<pre>In []: In []:</pre>	<pre>gdrive", force_remount=True).</pre>
In []:	gdrive/ sample_data/
In []:	TRAINDIR = 'gdrive/MyDrive/ee_628/proj/train/' cat_folder = 'cat/' dog_folder = 'dog/' Before, moving further, let us take a look at the images. This will give us an idea of what kind of data we are working with.
	<pre>from matplotlib.image import imread import matplotlib.pyplot as plt for i in range(9): plt.subplot(330 + 1 + i) filename = TRAINDIR+cat_folder + 'cat.' + str(i) + '.jpg' image = imread(filename) plt.imshow(image)</pre>
	plt.show()
	200 - 2
In []:	0 200 0 250 0 250
	plt.imshow(image) plt.show() 0 200 400 100
	200 - 250 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
	There are two things to note from the above sample of images:
T. (.)	 The images are all of different sizes and aspect ratios and need to be fitted to standard size. All images seem to be at least bigger than 150X150 pixels and therefore we can attempt to resize them all to this size. Below, we will first load in the data using ImageDataGenerator class from Keras.
In []:	<pre>from keras.preprocessing.image import ImageDataGenerator datagen = ImageDataGenerator(rotation_range = 10,</pre>
In []:	<pre>IMG_W = 150 train_generator = datagen.flow_from_directory(TRAINDIR,</pre>
In []:	Found 18750 images belonging to 2 classes. val_generator = datagen.flow_from_directory(TRAINDIR,
In []:	<pre>subset='validation') Found 6250 images belonging to 2 classes. test_generator = datagen.flow_from_directory('gdrive/MyDrive/ee_628/proj/', classes=['test1'],</pre>
	NOTE: As mentioned earlier, we do not really need the test_generator as we are not working with it. We have still loaded a generator for it because for the purposes of this method we generated some predictions and a csv file for the test data. Let us build the model now:
	<pre>from keras.models import Sequential from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense, Activation, Dropout, BatchNormalization model1 = Sequential() model1.add(Conv2D(filters=96, kernel size=(11,11), strides=(4,4), activation='relu', input shape=(IMG H</pre>
	<pre>, IMG_W, 3))) model1.add(BatchNormalization()) model1.add(MaxPooling2D(pool_size=(3,3), strides=(2,2))) model1.add(Conv2D(filters=256, kernel_size=(1,1), strides=(1,1), activation='relu', padding='same')) model1.add(BatchNormalization()) model1.add(MaxPooling2D(pool_size=(3,3), strides=(2,2))) model1.add(Conv2D(filters=384, kernel_size=(3,3), strides=(1,1), activation='relu', padding='same')) model1.add(BatchNormalization())</pre>
	<pre>model1.add(BatchNormalization()) model1.add(Conv2D(filters=256, kernel_size=(3,3), strides=(1,1), activation='relu', padding='same')) model1.add(BatchNormalization()) model1.add(MaxPooling2D(pool_size=(3,3), strides=(2,2))) model1.add(Flatten()) model1.add(Dense(4096, activation='relu')) model1.add(Dropout(0.5)) model1.add(Dense(4096, activation='relu'))</pre>
In []:	Model: "sequential"
	Layer (type) Output Shape Param # conv2d (Conv2D) (None, 35, 35, 96) 34944 batch_normalization (BatchNo (None, 35, 35, 96) 384 max_pooling2d (MaxPooling2D) (None, 17, 17, 96) 0
	conv2d_1 (Conv2D) (None, 17, 17, 256) 24832 batch_normalization_1 (Batch (None, 17, 17, 256) 1024 max_pooling2d_1 (MaxPooling2 (None, 8, 8, 256) 0 conv2d_2 (Conv2D) (None, 8, 8, 384) 885120
	batch_normalization_2 (Batch (None, 8, 8, 384) 1536 conv2d_3 (Conv2D) (None, 8, 8, 256) 884992 batch_normalization_3 (Batch (None, 8, 8, 256) 1024 max pooling2d 2 (MaxPooling2 (None, 3, 3, 256) 0
	flatten (Flatten) (None, 2304) 0 dense (Dense) (None, 4096) 9441280 dropout (Dropout) (None, 4096) 0
	dense_1 (Dense) (None, 4096) 16781312 dropout_1 (Dropout) (None, 4096) 0 dense_2 (Dense) (None, 1) 4097 ===================================
	Non-trainable params: 1,984 model1.compile(loss='binary_crossentropy',
In []:	<pre>history1 = model1.fit_generator(train_generator, validation_data=val_generator, epochs=20) /usr/local/lib/python3.7/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 '</pre> Epoch 1/20
	188/188 [===================================
	0.6349 - val_accuracy: 0.6269 Epoch 4/20 188/188 [===================================
	Epoch 6/20 188/188 [===================================
	Epoch 9/20 188/188 [===================================
	188/188 [===================================
	0.4076 - val_accuracy: 0.8246 Epoch 14/20 188/188 [===================================
	188/188 [===================================
	Epoch 19/20 188/188 [===================================
	history1.history {'accuracy': [0.5851200222969055,
	0.8363199830055237, 0.849120020866394, 0.8624533414840698, 0.8701333403587341, 0.8827199935913086, 0.8951466679573059, 0.9025066494941711,
	0.9023066494941711, 0.9083733558654785, 0.9156266450881958, 0.923146665096283, 0.9279999732971191, 0.9358400106430054, 0.9445866942405701, 0.9462933540344238],
	'loss': [1.3889658451080322, 0.6312090754508972, 0.5641945004463196, 0.5093401074409485, 0.4435144364833832, 0.40450748801231384, 0.37481480836868286,
	0.3507314622402191, 0.318170428276062, 0.30447256565093994, 0.2773495018482208, 0.2543911337852478, 0.23700104653835297, 0.2273014634847641, 0.21460409462451935,
	0.19635514914989471, 0.18171706795692444, 0.16720017790794373, 0.14417661726474762, 0.1427137702703476], 'val_accuracy': [0.5411199927330017, 0.54448002576828,
	0.6268799901008606, 0.6780800223350525, 0.6460800170898438, 0.7904000282287598, 0.7262399792671204, 0.7449600100517273, 0.7305600047111511, 0.8176000118255615,
	0.7579200267791748, 0.7014399766921997, 0.8246399760246277, 0.8615999817848206, 0.6772800087928772, 0.8156800270080566, 0.8236799836158752,
	0.8494399785995483, 0.809440016746521, 0.681439995765686], 'val_loss': [0.7118508815765381, 0.6897774934768677, 0.6349456906318665, 0.632263720035553, 0.6258352994918823,
	0.4374096989631653, 0.5438859462738037, 0.5171272158622742, 0.5136682391166687, 0.4033946394920349, 0.4714355170726776, 0.6591507792472839,
	0.407554566860199, 0.32073676586151123, 0.6800304651260376, 0.4928198754787445, 0.4269232749938965, 0.40840908885002136, 0.6208070516586304, 1.0475376844406128]}
In []:	<pre>epochs = [i for i in range(1,21)] plt.plot(epochs, history1.history['accuracy'], history1.history['val_accuracy']) plt.legend(['Training', 'Validation']) plt.title('Accuracy Measure over Epochs - AlexNet') plt.xlabel('Epoch')</pre>
	plt.ylabel('Accuracy') plt.show() Accuracy Measure over Epochs - AlexNet 0.95 Training Validation 0.85
	0.80 - Supplemental of the supplemental of the
	0.65
In []:	As we can see above, the training accuracy keeps on increasing, but we cannot keep increasing the epochs along with it. We see that the validation accuracy is fluctuating quite a bit. However, based on the current plot, we can make the deduction that the validation accuracy is still averaging around 0.75. If we run more epochs we would be able to make a clearer deduction and see where it is that the validation accuracy starts to converge. At that point we should stop the training of the neural net as it would lead to overfitting. Currently, we could have more epochs but due to time constraints, we have kept 20 epochs (which took over 6 hours!) plt.plot(epochs, history1.history['loss'], history1.history['val_loss'])
In []:	As we can see above, the training accuracy keeps on increasing, but we cannot keep increasing the epochs along with it. We see that the validation accuracy is fluctuating quite a bit. However, based on the current plot, we can make the deduction that the validation accuracy is still averaging around 0.75. If we run more epochs we would be able to make a clearer deduction and see where it is that the validation accuracy starts to converge. At that point we should stop the training of the neural net as it would lead to overfitting. Currently, we could have more epochs but due to time constraints, we have kept 20 epochs (which took over 6 hours!)
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In []:	As we can see above, the training accuracy keeps on increasing, but we cannot keep increasing the epochs along with it. We see that the validation accuracy is fluctuating quite a bit. However, based on the current plot, we can make the deduction that the validation accuracy is still averaging around 0.75. If we run more epochs we would be able to make a clearer deduction and see where it is that the validation accuracy starts to converge. At that point we should stop the training of the neural net as it would lead to overfitting. Currently, we could have more epochs but due to time constraints, we have kept 20 epochs (which took over 6 hours!) plt.plot(epochs, history1.history['loss'], history1.history['val_loss']) plt.title('Loss Measure over Epochs - AlexNet') plt.ylabel('Loss') plt.show() Loss Measure over Epochs - AlexNet Taining Walidation
<pre>In []:</pre>	As we can see above, the training accuracy keeps on increasing, but we cannot keep increasing the epochs along with it. We see that the validation accuracy is fluctuating quite a bit. However, based on the current plot, we can make the deduction that the validation accuracy is still averaging around 0.75. If we run more epochs we would be able to make a clearer deduction and see where it is that the validation accuracy starts to converge. At that point we should stop the training of the neural net as it would lead to overfitting. Currently, we could have more epochs but due to time constraints, we have kept 20 epochs (which took over 6 hours!) plt.plot (epochs, historyl.historyl'loss'), historyl.historyl[val_loss']) plt.title('Loss Deasure over Epochs - AlexNet') plt.ylabel('Loss') plt.slabel('Loss') plt.slabel('Loss
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