 1 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 005770.jpg | None |
| 2 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 001516.jpg | None |
| 3 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 006279.jpg | None |
| 4 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 007167.jpg | None |
| … | … | … | … |
| 7995 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 006260.jpg | None |
| 7996 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 005769.jpg | None |
| 7997 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 002006.jpg | None |
| 7998 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 003318.jpg | None |
| 7999 | /Users/clairerobbins/Documents/MS-DS CU Boulde… | 004477.jpg | None |

```
[8000 rows x 3 columns]
```

[8]:
```
train, validate = train_test_split(train, test_size=0.2)
```

[9]:
```
def clean_files(df):
    raw_data = []
    labels = []
    count = 0
    for index,row in df.iterrows():
        img = Image.open(row['path'])
        img = img.resize((224, 224), Image.ANTIALIAS)  # Resizing
        raw_data.append(img)
        labels.append(row['label'])
        count+=1
    return raw_data, labels
```

[10]:
```
train_raw, train_labels = clean_files(train)
validate_raw, validate_labels = clean_files(validate)
test_raw, test_labels = clean_files(test)
```

```
/var/folders/5c/fd850vrj48v7jb6xpw9dy4v00000gn/T/ipykernel_3293/1186364363.py:7:
DeprecationWarning: ANTIALIAS is deprecated and will be removed in Pillow 10
(2023-07-01). Use LANCZOS or Resampling.LANCZOS instead.
  img = img.resize((224, 224), Image.ANTIALIAS)  # Resizing
```

[11]:
```
train_raw2 = []
for i in train_raw:
    train_raw2.append(np.array(i))

validate_raw2 = []
for i in validate_raw:
    validate_raw2.append(np.array(i))

test_raw2 = []
for i in test_raw:
    test_raw2.append(np.array(i))
```

### 1.4 Model Building & Training

I built my model with the following specs:

- kernel size = (3, 3): a very average kernel size to capture a medium amount of detail
- pool size = (2, 2): a normal pool size to start with
- 3 layers + dense layer
- relu activation: mitigate vanishing gradient, common activation function
- binary crossentropy activation function: standard choice for binary classification

- adam optimizer: adaptive optimizer, typically best optimizer to start with

[12]:
```
kernel_size = (3, 3)
pool_size = (2, 2)
first_filters = 16
second_filters = 32
third_filters = 64

dropout_conv = 0.2
dropout_dense = 0.4

model = Sequential()

# Conv layer 1
model.add(Conv2D(first_filters, kernel_size, input_shape=(224, 224, 3)))
model.add(BatchNormalization())
model.add(Activation("relu"))
model.add(MaxPool2D(pool_size=pool_size))
model.add(Dropout(dropout_conv))

# Conv layer 2
model.add(Conv2D(second_filters, kernel_size))
model.add(BatchNormalization())
model.add(Activation("relu"))
model.add(MaxPool2D(pool_size=pool_size))
model.add(Dropout(dropout_conv))

# Conv layer 3
model.add(Conv2D(third_filters, kernel_size))
model.add(BatchNormalization())
model.add(Activation("relu"))
model.add(MaxPool2D(pool_size=pool_size))
model.add(Dropout(dropout_conv))

# Fully connected (dense) layer
model.add(Flatten())
model.add(Dense(128))
model.add(BatchNormalization())
model.add(Activation("relu"))
model.add(Dropout(dropout_dense))

# Activation function
model.add(Dense(1, activation="sigmoid"))

batch_size = 64
model.compile(loss='binary_crossentropy',
              optimizer='adam',
```

```
              metrics=['accuracy'])
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 conv2d (Conv2D)              (None, 222, 222, 16)      448

 batch_normalization (Batch   (None, 222, 222, 16)      64
 Normalization)

 activation (Activation)      (None, 222, 222, 16)      0

 max_pooling2d (MaxPooling2   (None, 111, 111, 16)      0
 D)

 dropout (Dropout)            (None, 111, 111, 16)      0

 conv2d_1 (Conv2D)            (None, 109, 109, 32)      4640

 batch_normalization_1 (Bat   (None, 109, 109, 32)      128
 chNormalization)

 activation_1 (Activation)    (None, 109, 109, 32)      0

 max_pooling2d_1 (MaxPoolin   (None, 54, 54, 32)        0
 g2D)

 dropout_1 (Dropout)          (None, 54, 54, 32)        0

 conv2d_2 (Conv2D)            (None, 52, 52, 64)        18496

 batch_normalization_2 (Bat   (None, 52, 52, 64)        256
 chNormalization)

 activation_2 (Activation)    (None, 52, 52, 64)        0

 max_pooling2d_2 (MaxPoolin   (None, 26, 26, 64)        0
 g2D)

 dropout_2 (Dropout)          (None, 26, 26, 64)        0

 flatten (Flatten)            (None, 43264)             0

 dense (Dense)                (None, 128)               5537920
```

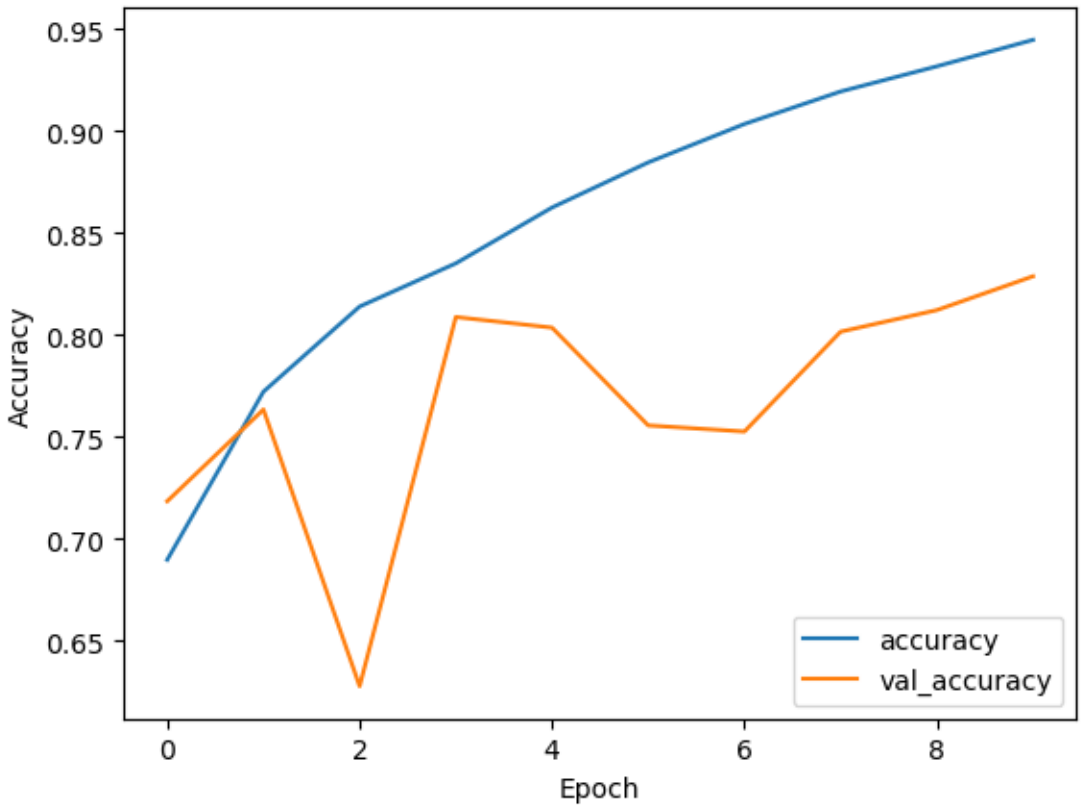
```
 batch_normalization_3 (Bat  (None, 128)               512
 chNormalization)

 activation_3 (Activation)   (None, 128)               0

 dropout_3 (Dropout)         (None, 128)               0

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 5562593 (21.22 MB)
Trainable params: 5562113 (21.22 MB)
Non-trainable params: 480 (1.88 KB)
_________________________________________________________________
```

[13]:
```
history = model.fit(np.array(train_raw2), np.array(train_labels), epochs=10,
          validation_data=(np.array(validate_raw2), np.array(validate_labels)))
```

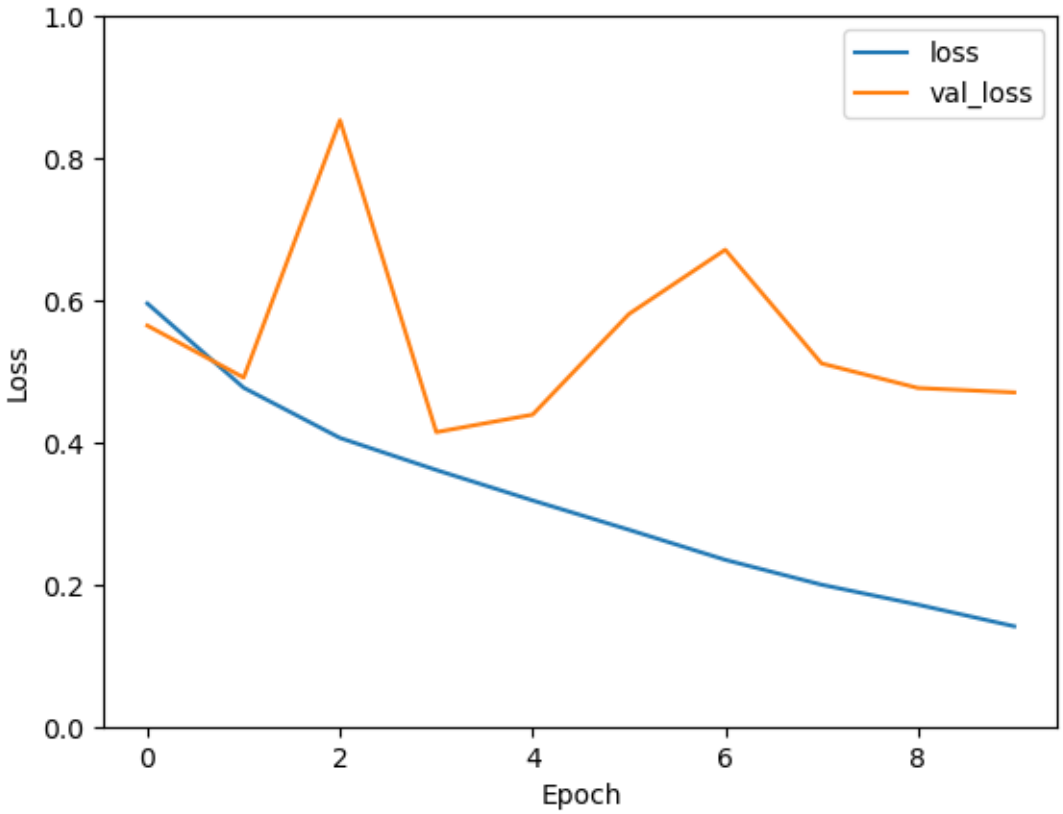
```
Epoch 1/10
625/625 [==============================] - 139s 221ms/step - loss: 0.5955 -
accuracy: 0.6896 - val_loss: 0.5644 - val_accuracy: 0.7184
Epoch 2/10
625/625 [==============================] - 138s 221ms/step - loss: 0.4769 -
accuracy: 0.7721 - val_loss: 0.4912 - val_accuracy: 0.7634
Epoch 3/10
625/625 [==============================] - 136s 217ms/step - loss: 0.4062 -
accuracy: 0.8140 - val_loss: 0.8535 - val_accuracy: 0.6276
Epoch 4/10
625/625 [==============================] - 136s 218ms/step - loss: 0.3611 -
accuracy: 0.8352 - val_loss: 0.4144 - val_accuracy: 0.8088
Epoch 5/10
625/625 [==============================] - 136s 218ms/step - loss: 0.3183 -
accuracy: 0.8626 - val_loss: 0.4390 - val_accuracy: 0.8036
Epoch 6/10
625/625 [==============================] - 136s 217ms/step - loss: 0.2770 -
accuracy: 0.8847 - val_loss: 0.5806 - val_accuracy: 0.7556
Epoch 7/10
625/625 [==============================] - 136s 217ms/step - loss: 0.2347 -
accuracy: 0.9036 - val_loss: 0.6711 - val_accuracy: 0.7526
Epoch 8/10
625/625 [==============================] - 137s 218ms/step - loss: 0.1997 -
accuracy: 0.9195 - val_loss: 0.5111 - val_accuracy: 0.8016
Epoch 9/10
625/625 [==============================] - 136s 218ms/step - loss: 0.1716 -
accuracy: 0.9319 - val_loss: 0.4765 - val_accuracy: 0.8122
Epoch 10/10
625/625 [==============================] - 136s 218ms/step - loss: 0.1412 -
accuracy: 0.9449 - val_loss: 0.4703 - val_accuracy: 0.8288
```

[14]:
```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label = 'val_accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(loc='lower right')
```

[14]: <matplotlib.legend.Legend at 0x76c586950>




[15]:
```
plt.plot(history.history['loss'], label='loss')
plt.plot(history.history['val_loss'], label = 'val_loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.ylim([0.0, 1])
plt.legend(loc='upper right');
```




[16]:
```
predictions = model.predict(np.array(test_raw2))
```

```
250/250 [==============================] - 13s 51ms/step
```

[17]:
```
# convert prediction percentages to binary classification
final_predictions = []
for i in predictions:
    if i > 0.5:
        final_predictions.append(1)
    else:
        final_predictions.append(0)
```

[18]:
```
# generate submission file
submission = pd.DataFrame({'id': test['id'], 'label': final_predictions})
submission.set_index('id')
submission.to_csv('submission.csv')
```

### 1.5 Conclusion

Despite the questionable validation accuracy and loss, my model performed quite well on the test data with 93% accuracy! After much trial and error, I landed on a model that is quite standard and not very fine-tuned, as I found it performed the best. I struggled to minimize my validation loss, something that I will continue to research and learn.