

Classification of Dogs and Cats Images - CNN Deep Learning!

```
In [1]: # Assigning GPU memory usage to 50%
from tensorflow.compat.v1 import ConfigProto
from tensorflow.compat.v1 import InteractiveSession

config = ConfigProto()
config.gpu_options.per_process_gpu_memory_fraction = 0.5
config.gpu_options.allow_growth = True
session = InteractiveSession(config=config)
```

```
In [3]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
In [4]: import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

doing Data Augmentation

```
In [42]: train_datagen = ImageDataGenerator(rescale = 1./255, shear_range = 0.2,zoom_range = 0.2,horizontal_flip
= True)
```

```
In [43]: test_datagen = ImageDataGenerator(rescale = 1./255)
```

Reading Data

Binary Classification

```
In [37]: training_data = train_datagen.flow_from_directory('cats n dogs/Cats and Dogs train', target_size = (64,
64), batch_size = 32, class_mode = 'binary')
```

Found 6200 images belonging to 2 classes.

```
In [38]: test_data = test_datagen.flow_from_directory('cats n dogs/Cats and Dogs test',target_size = (64, 64),ba
tch_size = 32,class_mode = 'binary')
```

Found 3600 images belonging to 2 classes.

Creating Convolutional Neural Network

```
In [39]: from tensorflow.keras.layers import Conv2D
```

```
In [40]: from tensorflow.keras.layers import Dense
```

```
In [41]: from tensorflow.keras.regularizers import l2
```

Creating Model

```
In [44]: cnn = tf.keras.models.Sequential()
```

Adding The CNN Layer

```
In [45]: cnn = tf.keras.models.Sequential()
```

Using Relu Activation Function !

```
In [46]: cnn.add(tf.keras.layers.Conv2D(filters=32,padding="same",kernel_size=3, activation='relu', strides=2, i
nput_shape=[64, 64, 3]))
```

Adding Max-Pooling

```
In [47]: cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
```

Adding the Second Layer

```
In [48]: cnn.add(tf.keras.layers.Conv2D(filters=32,padding='same',kernel_size=3, activation='relu'))
```

```
In [49]: cnn.add(tf.keras.layers.MaxPool2D(pool_size=2, strides=2))
```

Flattening..

```
In [50]: cnn.add(tf.keras.layers.Flatten())
```

Adding dense layer

```
In [51]: cnn.add(tf.keras.layers.Dense(units=128, activation='relu'))
```

Using Support Vector Machine (SVM) for last layer

Since , For Binary Classification, I will be using a LINEAR SVM

```
In [52]: cnn.add(Dense(1, kernel_regularizer=tf.keras.regularizers.l2(0.01),activation = 'linear'))
```

Initializing the Model

```
In [53]: cnn.summary()
```

Model: "sequential_3"		
Layer (type)	Output Shape	Param #
=====		
conv2d_2 (Conv2D)	(None, 32, 32, 32)	896

max_pooling2d_2 (MaxPooling2	(None, 16, 16, 32)	0

conv2d_3 (Conv2D)	(None, 16, 16, 32)	9248

max_pooling2d_3 (MaxPooling2	(None, 8, 8, 32)	0

flatten_1 (Flatten)	(None, 2048)	0

dense_2 (Dense)	(None, 128)	262272

dense_3 (Dense)	(None, 1)	129
=====		
Total params: 272,545		
Trainable params: 272,545		
Non-trainable params: 0		

Training the CNN Model

```
In [55]: # Compiling using ADAM OPTIMIZER
## Loss is declared hinge for the outer svm layer

cnn.compile(optimizer = 'adam', loss = 'hinge', metrics = ['accuracy'])
```

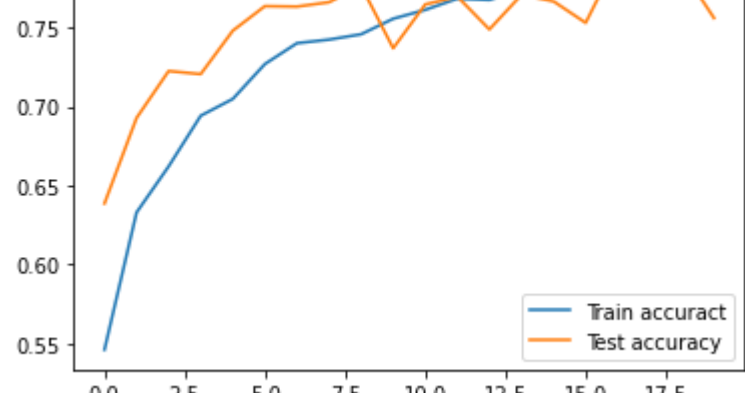
Now, Training the created Model , Doing Model fitting on the Training Data
And testing it on the Test data

```
In [56]: r=cnn.fit(x = training_data, validation_data = test_data, epochs = 20)
```

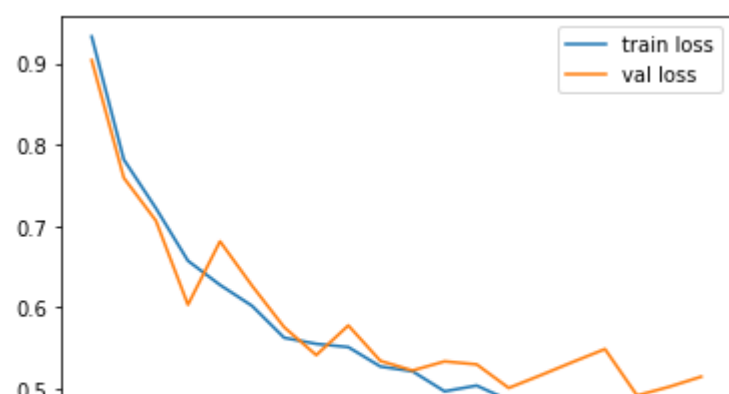
```
Epoch 1/20
194/194 [=====] - 59s 305ms/step - loss: 0.9329 - accuracy: 0.5460 - val_loss: 0.9038 - val_accuracy: 0.6386
Epoch 2/20
194/194 [=====] - 35s 178ms/step - loss: 0.7816 - accuracy: 0.6329 - val_loss: 0.7591 - val_accuracy: 0.6928
Epoch 3/20
194/194 [=====] - 30s 157ms/step - loss: 0.7218 - accuracy: 0.6621 - val_loss: 0.7064 - val_accuracy: 0.7225
Epoch 4/20
194/194 [=====] - 31s 157ms/step - loss: 0.6570 - accuracy: 0.6942 - val_loss: 0.6029 - val_accuracy: 0.7206
Epoch 5/20
194/194 [=====] - 31s 158ms/step - loss: 0.6273 - accuracy: 0.7048 - val_loss: 0.6809 - val_accuracy: 0.7481
Epoch 6/20
194/194 [=====] - 31s 158ms/step - loss: 0.6015 - accuracy: 0.7269 - val_loss: 0.6262 - val_accuracy: 0.7636
Epoch 7/20
194/194 [=====] - 32s 163ms/step - loss: 0.5623 - accuracy: 0.7402 - val_loss: 0.5752 - val_accuracy: 0.7633
Epoch 8/20
194/194 [=====] - 35s 180ms/step - loss: 0.5548 - accuracy: 0.7424 - val_loss: 0.5409 - val_accuracy: 0.7661
Epoch 9/20
194/194 [=====] - 33s 170ms/step - loss: 0.5508 - accuracy: 0.7458 - val_loss: 0.5774 - val_accuracy: 0.7764
Epoch 10/20
194/194 [=====] - 33s 169ms/step - loss: 0.5269 - accuracy: 0.7556 - val_loss: 0.5332 - val_accuracy: 0.7369
Epoch 11/20
194/194 [=====] - 33s 172ms/step - loss: 0.5211 - accuracy: 0.7613 - val_loss: 0.5220 - val_accuracy: 0.7647
Epoch 12/20
194/194 [=====] - 34s 176ms/step - loss: 0.4964 - accuracy: 0.7684 - val_loss: 0.5332 - val_accuracy: 0.7697
Epoch 13/20
194/194 [=====] - 33s 173ms/step - loss: 0.5035 - accuracy: 0.7676 - val_loss: 0.5295 - val_accuracy: 0.7489
Epoch 14/20
194/194 [=====] - 33s 172ms/step - loss: 0.4854 - accuracy: 0.7744 - val_loss: 0.5005 - val_accuracy: 0.7708
Epoch 15/20
194/194 [=====] - 34s 174ms/step - loss: 0.4745 - accuracy: 0.7805 - val_loss: 0.5162 - val_accuracy: 0.7667
Epoch 16/20
194/194 [=====] - 34s 173ms/step - loss: 0.4705 - accuracy: 0.7850 - val_loss: 0.5325 - val_accuracy: 0.7531
Epoch 17/20
194/194 [=====] - 34s 175ms/step - loss: 0.4583 - accuracy: 0.7890 - val_loss: 0.5484 - val_accuracy: 0.7936
Epoch 18/20
194/194 [=====] - 34s 173ms/step - loss: 0.4531 - accuracy: 0.7960 - val_loss: 0.4912 - val_accuracy: 0.7953
Epoch 19/20
194/194 [=====] - 33s 168ms/step - loss: 0.4556 - accuracy: 0.7895 - val_loss: 0.5019 - val_accuracy: 0.7869
Epoch 20/20
194/194 [=====] - 31s 157ms/step - loss: 0.4455 - accuracy: 0.7969 - val_loss: 0.5144 - val_accuracy: 0.7561
```

Plotting ACCURACY

```
In [57]: plt.plot(r.history['accuracy'], label='Train accuract')
plt.plot(r.history['val_accuracy'], label='Test accuracy')
plt.legend()
plt.show()
```



```
In [58]: plt.plot(r.history['loss'], label='train loss')
plt.plot(r.history['val_loss'], label='val loss')
plt.legend()
plt.show()
```



Saving The File

```
In [59]: from tensorflow.keras.models import load_model
cnn.save('model_dogcatcnn.h5')
```

Loading the Model

```
In [60]: model = load_model('model_dogcatcnn.h5')
```

Reading an image for Prediction

Taking an image from the test folder and testing it if the model is doing the right prediction!

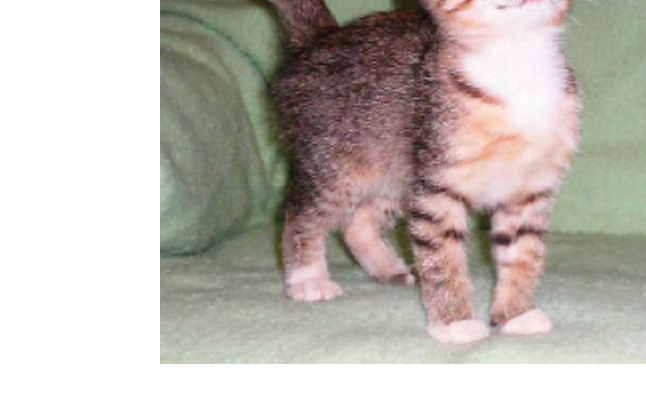
If the value of Array is NEGATIVE -> It's a CAT

If the value of Array is POSITIVE -> It's a DOG

```
In [61]: from tensorflow.keras.preprocessing import image
```

```
In [64]: img = image.load_img('cats n dogs/Cats and Dogs test/Cat test/cat.10983.jpg',target_size=(244,244))
```

```
In [65]: img
```



```
In [67]: img = image.load_img('cats n dogs/Cats and Dogs test/Cat test/cat.10983.jpg',target_size=(64,64))
img = image.img_to_array(img)
img=img/255
img = np.expand_dims(img, axis = 0)
result = cnn.predict(img)
```

```
In [68]: result
```

```
Out[68]: array([[ -0.96248984]], dtype=float32)
```

Since, the value of Array is NEGATIVE -> It's a CAT

Which means the prediction is right !

Now, Predicting for another image

```
In [73]: img2 = image.load_img('cats n dogs/Cats and Dogs test/Dog test/dog.9807.jpg',target_size=(244,244))
```

```
In [74]: img2
```



```
In [77]: img2 = image.load_img('cats n dogs/Cats and Dogs test/Dog test/dog.9807.jpg',target_size=(64,64))
img2 = image.img_to_array(img2)
img2=img2/255
img2 = np.expand_dims(img2, axis = 0)
result2 = cnn.predict(img2)
```

```
In [78]: result2
```

```
Out[78]: array([[ 4.6483774]], dtype=float32)
```

Since, the value of Array is POSITIVE -> It's a DOG

Which means the prediction is right !

```
In [ ]:
```