Dogs&Cats-classifier

February 23, 2021

0.0.1 Cats and Dogs Classifier using Convolutional Neural Networks

```
[1]: from google.colab import drive
     drive.mount('/content/drive')
    Mounted at /content/drive
[2]: ! ls drive/MyDrive/CATS_DOGS.zip
    drive/MyDrive/CATS_DOGS.zip
[4]: # libraries
     import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     plt.style.use('classic')
    0.0.2 Paths
[5]: # archive = '../Data/CATS_DOGS.zip' # local
     archive = 'drive/MyDrive/CATS_DOGS.zip' # colab
[6]: # unzipping
     import zipfile
     zip_obj = zipfile.ZipFile(file=archive)
[7]: import os
     if os.path.exists('drive/MyDrive/cd_data/'):
         print(True)
     else:
         print(False)
         print(os.mkdir('drive/MyDrive/cd_data/'))
         print('created!')
    False
```

1

None created!

```
[8]: # # extract to the location

# # zip_obj.extractall('../Data/') # local
zip_obj.extractall('drive/MyDrive/cd_data/') # colab
```

```
[9]: # train and validation paths

# train_dir = '../Data/CATS_DOGS/train/'
# valid_dir = '../Data/CATS_DOGS/test/'

train_dir = 'drive/MyDrive/cd_data/CATS_DOGS/train/'
valid_dir = 'drive/MyDrive/cd_data/CATS_DOGS/test/'
```

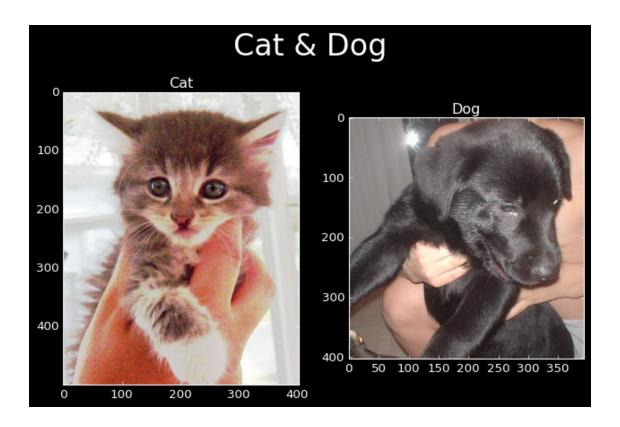
0.0.3 Raw Data

```
[10]: # random

# cat = '../Data/CATS_DOGS/train/CAT/100.jpg'
# dog = '../Data/CATS_DOGS/train/DOG/1050.jpg'

cat = 'drive/MyDrive/cd_data/CATS_DOGS/train/CAT/100.jpg'
dog = 'drive/MyDrive/cd_data/CATS_DOGS/train/DOG/1050.jpg'
```

```
plt.style.use('dark_background')
from PIL import Image
img_cat = Image.open(cat)
img_dog = Image.open(dog)
fig, axes = plt.subplots(1,2)
axes[0].imshow(np.array(img_cat),label='cat')
axes[0].set_title('Cat')
axes[1].imshow(np.array(img_dog),label='dog')
axes[1].set_title('Dog')
fig.suptitle('Cat & Dog',size=30)
fig.tight_layout()
```



```
[12]: Through this random image selection and observation, it is evident that shapes are not homogeneous;
```

[12]: '\nThrough this random image selection and obseravtion, \nit is evident that shapes are not homogeneous;\n'

0.0.4 Generators

- [13]: from tensorflow.keras.preprocessing.image import ImageDataGenerator
- [14]: help(ImageDataGenerator)

Help on class ImageDataGenerator in module tensorflow.python.keras.preprocessing.image:

 ${\tt class\ ImageDataGenerator(keras_preprocessing.image.image_data_generator.ImageDataGenerator)}$

Generate batches of tensor image data with real-time data augmentation.

The data will be looped over (in batches).

```
Arguments:
    featurewise_center: Boolean.
        Set input mean to 0 over the dataset, feature-wise.
    samplewise_center: Boolean. Set each sample mean to 0.
    featurewise std normalization: Boolean.
        Divide inputs by std of the dataset, feature-wise.
    samplewise_std_normalization: Boolean. Divide each input by its std.
    zca_epsilon: epsilon for ZCA whitening. Default is 1e-6.
    zca_whitening: Boolean. Apply ZCA whitening.
    rotation_range: Int. Degree range for random rotations.
    width_shift_range: Float, 1-D array-like or int
        - float: fraction of total width, if < 1, or pixels if >= 1.
        - 1-D array-like: random elements from the array.
        - int: integer number of pixels from interval
            `(-width_shift_range, +width_shift_range)`
        - With `width_shift_range=2` possible values
            are integers `[-1, 0, +1]`,
            same as with `width_shift_range=[-1, 0, +1]`,
            while with `width_shift_range=1.0` possible values are floats
            in the interval [-1.0, +1.0).
    height_shift_range: Float, 1-D array-like or int
        - float: fraction of total height, if < 1, or pixels if >= 1.
        - 1-D array-like: random elements from the array.
        - int: integer number of pixels from interval
            `(-height_shift_range, +height_shift_range)`
        - With `height_shift_range=2` possible values
            are integers `[-1, 0, +1]`,
            same as with `height_shift_range=[-1, 0, +1]`,
            while with `height_shift_range=1.0` possible values are floats
            in the interval [-1.0, +1.0).
    brightness_range: Tuple or list of two floats. Range for picking
        a brightness shift value from.
    shear_range: Float. Shear Intensity
        (Shear angle in counter-clockwise direction in degrees)
    zoom range: Float or [lower, upper]. Range for random zoom.
        If a float, `[lower, upper] = [1-zoom_range, 1+zoom_range]`.
    channel_shift_range: Float. Range for random channel shifts.
    fill_mode: One of {"constant", "nearest", "reflect" or "wrap"}.
        Default is 'nearest'.
       Points outside the boundaries of the input are filled
       according to the given mode:
        - 'constant': kkkkkkk|abcd|kkkkkkk (cval=k)
        - 'nearest': aaaaaaaa|abcd|dddddddd
        - 'reflect': abcddcba|abcd|dcbaabcd
        - 'wrap': abcdabcd|abcd|abcdabcd
    cval: Float or Int.
        Value used for points outside the boundaries
        when `fill_mode = "constant"`.
```

```
horizontal_flip: Boolean. Randomly flip inputs horizontally.
      vertical_flip: Boolean. Randomly flip inputs vertically.
      rescale: rescaling factor. Defaults to None.
          If None or 0, no rescaling is applied,
          otherwise we multiply the data by the value provided
           (after applying all other transformations).
      preprocessing_function: function that will be applied on each input.
          The function will run after the image is resized and augmented.
          The function should take one argument:
          one image (Numpy tensor with rank 3),
           and should output a Numpy tensor with the same shape.
      data_format: Image data format,
          either "channels_first" or "channels_last".
           "channels_last" mode means that the images should have shape
           `(samples, height, width, channels)`,
           "channels_first" mode means that the images should have shape
           `(samples, channels, height, width)`.
          It defaults to the `image_data_format` value found in your
          Keras config file at `~/.keras/keras.json`.
          If you never set it, then it will be "channels_last".
      validation_split: Float. Fraction of images reserved for validation
           (strictly between 0 and 1).
      dtype: Dtype to use for the generated arrays.
 Examples:
| Example of using `.flow(x, y)`:
  ```python
 (x_train, y_train), (x_test, y_test) = cifar10.load_data()
 y_train = np_utils.to_categorical(y_train, num_classes)
 y_test = np_utils.to_categorical(y_test, num_classes)
 datagen = ImageDataGenerator(
 featurewise_center=True,
 featurewise_std_normalization=True,
 rotation_range=20,
 width_shift_range=0.2,
 height_shift_range=0.2,
 horizontal_flip=True)
| # compute quantities required for featurewise normalization
| # (std, mean, and principal components if ZCA whitening is applied)
 datagen.fit(x_train)
 # fits the model on batches with real-time data augmentation:
model.fit(datagen.flow(x_train, y_train, batch_size=32),
 steps_per_epoch=len(x_train) / 32, epochs=epochs)
| # here's a more "manual" example
 for e in range(epochs):
 print('Epoch', e)
```

```
batches = 0
 for x_batch, y_batch in datagen.flow(x_train, y_train, batch_size=32):
 model.fit(x_batch, y_batch)
 batches += 1
 if batches >= len(x_train) / 32:
 # we need to break the loop by hand because
 # the generator loops indefinitely
 break
 Example of using `.flow_from_directory(directory)`:
 ```python
 train_datagen = ImageDataGenerator(
         rescale=1./255,
         shear_range=0.2,
         zoom_range=0.2,
         horizontal_flip=True)
 test_datagen = ImageDataGenerator(rescale=1./255)
 train_generator = train_datagen.flow_from_directory(
         'data/train',
         target_size=(150, 150),
         batch_size=32,
         class_mode='binary')
 validation_generator = test_datagen.flow_from_directory(
         'data/validation',
         target_size=(150, 150),
         batch_size=32,
         class_mode='binary')
 model.fit(
         train_generator,
         steps_per_epoch=2000,
         epochs=50,
         validation_data=validation_generator,
         validation_steps=800)
Example of transforming images and masks together.
```python
we create two instances with the same arguments
 data_gen_args = dict(featurewise_center=True,
 featurewise_std_normalization=True,
 rotation_range=90,
 width_shift_range=0.1,
 height_shift_range=0.1,
 zoom_range=0.2)
 image_datagen = ImageDataGenerator(**data_gen_args)
```

```
mask_datagen = ImageDataGenerator(**data_gen_args)
 | # Provide the same seed and keyword arguments to the fit and flow methods
 | seed = 1
 image_datagen.fit(images, augment=True, seed=seed)
 mask datagen.fit(masks, augment=True, seed=seed)
 image_generator = image_datagen.flow_from_directory(
 'data/images',
 class_mode=None,
 seed=seed)
 mask_generator = mask_datagen.flow_from_directory(
 'data/masks',
 class_mode=None,
 seed=seed)
 # combine generators into one which yields image and masks
 train_generator = zip(image_generator, mask_generator)
 model.fit(
 train_generator,
 steps_per_epoch=2000,
 epochs=50)
 Method resolution order:
 ImageDataGenerator
 keras_preprocessing.image.image_data_generator.ImageDataGenerator
 builtins.object
 Methods defined here:
 __init__(self, featurewise_center=False, samplewise_center=False,
featurewise_std_normalization=False, samplewise_std_normalization=False,
zca_whitening=False, zca_epsilon=1e-06, rotation_range=0, width_shift_range=0.0,
height_shift_range=0.0, brightness_range=None, shear_range=0.0, zoom_range=0.0,
channel_shift_range=0.0, fill_mode='nearest', cval=0.0, horizontal_flip=False,
vertical_flip=False, rescale=None, preprocessing_function=None,
data format=None, validation split=0.0, dtype=None)
 Initialize self. See help(type(self)) for accurate signature.
 flow(self, x, y=None, batch_size=32, shuffle=True, sample_weight=None,
seed=None, save_to_dir=None, save_prefix='', save_format='png', subset=None)
 Takes data & label arrays, generates batches of augmented data.
 Arguments:
 x: Input data. Numpy array of rank 4 or a tuple. If tuple, the first
 element should contain the images and the second element another
numpy
 array or a list of numpy arrays that gets passed to the output
without
 any modifications. Can be used to feed the model miscellaneous
```

```
data
 1
 along with the images. In case of grayscale data, the channels
axis of
 the image array should have value 1, in case of RGB data, it
should
 have value 3, and in case of RGBA data, it should have value 4.
 y: Labels.
 batch_size: Int (default: 32).
 shuffle: Boolean (default: True).
 sample_weight: Sample weights.
 seed: Int (default: None).
 save_to_dir: None or str (default: None). This allows you to
optionally
 specify a directory to which to save the augmented pictures being
 generated (useful for visualizing what you are doing).
 save_prefix: Str (default: `''`). Prefix to use for filenames of
saved
 pictures (only relevant if `save_to_dir` is set).
 save_format: one of "png", "jpeg"
 (only relevant if `save_to_dir` is set). Default: "png".
 subset: Subset of data (`"training"` or `"validation"`) if
 `validation_split` is set in `ImageDataGenerator`.
 Returns:
 An `Iterator` yielding tuples of `(x, y)`
 where `x` is a numpy array of image data
 (in the case of a single image input) or a list
 of numpy arrays (in the case with
 additional inputs) and `y` is a numpy array
 of corresponding labels. If 'sample_weight' is not None,
 the yielded tuples are of the form `(x, y, sample_weight)`.
 If `y` is None, only the numpy array `x` is returned.
 flow_from_dataframe(self, dataframe, directory=None, x_col='filename',
y_col='class', weight_col=None, target_size=(256, 256), color_mode='rgb',
classes=None, class_mode='categorical', batch_size=32, shuffle=True, seed=None,
save_to_dir=None, save_prefix='', save_format='png', subset=None,
interpolation='nearest', validate_filenames=True, **kwargs)
 Takes the dataframe and the path to a directory + generates batches.
 The generated batches contain augmented/normalized data.
 **A simple tutorial can be found **[here](
 http://bit.ly/keras_flow_from_dataframe).
 Arguments:
 dataframe: Pandas dataframe containing the filepaths relative to
 `directory` (or absolute paths if `directory` is None) of the
```

```
images
 in a string column. It should include other column/s
 depending on the `class_mode`: - if `class_mode` is
`"categorical"`
 (default value) it must include the `y_col` column with the
 class/es of each image. Values in column can be
string/list/tuple
 if a single class or list/tuple if multiple classes. - if
 `class_mode` is `"binary"` or `"sparse"` it must include the
given
 'y_col' column with class values as strings. - if 'class_mode'
is
 `"raw"` or `"multi_output"` it should contain the columns
 specified in `y_col`. - if `class_mode` is `"input"` or `None`
no
 extra column is needed.
 directory: string, path to the directory to read images from. If
`None`,
 data in `x_col` column should be absolute paths.
 x_col: string, column in `dataframe` that contains the filenames (or
 absolute paths if `directory` is `None`).
 y_col: string or list, column/s in `dataframe` that has the target
data.
 weight_col: string, column in `dataframe` that contains the sample
 weights. Default: `None`.
 target_size: tuple of integers `(height, width)`, default: `(256,
256) `.
 The dimensions to which all images found will be resized.
 color_mode: one of "grayscale", "rgb", "rgba". Default: "rgb".
Whether
 the images will be converted to have 1 or 3 color channels.
 1
 classes: optional list of classes (e.g. `['dogs', 'cats']`). Default
is
 None. If not provided, the list of classes will be automatically
 inferred from the `y_col`, which will map to the label indices,
will
 be alphanumeric). The dictionary containing the mapping from class
 names to class indices can be obtained via the attribute
 `class_indices`.
 class_mode: one of "binary", "categorical", "input", "multi_output",
 "raw", sparse" or None. Default: "categorical".
 Mode for yielding the targets:
 - `"binary"`: 1D numpy array of binary labels,
 - `"categorical"`: 2D numpy array of one-hot encoded labels.
 Supports multi-label output.
 - `"input": images identical to input images (mainly used to
work
 1
 with autoencoders),
```

```
- `"multi_output"`: list with the values of the different
columns,
 - `"raw"`: numpy array of values in `y_col` column(s),
 - `"sparse": 1D numpy array of integer labels, - `None`, no
targets
 are returned (the generator will only yield batches of image
data,
 which is useful to use in `model.predict()`).
 batch_size: size of the batches of data (default: 32).
 shuffle: whether to shuffle the data (default: True)
 seed: optional random seed for shuffling and transformations.
 save_to_dir: None or str (default: None). This allows you to
optionally
 specify a directory to which to save the augmented pictures being
 generated (useful for visualizing what you are doing).
 save_prefix: str. Prefix to use for filenames of saved pictures
(only
 relevant if `save_to_dir` is set).
 save_format: one of "png", "jpeg"
 (only relevant if `save_to_dir` is set). Default: "png".
 subset: Subset of data (`"training"` or `"validation"`) if
 `validation_split` is set in `ImageDataGenerator`.
 interpolation: Interpolation method used to resample the image if
the
 Т
 target size is different from that of the loaded image. Supported
 methods are `"nearest"`, `"bilinear"`, and `"bicubic"`. If PIL
version
 1.1.3 or newer is installed, `"lanczos"` is also supported. If PIL
 1
 version 3.4.0 or newer is installed, `"box"` and `"hamming"` are
also
 supported. By default, `"nearest"` is used.
 validate_filenames: Boolean, whether to validate image filenames in
 `x col`. If `True`, invalid images will be ignored. Disabling this
 option can lead to speed-up in the execution of this function.
 Defaults to `True`.
 **kwargs: legacy arguments for raising deprecation warnings.
 Returns:
 A `DataFrameIterator` yielding tuples of `(x, y)`
 where `x` is a numpy array containing a batch
 of images with shape `(batch_size, *target_size, channels)`
 and `y` is a numpy array of corresponding labels.
 flow_from_directory(self, directory, target_size=(256, 256),
color_mode='rgb', classes=None, class_mode='categorical', batch_size=32,
shuffle=True, seed=None, save_to_dir=None, save_prefix='', save_format='png',
follow_links=False, subset=None, interpolation='nearest')
 Takes the path to a directory & generates batches of augmented data.
```

```
Arguments:
 directory: string, path to the target directory. It should contain
one
 subdirectory per class. Any PNG, JPG, BMP, PPM or TIF images
 inside
 each of the subdirectories directory tree will be included in the
 generator. See [this script](
https://gist.github.com/fchollet/0830affa1f7f19fd47b06d4cf89ed44d)
 for more details.
 target_size: Tuple of integers `(height, width)`, defaults to `(256,
 256) `. The dimensions to which all images found will be resized.
 color_mode: One of "grayscale", "rgb", "rgba". Default: "rgb".
Whether
 the images will be converted to have 1, 3, or 4 channels.
 classes: Optional list of class subdirectories
 (e.g. `['dogs', 'cats']`). Default: None. If not provided, the
list
 of classes will be automatically inferred from the
subdirectory
 names/structure under `directory`, where each subdirectory
will be
 treated as a different class (and the order of the classes,
which
 will map to the label indices, will be alphanumeric). The
 dictionary containing the mapping from class names to class
 indices can be obtained via the attribute `class_indices`.
 class_mode: One of "categorical", "binary", "sparse",
 "input", or None. Default: "categorical".
 Determines the type of label arrays that are returned: -
 "categorical" will be 2D one-hot encoded labels, - "binary"
will
 be 1D binary labels, "sparse" will be 1D integer labels, -
"input"
 will be images identical to input images (mainly used to work
with
 autoencoders). - If None, no labels are returned (the
generator
 will only yield batches of image data, which is useful to use
with
 `model.predict()`). Please note that in case of
 class_mode None, the data still needs to reside in a
subdirectory
 of `directory` for it to work correctly.
 batch_size: Size of the batches of data (default: 32).
 shuffle: Whether to shuffle the data (default: True) If set to
False,
```

```
sorts the data in alphanumeric order.
 seed: Optional random seed for shuffling and transformations.
 save_to_dir: None or str (default: None). This allows you to
optionally
 specify a directory to which to save the augmented pictures being
 generated (useful for visualizing what you are doing).
 save_prefix: Str. Prefix to use for filenames of saved pictures
(only
 relevant if `save_to_dir` is set).
 save_format: One of "png", "jpeg"
 (only relevant if `save_to_dir` is set). Default: "png".
 follow_links: Whether to follow symlinks inside
 class subdirectories (default: False).
 subset: Subset of data (`"training"` or `"validation"`) if
 `validation_split` is set in `ImageDataGenerator`.
 interpolation: Interpolation method used to resample the image if
the
 target size is different from that of the loaded image. Supported
 methods are `"nearest"`, `"bilinear"`, and `"bicubic"`. If PIL
version
 1.1.3 or newer is installed, ""lanczos" is also supported. If PIL
 Τ
 version 3.4.0 or newer is installed, "box" and "hamming" are
also
 supported. By default, "mearest" is used.
 Returns:
 A `DirectoryIterator` yielding tuples of `(x, y)`
 where `x` is a numpy array containing a batch
 of images with shape `(batch_size, *target_size, channels)`
 and `y` is a numpy array of corresponding labels.
 Methods inherited from
keras_preprocessing.image.image_data_generator.ImageDataGenerator:
 apply_transform(self, x, transform_parameters)
 Applies a transformation to an image according to given parameters.
 # Arguments
 x: 3D tensor, single image.
 transform_parameters: Dictionary with string - parameter pairs
 describing the transformation.
 Currently, the following parameters
 from the dictionary are used:
 - `'theta'`: Float. Rotation angle in degrees.
 - `'tx'`: Float. Shift in the x direction.
 - `'ty'`: Float. Shift in the y direction.
 - `'shear'`: Float. Shear angle in degrees.
```

```
- \'zx': Float. Zoom in the x direction.
 - `'zy'`: Float. Zoom in the y direction.
 - `'flip_horizontal'`: Boolean. Horizontal flip.
 - `'flip_vertical'`: Boolean. Vertical flip.
 - `'channel_shift_intensity'`: Float. Channel shift intensity.
 - `'brightness'`: Float. Brightness shift intensity.
 # Returns
 A transformed version of the input (same shape).
fit(self, x, augment=False, rounds=1, seed=None)
 Fits the data generator to some sample data.
 This computes the internal data stats related to the
 data-dependent transformations, based on an array of sample data.
 Only required if `featurewise_center` or
 `featurewise_std_normalization` or `zca_whitening` are set to True.
 When `rescale` is set to a value, rescaling is applied to
 sample data before computing the internal data stats.
 # Arguments
 x: Sample data. Should have rank 4.
 In case of grayscale data,
 the channels axis should have value 1, in case
 of RGB data, it should have value 3, and in case
 of RGBA data, it should have value 4.
 augment: Boolean (default: False).
 Whether to fit on randomly augmented samples.
 rounds: Int (default: 1).
 If using data augmentation (`augment=True`),
 this is how many augmentation passes over the data to use.
 seed: Int (default: None). Random seed.
get_random_transform(self, img_shape, seed=None)
 Generates random parameters for a transformation.
 # Arguments
 seed: Random seed.
 img_shape: Tuple of integers.
 Shape of the image that is transformed.
 # Returns
 A dictionary containing randomly chosen parameters describing the
 transformation.
random_transform(self, x, seed=None)
```

```
Arguments
 x: 3D tensor, single image.
 seed: Random seed.
 # Returns
 A randomly transformed version of the input (same shape).
 standardize(self, x)
 Applies the normalization configuration in-place to a batch of inputs.
 `x` is changed in-place since the function is mainly used internally
 to standardize images and feed them to your network. If a copy of `x`
 would be created instead it would have a significant performance cost.
 If you want to apply this method without changing the input in-place
 you can call the method creating a copy before:
 standardize(np.copy(x))
 # Arguments
 x: Batch of inputs to be normalized.
 # Returns
 The inputs, normalized.
 Data descriptors inherited from
 keras_preprocessing.image.image_data_generator.ImageDataGenerator:
 __dict__
 dictionary for instance variables (if defined)
 __weakref__
 list of weak references to the object (if defined)
[15]: train_gen = ImageDataGenerator(rescale=1/255.)
 val_gen = ImageDataGenerator(rescale=1/255.)
[16]: # both cats and dogs combined
 train_generator = train_gen.
 -flow_from_directory(train_dir,target_size=(128,128),batch_size=64,shuffle=True,class_mode='
 validation_generator = val_gen.
 -flow_from_directory(valid_dir,target_size=(128,128),batch_size=64,shuffle=False,class_mode=
 Found 18743 images belonging to 2 classes.
 Found 6251 images belonging to 2 classes.
```

Applies a random transformation to an image.

Generators does almost everything that we need in a robust way by just parameterizing what we need. in this case because the image shapes where Heterogeneous in nature, we took a target size of 128,128 to transform every image into that size.

```
[17]: total_data = train_generator.samples + validation_generator.samples
 print('Classes Include : ',train_generator.class_indices)
 print('Train Samples : ', train_generator.samples)
 print('Validation/Test Samples : ', validation_generator.samples)
 print('Total Samples present (cats+dogs) : ', total_data)
 print('Transformed Image shape : ',train_generator.image_shape)
 print('Color Channels : (RGB)', train_generator.image_shape[2])
Classes Include : {'CAT': 0, 'DOG': 1}
```

Train Samples: 18743
Validation/Test Samples: 6251
Total Samples present (cats+dogs): 24994
Transformed Image shape: (128, 128, 3)
Color Channels: (RGB) 3

## 0.0.5 Ordinary Convolutional Neural Network Method

```
[18]: import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Flatten,

→BatchNormalization, Activation, Dropout
```

```
[35]: net.summary()
 Model: "sequential_1"
 Layer (type) Output Shape
 Param #

 conv2d_3 (Conv2D)
 (None, 126, 126, 32)
 max_pooling2d_3 (MaxPooling2 (None, 63, 63, 32) 0
 conv2d_4 (Conv2D)
 (None, 61, 61, 64)
 max_pooling2d_4 (MaxPooling2 (None, 30, 30, 64)
 (None, 28, 28, 128) 73856
 conv2d 5 (Conv2D)
 max_pooling2d_5 (MaxPooling2 (None, 14, 14, 128)

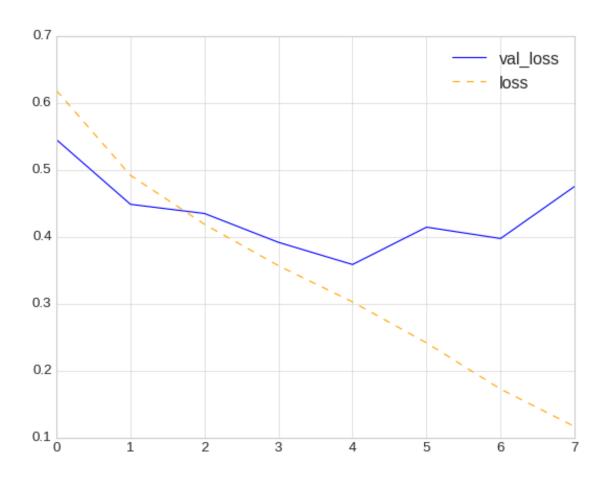
 (None, 25088)
 flatten_1 (Flatten)
 dense_2 (Dense)
 (None, 512)
 12845568
 dense_3 (Dense) (None, 1)
 513

 Total params: 12,939,329
 Trainable params: 12,939,329
 Non-trainable params: 0

[36]: from tensorflow.keras.callbacks import EarlyStopping
 adam = tf.keras.optimizers.Adam(lr=0.001)
[37]: net.compile(optimizer=adam, loss='binary_crossentropy', metrics=['accuracy'])
[38]:
 early_stop = EarlyStopping(patience=3)
[39]: import time
 start = time.perf_counter()
 perf = net.fit_generator(train_generator, epochs=15,__
 →callbacks=[early_stop], validation_data=validation_generator)
 elapsed = time.perf_counter()- start
 print('Elapsed {}'.format(elapsed/60))
```

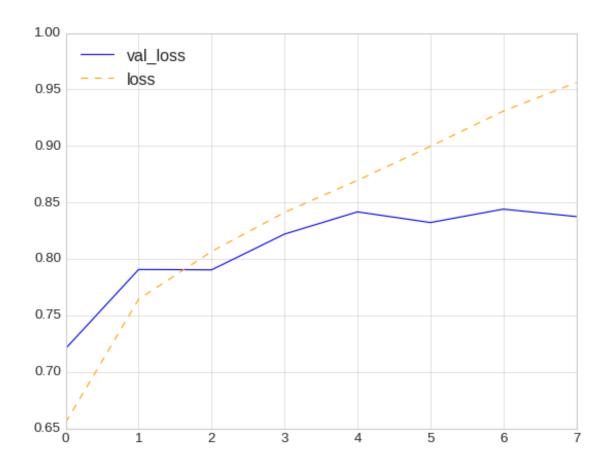
```
/usr/local/lib/python3.6/dist-
packages/tensorflow/python/keras/engine/training.py:1844: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version.
Please use `Model.fit`, which supports generators.
 warnings.warn('`Model.fit_generator` is deprecated and '
Epoch 1/15
 2/293 [...] - ETA: 1:07 - loss: 1.2549 - accuracy:
0.4570
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
Possibly corrupt EXIF data. Expecting to read 32 bytes but only got 0. Skipping
 " Skipping tag %s" % (size, len(data), tag)
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
Possibly corrupt EXIF data. Expecting to read 5 bytes but only got 0. Skipping
tag 271
 " Skipping tag %s" % (size, len(data), tag)
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
Possibly corrupt EXIF data. Expecting to read 8 bytes but only got 0. Skipping
tag 272
 " Skipping tag %s" % (size, len(data), tag)
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
Possibly corrupt EXIF data. Expecting to read 8 bytes but only got 0. Skipping
tag 282
 " Skipping tag %s" % (size, len(data), tag)
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
Possibly corrupt EXIF data. Expecting to read 8 bytes but only got 0. Skipping
tag 283
 " Skipping tag %s" % (size, len(data), tag)
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
Possibly corrupt EXIF data. Expecting to read 20 bytes but only got 0. Skipping
tag 306
 "Skipping tag %s" % (size, len(data), tag)
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
Possibly corrupt EXIF data. Expecting to read 48 bytes but only got 0. Skipping
tag 532
 "Skipping tag %s" % (size, len(data), tag)
/usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:788: UserWarning:
Corrupt EXIF data. Expecting to read 2 bytes but only got 0.
 warnings.warn(str(msg))
293/293 [===========] - 92s 312ms/step - loss: 0.6959 -
accuracy: 0.5951 - val_loss: 0.5447 - val_accuracy: 0.7207
Epoch 2/15
accuracy: 0.7472 - val_loss: 0.4482 - val_accuracy: 0.7906
Epoch 3/15
```

```
accuracy: 0.8010 - val_loss: 0.4345 - val_accuracy: 0.7903
 Epoch 4/15
 accuracy: 0.8409 - val_loss: 0.3913 - val_accuracy: 0.8219
 Epoch 5/15
 293/293 [============] - 92s 313ms/step - loss: 0.3031 -
 accuracy: 0.8719 - val_loss: 0.3582 - val_accuracy: 0.8416
 Epoch 6/15
 293/293 [============] - 92s 314ms/step - loss: 0.2391 -
 accuracy: 0.9005 - val_loss: 0.4140 - val_accuracy: 0.8322
 Epoch 7/15
 accuracy: 0.9329 - val_loss: 0.3971 - val_accuracy: 0.8440
 Epoch 8/15
 accuracy: 0.9560 - val_loss: 0.4748 - val_accuracy: 0.8375
 Elapsed 12.185325518533329
[40]: loss, acc = net.evaluate_generator(validation_generator)
 /usr/local/lib/python3.6/dist-
 packages/tensorflow/python/keras/engine/training.py:1877: UserWarning:
 `Model.evaluate_generator` is deprecated and will be removed in a future
 version. Please use `Model.evaluate`, which supports generators.
 warnings.warn('`Model.evaluate_generator` is deprecated and '
[44]: # validation Accuracy
 print('Validation Accuracy - {:.2f}%'.format(acc*100))
 print('validation loss - {:.2f}'.format(loss))
 Validation Accuracy - 83.75%
 validation loss - 0.47
[43]: history = pd.DataFrame(perf.history)
[43]:
[45]: plt.style.use('seaborn-whitegrid')
 plt.plot(history['val_loss'], ls='-',color='blue',label='val_loss')
 plt.plot(history['loss'],ls='--',color='orange',label='loss')
 plt.legend()
[45]: <matplotlib.legend.Legend at 0x7f234a9e0198>
```



```
[50]: plt.style.use('seaborn-whitegrid')
 plt.plot(history['val_accuracy'], ls='-',color='blue',label='val_loss')
 plt.plot(history['accuracy'],ls='--',color='orange',label='loss')
 plt.legend(loc='upper left')
```

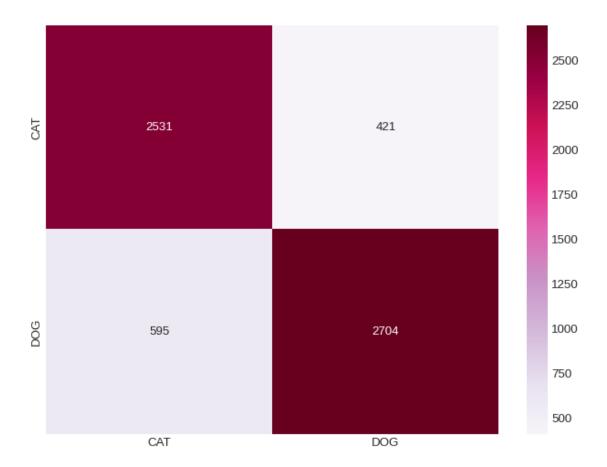
[50]: <matplotlib.legend.Legend at 0x7f234a6bb4a8>



```
[54]: from sklearn.metrics import classification_report, confusion_matrix
[55]: print(classification_report(preds, validation_generator.classes))
 precision
 recall f1-score
 support
 False
 0.81
 0.86
 0.83
 2952
 True
 0.87
 0.82
 0.84
 3299
 0.84
 6251
 accuracy
 macro avg
 0.84
 0.84
 0.84
 6251
 weighted avg
 0.84
 0.84
 0.84
 6251
 []:
[56]: plt.figure(figsize=(10,7))
 plt.suptitle('Confusion Matrix')
 confmat = pd.DataFrame(confusion_matrix(preds, validation_generator.classes),_
 →columns=validation_generator.class_indices.keys())
 confmat.index = validation_generator.class_indices.keys()
 sns.heatmap(confmat, annot=True, fmt='d', cmap='PuRd')
```

[56]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f23ac2deba8>

#### Confusion Matrix



The Classic case of Misclassifying dogs as cats and cats as dogs. the latter one is mostly happening i.cats as dogs classification

```
[94]: net.save('CovnNet(cats&dogs).h5')
```

### 0.0.6 Inference

While the training Set Accuracy steadily increases till it reaches 90 the validation accuracy is stall at 80's, it is clearly the case of overfitting or high variance scenario.

```
[83]: from tensorflow.keras.applications import MobileNetV2

[84]: train_generator.image_shape

[84]: (128, 128, 3)

[85]: conv_base = MobileNetV2(input_shape=train_generator.image_shape, □

→include top=False, weights='imagenet')
```

```
[86]: conv_base.trainable
[86]: True
[87]: # freezing layers
 conv_base.trainable= False
[88]: conv_base.summary()
 Model: "mobilenetv2_1.00_128"
 Output Shape Param # Connected to
 Layer (type)

 ==========
 input_2 (InputLayer)
 [(None, 128, 128, 3) 0

 (None, 64, 64, 32) 864 input_2[0][0]
 Conv1 (Conv2D)

 bn_Conv1 (BatchNormalization) (None, 64, 64, 32) 128 Conv1[0][0]
 Conv1_relu (ReLU)
 (None, 64, 64, 32) 0 bn_Conv1[0][0]
 expanded_conv_depthwise (Depthw (None, 64, 64, 32)
 288
 Conv1_relu[0][0]
 expanded_conv_depthwise_BN (Bat (None, 64, 64, 32) 128
 expanded_conv_depthwise[0][0]

 expanded_conv_depthwise_relu (R (None, 64, 64, 32) 0
 expanded_conv_depthwise_BN[0][0]
 expanded_conv_project (Conv2D) (None, 64, 64, 16)
 512
 expanded_conv_depthwise_relu[0][0

 expanded_conv_project_BN (Batch (None, 64, 64, 16) 64
 expanded_conv_project[0][0]
```

block_1_expand (Conv2D) expanded_conv_project_BN[0][0]	(None,	64,	64,	96)	1536
block_1_expand_BN (BatchNormaliblock_1_expand[0][0]				96)	384
block_1_expand_relu (ReLU) block_1_expand_BN[0][0]	(None,			96)	0
block_1_pad (ZeroPadding2D) block_1_expand_relu[0][0]	(None,	65,	65,	96)	0
block_1_depthwise (DepthwiseCon block_1_pad[0][0]	(None,	32,	32,	96)	864
block_1_depthwise_BN (BatchNorm block_1_depthwise[0][0]					384
block_1_depthwise_relu (ReLU) block_1_depthwise_BN[0][0]	(None,	32,	32,	96)	0
block_1_project (Conv2D) block_1_depthwise_relu[0][0]	(None,				2304
block_1_project_BN (BatchNormal block_1_project[0][0]	,	Í	Í	·	96
block_2_expand (Conv2D) block_1_project_BN[0][0]	(None,	32,	32,	144)	
block_2_expand_BN (BatchNormaliblock_2_expand[0][0]	(None,	32,	32,	144)	
block_2_expand_relu (ReLU) block_2_expand_BN[0][0]	(None,	32,	32,	144)	
				<b>-</b>	:

block_2_depthwise (DepthwiseCon block_2_expand_relu[0][0]	(None,	32,	32,	144)	1296
block_2_depthwise_BN (BatchNorm block_2_depthwise[0][0]	(None,	32,	32,	144)	576
block_2_depthwise_relu (ReLU) block_2_depthwise_BN[0][0]	(None,	32,			0
block_2_project (Conv2D) block_2_depthwise_relu[0][0]	(None,	32,	32,	24)	3456
block_2_project[0][0]	(None,	32,	32,	24)	96
block_2_add (Add) block_1_project_BN[0][0] block_2_project_BN[0][0]	(None,	32,	32,	24)	0
block_3_expand (Conv2D) block_2_add[0][0]	(None,				3456
block_3_expand_BN (BatchNormaliblock_3_expand[0][0]	(None,	32,	32,	144)	576
block_3_expand_relu (ReLU) block_3_expand_BN[0][0]	(None,	32,	32,	144)	0
block_3_pad (ZeroPadding2D) block_3_expand_relu[0][0]	(None,				0
block_3_depthwise (DepthwiseCon block_3_pad[0][0]					
block_3_depthwise_BN (BatchNorm block_3_depthwise[0][0]	(None,	16,	16,	144)	576

```
block_3_depthwise_relu (ReLU) (None, 16, 16, 144) 0
block_3_depthwise_BN[0][0]
block_3_project (Conv2D)
 (None, 16, 16, 32) 4608
block 3 depthwise relu[0][0]

block_3_project_BN (BatchNormal (None, 16, 16, 32) 128
block_3_project[0][0]
block_4_expand (Conv2D)
 (None, 16, 16, 192) 6144
block_3_project_BN[0][0]
block_4_expand_BN (BatchNormali (None, 16, 16, 192) 768
block_4_expand[0][0]

block_4_expand_relu (ReLU) (None, 16, 16, 192) 0
block_4_expand_BN[0][0]

block_4_depthwise (DepthwiseCon (None, 16, 16, 192) 1728
block_4_expand_relu[0][0]

block_4_depthwise_BN (BatchNorm (None, 16, 16, 192) 768
block_4_depthwise[0][0]

block_4_depthwise_relu (ReLU) (None, 16, 16, 192) 0
block 4 depthwise BN[0][0]

block_4_project (Conv2D) (None, 16, 16, 32) 6144
block_4_depthwise_relu[0][0]

block_4_project_BN (BatchNormal (None, 16, 16, 32)
block_4_project[0][0]
block_4_add (Add)
 (None, 16, 16, 32) 0
block_3_project_BN[0][0]
block_4_project_BN[0][0]
```

block_5_expand (Conv2D) block_4_add[0][0]	(None,	16,	16,	192)	6144
block_5_expand_BN (BatchNormaliblock_5_expand[0][0]					768
block_5_expand_relu (ReLU) block_5_expand_BN[0][0]	(None,	16,	16,	192)	0
block_5_depthwise (DepthwiseCon block_5_expand_relu[0][0]	(None,	16,	16,	192)	1728
block_5_depthwise_BN (BatchNorm block_5_depthwise[0][0]	(None,	16,	16,	192)	768
block_5_depthwise_relu (ReLU) block_5_depthwise_BN[0][0]	(None,				
block_5_project (Conv2D) block_5_depthwise_relu[0][0]	(None,	16,	16,	32)	6144
block_5_project[0][0]					128
block_5_add (Add) block_4_add[0][0] block_5_project_BN[0][0]	(None,	16,	16,	32)	0
block_6_expand (Conv2D) block_5_add[0][0]	(None,				
block_6_expand_BN (BatchNormaliblock_6_expand[0][0]					
block_6_expand_relu (ReLU)	(None,				

block_6_expand_BN[0][0]		
block_6_pad (ZeroPadding2D) block_6_expand_relu[0][0]	(None, 17, 17, 192)	0
block_6_depthwise (DepthwiseCon block_6_pad[0][0]	(None, 8, 8, 192)	1728
block_6_depthwise_BN (BatchNorm block_6_depthwise[0][0]	(None, 8, 8, 192)	768
block_6_depthwise_relu (ReLU) block_6_depthwise_BN[0][0]	(None, 8, 8, 192)	0
block_6_project (Conv2D) block_6_depthwise_relu[0][0]	(None, 8, 8, 64)	12288
block_6_project_BN (BatchNormal block_6_project[0][0]	(None, 8, 8, 64)	256
block_7_expand (Conv2D) block_6_project_BN[0][0]	(None, 8, 8, 384)	24576
block_7_expand_BN (BatchNormaliblock_7_expand[0][0]	(None, 8, 8, 384)	1536
block_7_expand_relu (ReLU) block_7_expand_BN[0][0]	(None, 8, 8, 384)	0
block_7_depthwise (DepthwiseCon block_7_expand_relu[0][0]		3456
block_7_depthwise_BN (BatchNorm block_7_depthwise[0][0]	(None, 8, 8, 384)	1536
block_7_depthwise_relu (ReLU)		0

block_7_depthwise_BN[0][0]		
block_7_project (Conv2D) block_7_depthwise_relu[0][0]	(None, 8, 8, 64)	24576
block_7_project_BN (BatchNormal block_7_project[0][0]	(None, 8, 8, 64)	256
block_7_add (Add) block_6_project_BN[0][0] block_7_project_BN[0][0]	(None, 8, 8, 64)	0
block_8_expand (Conv2D) block_7_add[0][0]	(None, 8, 8, 384)	24576
block_8_expand_BN (BatchNormaliblock_8_expand[0][0]	(None, 8, 8, 384)	1536
block_8_expand_relu (ReLU) block_8_expand_BN[0][0]	(None, 8, 8, 384)	0
block_8_depthwise (DepthwiseCon block_8_expand_relu[0][0]	(None, 8, 8, 384)	3456
block_8_depthwise_BN (BatchNorm block_8_depthwise[0][0]		1536
block_8_depthwise_relu (ReLU) block_8_depthwise_BN[0][0]	(None, 8, 8, 384)	0
block_8_project (Conv2D) block_8_depthwise_relu[0][0]	(None, 8, 8, 64)	24576
block_8_project_BN (BatchNormal block_8_project[0][0]	(None, 8, 8, 64)	256

block_8_add (Add) block_7_add[0][0] block_8_project_BN[0][0]	(None,	8,	8,	64)	0
block_9_expand (Conv2D) block_8_add[0][0]	(None,	8,	8,	384)	24576
block_9_expand_BN (BatchNormaliblock_9_expand[0][0]	(None,	8,	8,	384)	1536
block_9_expand_relu (ReLU) block_9_expand_BN[0][0]	(None,	8,	8,	384)	0
block_9_depthwise (DepthwiseCon block_9_expand_relu[0][0]	(None,	8,	8,	384)	3456
block_9_depthwise_BN (BatchNorm block_9_depthwise[0][0]	(None,	8,	8,	384)	1536
block_9_depthwise_relu (ReLU) block_9_depthwise_BN[0][0]	(None,	8,	8,	384)	0
block_9_project (Conv2D) block_9_depthwise_relu[0][0]	(None,	8,	8,	64)	24576
block_9_project_BN (BatchNormal block_9_project[0][0]					256
block_9_add (Add) block_8_add[0][0] block_9_project_BN[0][0]				64)	0
block_10_expand (Conv2D) block_9_add[0][0]				384)	24576
block_10_expand_BN (BatchNormal block_10_expand[0][0]	(None,	8,	8,	384)	1536

block_10_expand_relu (ReLU) block_10_expand_BN[0][0]	(None, 8, 8, 384)	0
block_10_depthwise (DepthwiseCoblock_10_expand_relu[0][0]	(None, 8, 8, 384)	3456
block_10_depthwise_BN (BatchNorblock_10_depthwise[0][0]	(None, 8, 8, 384)	1536
block_10_depthwise_relu (ReLU) block_10_depthwise_BN[0][0]	(None, 8, 8, 384)	0
block_10_project (Conv2D) block_10_depthwise_relu[0][0]	(None, 8, 8, 96)	36864
block_10_project_BN (BatchNormablock_10_project[0][0]		384
block_11_expand (Conv2D) block_10_project_BN[0][0]	(None, 8, 8, 576)	55296
block_11_expand_BN (BatchNormal block_11_expand[0][0]	(None, 8, 8, 576)	2304
block_11_expand_relu (ReLU) block_11_expand_BN[0][0]	(None, 8, 8, 576)	0
block_11_depthwise (DepthwiseCoblock_11_expand_relu[0][0]		5184
block_11_depthwise_BN (BatchNorblock_11_depthwise[0][0]	(None, 8, 8, 576)	2304
block_11_depthwise_relu (ReLU) block_11_depthwise_BN[0][0]	(None, 8, 8, 576)	0

block_11_project (Conv2D) block_11_depthwise_relu[0][0]	(None, 8, 8, 96)	) 55296
block_11_project_BN (BatchNorma block_11_project[0][0]	(None, 8, 8, 96)	) 384
block_11_add (Add) block_10_project_BN[0][0] block_11_project_BN[0][0]	(None, 8, 8, 96)	) 0
block_12_expand (Conv2D) block_11_add[0][0]	(None, 8, 8, 576	6) 55296
block_12_expand_BN (BatchNormal block_12_expand[0][0]	(None, 8, 8, 576	6) 2304
block_12_expand_BN[0][0]	(None, 8, 8, 576	6) 0
block_12_depthwise (DepthwiseCoblock_12_expand_relu[0][0]	(None, 8, 8, 576	6) 5184
block_12_depthwise[0][0]	(None, 8, 8, 576	6) 2304
block_12_depthwise_BN[0][0]		6) 0
block_12_project (Conv2D) block_12_depthwise_relu[0][0]	(None, 8, 8, 96)	
block_12_project[0][0]		) 384
block_12_add (Add)	(None, 8, 8, 96)	

block_11_add[0][0] block_12_project_BN[0][0]					
block_13_expand (Conv2D) block_12_add[0][0]	(None,	8,	8,	576)	55296
block_13_expand_BN (BatchNormal block_13_expand[0][0]	(None,	8,	8,	576)	2304
block_13_expand_relu (ReLU) block_13_expand_BN[0][0]	(None,	8,	8,	576)	0
block_13_pad (ZeroPadding2D) block_13_expand_relu[0][0]	(None,	9,	9,	576)	0
block_13_depthwise (DepthwiseCoblock_13_pad[0][0]				576)	5184
block_13_depthwise_BN (BatchNorblock_13_depthwise[0][0]				576)	2304
block_13_depthwise_relu (ReLU) block_13_depthwise_BN[0][0]	(None,	4,	4,	576)	0
block_13_project (Conv2D) block_13_depthwise_relu[0][0]	(None,	,	,		92160
block_13_project_BN (BatchNorma block_13_project[0][0]	(None,	4,	4,	160)	640
block_14_expand (Conv2D) block_13_project_BN[0][0]	(None,	4,	4,	960)	
block_14_expand_BN (BatchNormal block_14_expand[0][0]					3840
	<b>-</b>			<b>_</b>	<b></b>

block_14_expand_relu (ReLU) block_14_expand_BN[0][0]	(None,	4,	4,	960)	0
block_14_depthwise (DepthwiseCoblock_14_expand_relu[0][0]	(None,	4,	4,	960)	8640
block_14_depthwise_BN (BatchNorblock_14_depthwise[0][0]	(None,	4,	4,	960)	3840
block_14_depthwise_relu (ReLU) block_14_depthwise_BN[0][0]	(None,	4,	4,	960)	0
block_14_project (Conv2D) block_14_depthwise_relu[0][0]	(None,	4,	4,	160)	153600
block_14_project_BN (BatchNorma block_14_project[0][0]	(None,	4,	4,	160)	640
block_14_add (Add) block_13_project_BN[0][0] block_14_project_BN[0][0]	(None,	4,	4,	160)	0
block_15_expand (Conv2D) block_14_add[0][0]	(None,	4,	4,	960)	153600
block_15_expand_BN (BatchNormal block_15_expand[0][0]	(None,	4,	4,	960)	3840
block_15_expand_relu (ReLU) block_15_expand_BN[0][0]	(None,				0
block_15_depthwise (DepthwiseCoblock_15_expand_relu[0][0]					8640
block_15_depthwise_BN (BatchNorblock_15_depthwise[0][0]	(None,	4,	4,	960)	3840

```
block_15_depthwise_relu (ReLU) (None, 4, 4, 960)
block_15_depthwise_BN[0][0]
block_15_project (Conv2D)
 (None, 4, 4, 160) 153600
block 15 depthwise relu[0][0]

block_15_project_BN (BatchNorma (None, 4, 4, 160) 640
block_15_project[0][0]
block_15_add (Add)
 (None, 4, 4, 160)
block_14_add[0][0]
block_15_project_BN[0][0]
block_16_expand (Conv2D) (None, 4, 4, 960)
 153600
block_15_add[0][0]

block_16_expand_BN (BatchNormal (None, 4, 4, 960)
 3840
block_16_expand[0][0]

block_16_expand_relu (ReLU) (None, 4, 4, 960) 0
block_16_expand_BN[0][0]

block_16_depthwise (DepthwiseCo (None, 4, 4, 960)
 8640
block_16_expand_relu[0][0]

block_16_depthwise_BN (BatchNor (None, 4, 4, 960)
 3840
block 16 depthwise[0][0]

block_16_depthwise_relu (ReLU) (None, 4, 4, 960)
block_16_depthwise_BN[0][0]

block_16_project (Conv2D)
 (None, 4, 4, 320) 307200
block_16_depthwise_relu[0][0]

block_16_project_BN (BatchNorma (None, 4, 4, 320)
 1280
block_16_project[0][0]
```

```
Conv_1 (Conv2D)
 (None, 4, 4, 1280) 409600
 block_16_project_BN[0][0]
 Conv_1_bn (BatchNormalization) (None, 4, 4, 1280) 5120 Conv_1[0][0]

 out_relu (ReLU)
 (None, 4, 4, 1280) 0
 Conv_1_bn[0][0]

 ==============
 Total params: 2,257,984
 Trainable params: 0
 Non-trainable params: 2,257,984

[90]: model = Sequential()
 model.add(conv_base)
 model.add(Flatten())
 model.add(Dense(128, activation='relu'))
 model.add(Dense(1,activation='sigmoid'))
[92]: model.summary()
 Model: "sequential_4"
 Output Shape
 Layer (type)
 mobilenetv2_1.00_128 (Functi (None, 4, 4, 1280)
 2257984

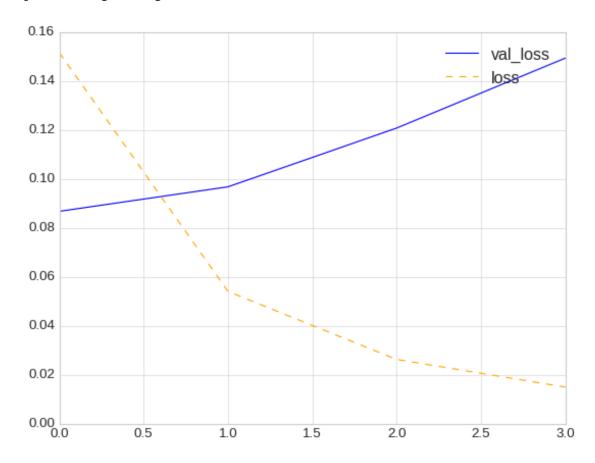
 flatten_6 (Flatten)
 (None, 20480)
 dense_12 (Dense)
 (None, 128)
 2621568
 dense_13 (Dense)
 (None, 1)
 129

 Total params: 4,879,681
 Trainable params: 2,621,697
 Non-trainable params: 2,257,984
```

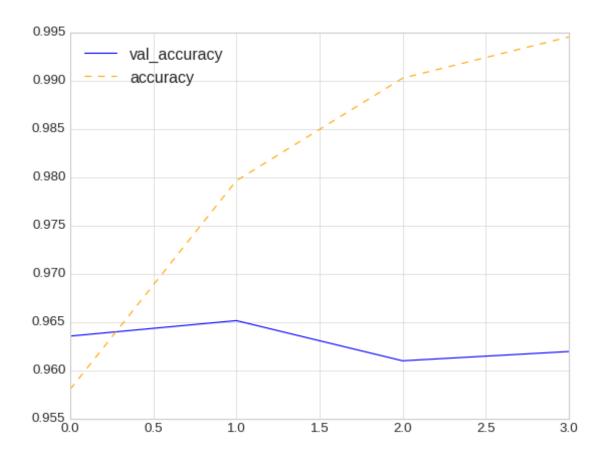
```
[95]: model.compile(optimizer='adam', loss='binary_crossentropy',metrics=['accuracy'])
[96]: import time
 start = time.perf_counter()
 perf = model.fit_generator(train_generator, epochs=15,__
 →callbacks=[early_stop], validation_data=validation_generator)
 elapsed = time.perf_counter()- start
 print('Elapsed {}'.format(elapsed/60))
 /usr/local/lib/python3.6/dist-
 packages/tensorflow/python/keras/engine/training.py:1844: UserWarning:
 `Model.fit_generator` is deprecated and will be removed in a future version.
 Please use `Model.fit`, which supports generators.
 warnings.warn('`Model.fit_generator` is deprecated and '
 Epoch 1/15
 0.9396
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
 Possibly corrupt EXIF data. Expecting to read 32 bytes but only got 0. Skipping
 tag 270
 " Skipping tag %s" % (size, len(data), tag)
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
 Possibly corrupt EXIF data. Expecting to read 5 bytes but only got 0. Skipping
 tag 271
 " Skipping tag %s" % (size, len(data), tag)
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
 Possibly corrupt EXIF data. Expecting to read 8 bytes but only got 0. Skipping
 tag 272
 "Skipping tag %s" % (size, len(data), tag)
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
 Possibly corrupt EXIF data. Expecting to read 8 bytes but only got 0. Skipping
 tag 282
 " Skipping tag %s" % (size, len(data), tag)
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
 Possibly corrupt EXIF data. Expecting to read 8 bytes but only got 0. Skipping
 tag 283
 " Skipping tag %s" % (size, len(data), tag)
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
 Possibly corrupt EXIF data. Expecting to read 20 bytes but only got 0. Skipping
 tag 306
 " Skipping tag %s" % (size, len(data), tag)
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:770: UserWarning:
```

```
Possibly corrupt EXIF data. Expecting to read 48 bytes but only got 0. Skipping
 tag 532
 "Skipping tag %s" % (size, len(data), tag)
 /usr/local/lib/python3.6/dist-packages/PIL/TiffImagePlugin.py:788: UserWarning:
 Corrupt EXIF data. Expecting to read 2 bytes but only got 0.
 warnings.warn(str(msg))
 accuracy: 0.9410 - val_loss: 0.0867 - val_accuracy: 0.9635
 Epoch 2/15
 293/293 [============] - 89s 303ms/step - loss: 0.0524 -
 accuracy: 0.9800 - val_loss: 0.0967 - val_accuracy: 0.9651
 Epoch 3/15
 accuracy: 0.9907 - val_loss: 0.1207 - val_accuracy: 0.9610
 Epoch 4/15
 accuracy: 0.9939 - val_loss: 0.1493 - val_accuracy: 0.9619
 Elapsed 5.979793827750003
[97]: new_loss, new_acc = model.evaluate_generator(validation_generator)
 /usr/local/lib/python3.6/dist-
 packages/tensorflow/python/keras/engine/training.py:1877: UserWarning:
 `Model.evaluate_generator` is deprecated and will be removed in a future
 version. Please use `Model.evaluate`, which supports generators.
 warnings.warn('`Model.evaluate_generator` is deprecated and '
[98]: print('Validation Accuracy - {:.2f}%'.format(new_acc*100))
 print('validation loss - {:.2f}'.format(new_loss))
 Validation Accuracy - 96.19%
 validation loss - 0.15
[99]: model_history = pd.DataFrame(perf.history)
[100]: model_history
[100]:
 loss accuracy val_loss val_accuracy
 0 0.151495 0.958011 0.086692
 0.963526
 1 0.053979 0.979619 0.096691
 0.965126
 2 0.026196 0.990236 0.120692
 0.960966
 3 0.014898 0.994505 0.149257
 0.961926
[101]: plt.style.use('seaborn-whitegrid')
 plt.plot(model_history['val_loss'], ls='-',color='blue',label='val_loss')
 plt.plot(model_history['loss'],ls='--',color='orange',label='loss')
 plt.legend()
```

[101]: <matplotlib.legend.Legend at 0x7f22163a81d0>



[103]: <matplotlib.legend.Legend at 0x7f22149be6d8>



```
[104]: pred_probs = model.predict_generator(validation_generator)
preds = pred_probs > 0.5
```

/usr/local/lib/python3.6/dist-

packages/tensorflow/python/keras/engine/training.py:1905: UserWarning:

`Model.predict\_generator` is deprecated and will be removed in a future version. Please use `Model.predict`, which supports generators.

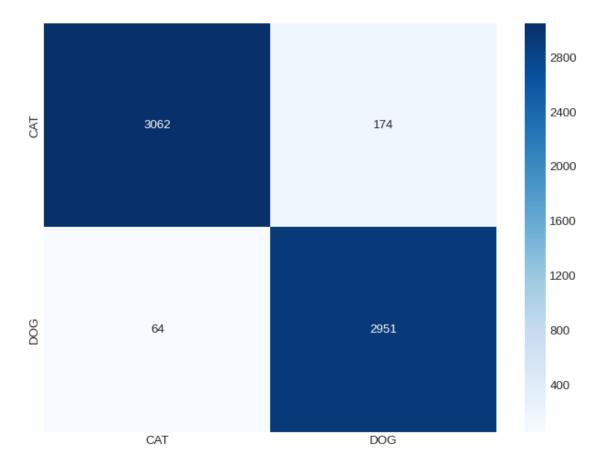
warnings.warn('`Model.predict\_generator` is deprecated and '

[105]: print(classification\_report(preds, validation\_generator.classes))

	precision	recall	f1-score	support
False	0.98	0.95	0.96	3236
True	0.94	0.98	0.96	3015
accuracy			0.96	6251
macro avg	0.96	0.96	0.96	6251
weighted avg	0.96	0.96	0.96	6251

[106]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f22163e8d68>

#### Confusion Matrix



## 1 Inference-2

With MobileNetV2 + custom output layer, the model achieved 99% on training set and 96% on the Validation Set, this difference indicates that the model is overfitting on the training set, but this is not prominent to finetune futher generally. But to create a state of the art cats & dogs classifier we can futhur fine-tune it to reduce that 3% of variance with techniques like Dropout and L2 Regularisation.

```
[107]: model.save('Cats&Dogs-MovbileNetv2.h5')
```

### 1.1 Miscellaneous

```
[108]: import os
 path = './samples/'
 overview_path = './samples/overview.txt'
 eval_path = './samples/evaluate.txt'

if os.path.exists(path):
 print('samples dir, exists..checking for dictionaries existence..')

 if os.path.exists(overview_path) and os.path.exists(eval_path):
 print('Data exists. no need of overwritting.')
 else:
 print("overview and eval doesn't exist, proceed to step-2")

else:
 print("samples/ dir is non-existent, Establishing one..")
 os.mkdir(path) # samples directory
```

samples/ dir is non-existent, Establishing one..

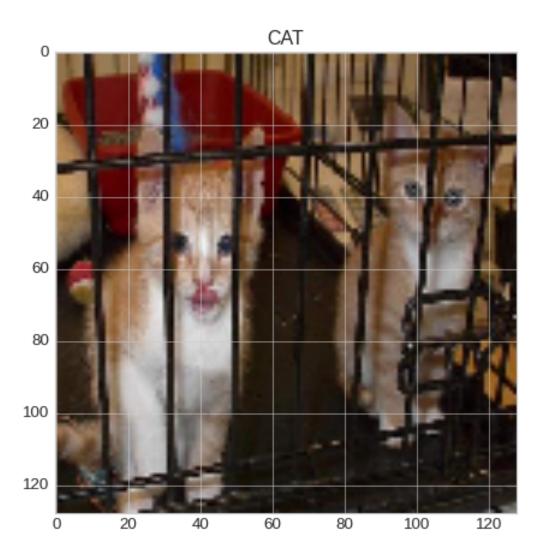
```
[110]: x_train, y_train = next(train_generator) # one batch
x_test, y_test = next(validation_generator) # one batch
```

```
[136]: classes = np.array(list(validation_generator.class_indices))
x = np.array((x_train[0], x_train[7], x_train[10]))
y = np.array((y_train[0], y_train[7], y_train[10]))
```

```
[147]: y = ['CAT', 'DOG', 'CAT']
```

```
[148]: plt.imshow(x[2]) plt.title(y[2])
```

[148]: Text(0.5, 1.0, 'CAT')



```
dimensions = x_train.shape
 #labels : str(list of unique target values)
 targets = list(validation_generator.class_indices.values())
 #nd.array
 data = x
 #nd.array or class_names
 labels = y
 vars0 = ['kind','dimensions', 'targets', 'data', 'labels']
 # filling overview_dict
 for x in vars0:
 try:
 overview_dict[x] = eval(x)
 except:
 overview_dict[x] = x
 # evaluate_dict
 eval_dict = {'test_cases' : x_train, 'true': y_train, 'class_names':_
 →['CAT','DOG'] ,'model':'/model.h5'}
[159]: import pickle
 # dump 1
 with open(overview_path,'wb') as f:
 pickle.dump(overview_dict,f)
 # dump 2
 with open(eval_path, 'wb') as f:
 pickle.dump(eval_dict,f)
[160]: model.summary()
 Model: "sequential 4"

 Layer (type)
 Output Shape Param #
 mobilenetv2_1.00_128 (Functi (None, 4, 4, 1280) 2257984

 flatten_6 (Flatten) (None, 20480)

 dense_12 (Dense)
 (None, 128)
 2621568
 dense_13 (Dense) (None, 1)
 129
 Total params: 4,879,681
 Trainable params: 2,621,697
```

## Non-trainable params: 2,257,984

-----

s = '''			
Model: "sequential_4"			
Layer (type)	Output	Shape	Param #
mobilenetv2_1.00_128 (Functi	(None,	4, 4, 1280)	2257984
flatten_6 (Flatten)			
dense_12 (Dense)			2621568
dense_13 (Dense)	(None,	1)	129
Total params: 4,879,681 Trainable params: 2,621,697 Non-trainable params: 2,257,9			
111			

report = '''					
	precision	recall	f1-score	support	
False	0.98	0.95	0.96	3236	
True	0.94	0.98	0.96	3015	
accuracy			0.96	6251	
macro avg	0.96	0.96	0.96	6251	
weighted avg	0.96	0.96	0.96	6251	
1.1.1					
	False True accuracy macro avg weighted avg	precision  False 0.98 True 0.94  accuracy macro avg 0.96 weighted avg 0.96	precision recall  False 0.98 0.95 True 0.94 0.98  accuracy macro avg 0.96 0.96 weighted avg 0.96 0.96	precision recall f1-score  False 0.98 0.95 0.96 True 0.94 0.98 0.96  accuracy 0.96 macro avg 0.96 0.96 0.96 weighted avg 0.96 0.96 0.96	precision         recall         f1-score         support           False         0.98         0.95         0.96         3236           True         0.94         0.98         0.96         3015           accuracy         0.96         6251           macro avg         0.96         0.96         0.96         6251           weighted avg         0.96         0.96         0.96         6251

# []:

# [166]: synopsis = '''

For this problem two Implementations were used with Two inferences at the end  $_{\!\sqcup}$   $_{\!\hookrightarrow}\text{of}$  each implementation

exe-1 = ConvNet from Scratch

- \* A ConvNet was built from scratch with 3 Conv2D, 3 MaxPool, 1 Flatten and  $2_{\sqcup}$   $\hookrightarrow$ Dense Layers with Output function as Sigmoid ( you can find the  $_{\sqcup}$   $\hookrightarrow$  implementation in the ipynb-pdf ).
- \* This ConvNet was set for 15 epochs with EarlyStopping Callback of patience 3. $_{\sqcup}$   $_{\hookrightarrow}$ The Elapsed Training time was 12.18 Mins on Cloud GPU instance of only 8 $_{\sqcup}$   $_{\hookrightarrow}$ epochs of the stipulated 15.
- \* Attained Training Accuracy 95.60% and Validation Accuracy 83.75% with approx. 8% difference, This network was overfitting with an average f1-score of 84%.
- \* This Network had the classic case of misclassifying cats as dogs.

#### exe-2 = MobileNetv2 ( Frozen )

- \* Convbase of MobileNetV2 with ImageNet weights and Frozen layers was →constructed.
- \* Custom Output layers of 1 Flatten, 2 Dense was attached at the end.
- \* Same as the previous implementation the model was set to 15 epochs with same  $_{\sqcup}$   $_{\hookrightarrow}$ EarlyStopping Setup. Elapsed Training time is 5 Mins with 3 Epochs of  $_{\sqcup}$   $_{\hookrightarrow}$ Training.
- \* This Time the Model Performed well enough with the pre-trained ImageNet $_{\sqcup}$   $_{\hookrightarrow}$ Weights. The misclassification problem from the first case was smoothened.
- \* With \*\*MobileNetV2\*\* + custom output layer, the model achieved 99% on  $_{\square}$   $_{\hookrightarrow}$  training set and 96% on the Validation Set, this difference indicates that  $_{\square}$   $_{\hookrightarrow}$  the model is overfitting on the training set, but this is not prominent to  $_{\square}$   $_{\hookrightarrow}$  fine tune further generally. But to create a state of the art cats & dogs  $_{\square}$   $_{\hookrightarrow}$  classifier we can futhur fine-tune it to reduce that 3% of variance with  $_{\square}$   $_{\hookrightarrow}$  techniques like Dropout and L2 Regularisation.

1.1.1

### [167]: print(synopsis)

For this problem two Implementations were used with Two inferences at the end of each implementation

### exe-1 = ConvNet from Scratch

- \* A ConvNet was built from scratch with 3 Conv2D, 3 MaxPool, 1 Flatten and 2 Dense Layers with Output function as Sigmoid ( you can find the implementation in the ipynb-pdf ).
- \* This ConvNet was set for 15 epochs with EarlyStopping Callback of patience 3. The Elapsed Training time was 12.18 Mins on Cloud GPU instance of only 8 epochs of the stipulated 15.

- \* Attained Training Accuracy 95.60% and Validation Accuracy 83.75% with approx. 8% difference, This network was overfitting with an average f1-score of 84%.
- \* This Network had the classic case of misclassifying cats as dogs.

```
exe-2 = MobileNetv2 (Frozen)
```

- \* Convbase of MobileNetV2 with ImageNet weights and Frozen layers was constructed.
- \* Custom Output layers of 1 Flatten, 2 Dense was attached at the end.
- \* Same as the previous implementation the model was set to 15 epochs with same EarlyStopping Setup. Elapsed Training time is 5 Mins with 3 Epochs of Training.
- \* This Time the Model Performed well enough with the pre-trained ImageNet Weights. The misclassification problem from the first case was smoothened.
- \* With \*\*MobileNetV2\*\* + custom output layer, the model achieved 99% on training set and 96% on the Validation Set, this difference indicates that the model is overfitting on the training set, but this is not prominent to fine tune further generally. But to create a state of the art cats & dogs classifier we can futhur fine-tune it to reduce that 3% of variance with techniques like Dropout and L2 Regularisation.

```
[170]: desc = '''A simple Cats and Dogs Image Dataset with 24994 samples of both cats
 →and dog pictures combined.'''
 project_name = 'Cats & Dogs Classifier'
 framework = 'Keras'
 prediction_type = 'Classification of 2 Targets'
 network_type = 'MobileNetV2'
 architecture = s
 layers = '19 Residual Units + 3 Custom Output Layers'
 hidden_units = 2
 activations = "['relu', 'sigmoid']"
 epochs = "Set of 15, Trained for 3 (EarlyStopping) "
 metrics = "Accuracy"
 loss = "Binary Cross-Entropy"
 optimiser = 'Adam'
 learning_rate = 0.001
 batch_size = 64
 train_performance = '99.45%'
 test_performance = '96.14%'
 classification report = report
 elapsed = "5Min, runtime : Colab Cloud GPU"
 summary = synopsis
 ipynb = './Projects/Transfer-Learning/Dogs&Cats/Dogs&Cats-classifier.pdf'
 plots = './Projects/Transfer-Learning/Dogs&Cats/Plots'
```

```
[184]: p = {}
[194]: var = ['desc', 'project name', |

→'framework', 'prediction_type', 'network_type', 'architecture', 'layers', 'hidden_units', 'activa
 param = \{\}
 for val in var:
 try:
 param[val] = eval(val)
 except:
 param[val] = val
 # check if anything is missing
[195]: param
[195]: {'activations': "['relu', 'sigmoid']",
 'architecture': '\nModel: "sequential_4"\n_____
 _____\nLayer (type)
 Output Shape
 Param # \n===========\nm
 obilenetv2_1.00_128 (Functi (None, 4, 4, 1280)
 2257984
 \n_____\nflatten_6
 (Flatten)
 (None, 20480)
 \n_____\ndense_12
 2621568
 (None, 128)
 \n_____\ndense_13
 (None, 1)
 (Dense)
 129
 \n========\nTotal
 params: 4,879,681\nTrainable params: 2,621,697\nNon-trainable params: 2,257,984\
 \texttt{n} = \texttt{n} \cdot
 'batch_size': 64,
 'classification_report': '\n
 \n
 precision
 recall
 0.98 0.95
 0.96
 f1-score
 3236\n
 True
 accuracy
 macro avg 0.96 0.96
 0.96
 6251\n
 0.96
 6251\nweighted
 0.96
 6251\n\n\n',
 0.96
 0.96
 'desc': 'A simple Cats and Dogs Image Dataset with 24994 samples of both cats
 and dog pictures combined.',
 'elapsed': '5Min, runtime : Colab Cloud GPU',
 'epochs': 'Set of 15, Trained for 3 (EarlyStopping)',
 'framework': 'Keras',
 'hidden_units': 2,
 'ipynb': './Projects/Transfer-Learning/Dogs&Cats/Dogs&Cats-classifier.pdf',
 'layers': '19 Residual Units + 3 Custom Output Layers',
 'learning_rate': 0.001,
```

```
'loss': 'Binary Cross-Entropy',
 'metrics': 'Accuracy',
 'network_type': 'MobileNetV2',
 'optimiser': 'Adam',
 'plots': './Projects/Transfer-Learning/Dogs&Cats/Plots',
 'prediction_type': 'Classification of 2 Targets',
 'project name': 'Cats & Dogs Classifier',
 'summary': '\n\nFor this problem two Implementations were used with Two
 inferences at the end of each implementation\n\nexe-1 = ConvNet from
 Scratch\n\n* A ConvNet was built from scratch with 3 Conv2D, 3 MaxPool, 1
 Flatten and 2 Dense Layers with Output function as Sigmoid (you can find the
 implementation in the ipynb-pdf). \n* This ConvNet was set for 15 epochs with
 EarlyStopping Callback of patience 3. The Elapsed Training time was 12.18 Mins
 on Cloud GPU instance of only 8 epochs of the stipulated 15.\n* Attained
 Training Accuracy - 95.60% and Validation Accuracy - 83.75% with approx. 8%
 difference, This network was overfitting with an average f1-score of 84%.\n*
 This Network had the classic case of misclassifying cats as dogs.\n\
 MobileNetv2 (Frozen)\n\n* Convbase of MobileNetV2 with ImageNet weights and
 Frozen layers was constructed.\n* Custom Output layers of 1 Flatten, 2 Dense was
 attached at the end.\n* Same as the previous implementation the model was set to
 15 epochs with same EarlyStopping Setup. Elapsed Training time is 5 Mins with 3
 Epochs of Training.\n* This Time the Model Performed well enough with the pre-
 trained ImageNet Weights. The misclassification problem from the first case was
 smoothened. \n* With **MobileNetV2** + custom output layer, the model achieved
 99% on training set and 96% on the Validation Set, this difference indicates
 that the model is overfitting on the training set, but this is not prominent to
 fine tune further generally. But to create a state of the art cats & dogs
 classifier we can futhur fine-tune it to reduce that 3% of variance with
 techniques like Dropout and L2 Regularisation.\n\n\n',
 'test_performance': '96.14%',
 'train_performance': '99.45%'}
[196]: import pickle
 file = open("artefacts.txt", "wb")
 dictionary = param
 pickle.dump(dictionary, file)
 file.close()
 []:
```