

**FEDERAL STATE AUTONOMOUS EDUCATIONAL INSTITUTION OF
HIGHER EDUCATION
ST. PETERSBURG NATIONAL RESEARCH UNIVERSITY OF
INFORMATION TECHNOLOGIES, MECHANICS AND OPTICS**

Faculty of Information Technologies and Programming
Program track 01.04.02 Applied Mathematics and Informatics
Machine Learning and Data Analysis

**REPORT
On the Course Project for Image Processing**

Topic:
Classify Images of dogs and cats using
Deep Convolutional Neural Networks

Mohamed Saber
M42332

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Introduction

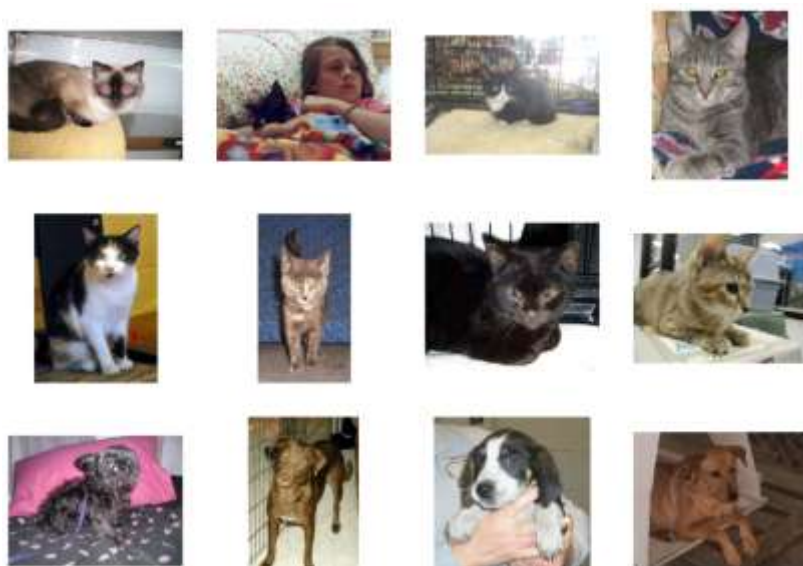
Develop a DCNN to Classify images of Dogs and Cats. although the problem sounds simple, it was only effectively addressed in the last few years using deep learning convolutional neural networks. While the dataset is effectively solved, it can be used as the basis for learning and practicing how to develop, evaluate, and use convolutional deep learning neural networks for image classification from scratch.

This includes how to develop a robust test harness for estimating the performance of the model, explore improvements to the model, and to save the model and later load it to make predictions on new data.

Dataset

The [dogs vs cats dataset](#) refers to a dataset used for a Kaggle machine learning competition. The dataset is comprised of photos of dogs and cats provided as a subset of photos from a much larger dataset of 3 million manually annotated photos.

The 2,000 images used in this exercise are excerpted from the "Dogs vs. Cats" dataset available on Kaggle, which contains 25,000 images. Here, we use a subset of the full dataset to decrease training time for educational purposes.



Approach

The images that will go into our convnet are 200 x 200 color images (in the next section on Data Preprocessing, I'll add handling to resize all the images to 200 x 200 before feeding them into the neural network).

Let's code up the architecture. We will stack 3 {convolution + relu + maxpooling} modules. Our convolutions operate on 3x3 windows and our maxpooling layers operate on 2x2 windows. Our first convolution extracts 32 filters, the following one extracts 64 filters, the following one extracts 128 filters and the last one extracts 256 filters.

From reviewing the learning curves for the model during training, the model showed strong signs of overfitting. So I will use two approaches to attempt to address this overfitting: dropout regularization and data augmentation.

I build a classifier model from scratch that is able to distinguish dogs from cats. I will follow these steps:

1. Explore the example data
2. Building ConvNet Models:
 - A. Model A: One Block CNN - Single Convolutional layer with 32 filters followed by a max-pooling layer.
 - B. Model B: Two Block CNN model extends the one block model and adds a second block with 64 filters.
 - C. Model C: Three Block CNN model extends the two block model and adds a third block with 128 filters.
 - D. Model D: Four Block CNN model extends the three block model and adds a fourth block with 256 filters.
 - E. Model E: 3CNN and Dropout Regularization
 - F. Model F: 3CNN and Data Augmentation
 - G. Model V: Explore Transfer Learning model is one of the VGG models, such as VGG-16 with 16 layers
3. Plot Evaluating Accuracy and Loss for the My Model
4. Make Prediction

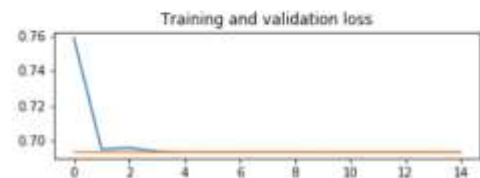
Experiments

Model A: One Block CNN - Single Convolutional layer with 32 filters followed by a max-pooling layer.

Model: "sequential_16"

Layer (type)	Output Shape	Param #
conv2d_34 (Conv2D)	(None, 200, 200, 32)	896
max_pooling2d_34 (MaxPooling)	(None, 100, 100, 32)	0
flatten_15 (Flatten)	(None, 320000)	0
dense_29 (Dense)	(None, 128)	40960128
dense_30 (Dense)	(None, 1)	129

Total params: 40,961,153
Trainable params: 40,961,153
Non-trainable params: 0

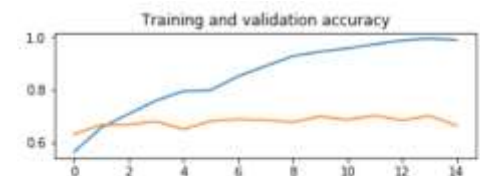


Model B: Two Block CNN model extends the one block model and adds a second block with 64 filters.

Model: "sequential_8"

Layer (type)	Output Shape	Param #
conv2d_12 (Conv2D)	(None, 200, 200, 32)	896
max_pooling2d_12 (MaxPooling)	(None, 100, 100, 32)	0
conv2d_13 (Conv2D)	(None, 100, 100, 64)	18496
max_pooling2d_13 (MaxPooling)	(None, 50, 50, 64)	0
flatten_8 (Flatten)	(None, 160000)	0
dense_15 (Dense)	(None, 128)	20480128
dense_16 (Dense)	(None, 1)	129

Total params: 20,499,649
Trainable params: 20,499,649
Non-trainable params: 0

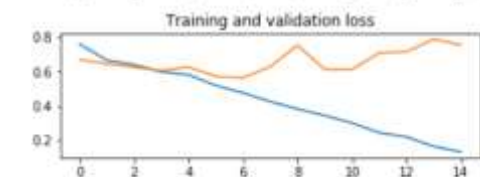


Model C: Three Block CNN model extends the two block model and adds a third block with 128 filters.

Model: "sequential_10"

Layer (type)	Output Shape	Param #
conv2d_17 (Conv2D)	(None, 200, 200, 32)	896
max_pooling2d_17 (MaxPooling)	(None, 100, 100, 32)	0
conv2d_18 (Conv2D)	(None, 100, 100, 64)	18496
max_pooling2d_18 (MaxPooling)	(None, 50, 50, 64)	0
conv2d_19 (Conv2D)	(None, 50, 50, 128)	73856
max_pooling2d_19 (MaxPooling)	(None, 25, 25, 128)	0
Flatten_10 (Flatten)	(None, 80000)	0
dense_19 (Dense)	(None, 128)	10240128
dense_20 (Dense)	(None, 1)	129

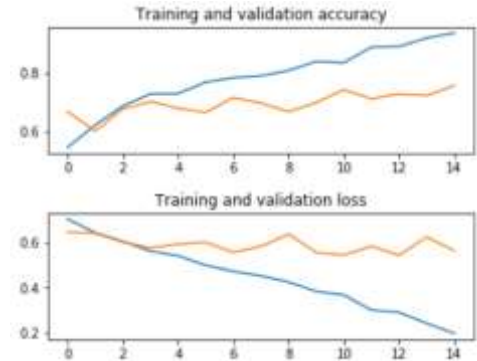
Total params: 10,333,505
Trainable params: 10,333,505
Non-trainable params: 0



Model D: Four Block CNN model extends the three block model and adds a fourth block with 256 filters.

Model: "sequential_12"

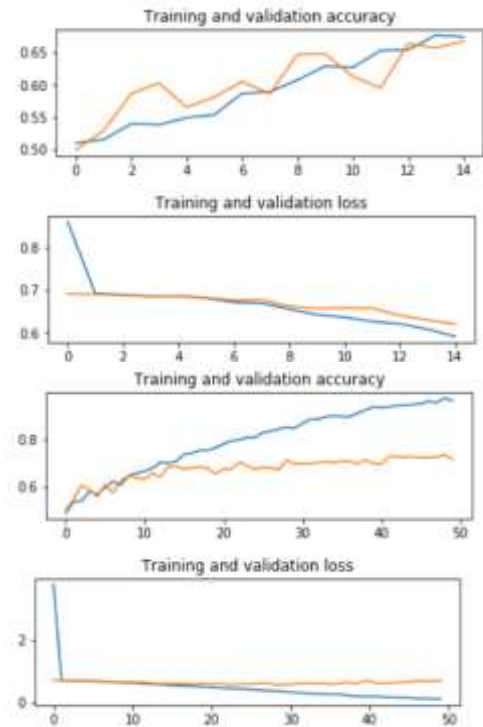
Layer (type)	Output Shape	Param #
conv2d_23 (Conv2D)	(None, 200, 200, 32)	896
max_pooling2d_23 (MaxPooling)	(None, 100, 100, 32)	0
conv2d_24 (Conv2D)	(None, 100, 100, 64)	18496
max_pooling2d_24 (MaxPooling)	(None, 50, 50, 64)	0
conv2d_25 (Conv2D)	(None, 50, 50, 128)	73856
max_pooling2d_25 (MaxPooling)	(None, 25, 25, 128)	0
conv2d_26 (Conv2D)	(None, 25, 25, 256)	295168
max_pooling2d_26 (MaxPooling)	(None, 12, 12, 256)	0
flatten_12 (Flatten)	(None, 36864)	0
dense_23 (Dense)	(None, 128)	4718720
dense_24 (Dense)	(None, 1)	129
Total params: 5,107,265		
Trainable params: 5,107,265		
Non-trainable params: 0		



Model E: 3CNN and Dropout Regularization

Model: "sequential_21"

Layer (type)	Output Shape	Param #
conv2d_47 (Conv2D)	(None, 200, 200, 32)	896
max_pooling2d_47 (MaxPooling)	(None, 100, 100, 32)	0
dropout_13 (Dropout)	(None, 100, 100, 32)	0
conv2d_48 (Conv2D)	(None, 100, 100, 64)	18496
max_pooling2d_48 (MaxPooling)	(None, 50, 50, 64)	0
dropout_14 (Dropout)	(None, 50, 50, 64)	0
conv2d_49 (Conv2D)	(None, 50, 50, 128)	73856
max_pooling2d_49 (MaxPooling)	(None, 25, 25, 128)	0
dropout_15 (Dropout)	(None, 25, 25, 128)	0
flatten_20 (Flatten)	(None, 80000)	0
dense_39 (Dense)	(None, 128)	10240128
dropout_16 (Dropout)	(None, 128)	0
dense_40 (Dense)	(None, 1)	129
Total params: 10,333,505		
Trainable params: 10,333,505		
Non-trainable params: 0		



Model F: 3CNN and Data Augmentation

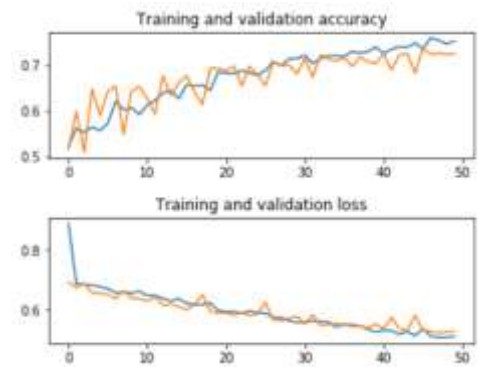
```
[ ] # create data generators
train_datagen = ImageDataGenerator(rescale=1.0/255.0, width_shift_range=0.1, height_shift_range=0.1, horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1.0/255.0)

# prepare iterators
train_it = train_datagen.flow_from_directory(
    train_dir,
    target_size=(200, 200),
    batch_size=64,
    class_mode='binary')

test_it = test_datagen.flow_from_directory(
    validation_dir,
    target_size=(200, 200),
    batch_size=64,
    class_mode='binary')
```

Model: "sequential_43"

Layer (type)	Output Shape	Param #
conv2d_113 (Conv2D)	(None, 200, 200, 32)	896
max_pooling2d_113 (MaxPooling2D)	(None, 100, 100, 32)	0
conv2d_114 (Conv2D)	(None, 100, 100, 64)	18496
max_pooling2d_114 (MaxPooling2D)	(None, 50, 50, 64)	0
conv2d_115 (Conv2D)	(None, 50, 50, 128)	73856
max_pooling2d_115 (MaxPooling2D)	(None, 25, 25, 128)	0
flatten_42 (Flatten)	(None, 80000)	0
dense_83 (Dense)	(None, 128)	10240128
dense_84 (Dense)	(None, 1)	129
Total params: 10,333,505		
Trainable params: 10,333,505		
Non-trainable params: 0		



Model V: Explore Transfer Learning model is one of the VGG models, such as VGG-16 with 16 layers - Build Model V

```
def modelV():
    # load model
    model = VGG16(include_top=False, input_shape=(224, 224, 3))

    # mark loaded layers as not trainable
    for layer in model.layers:
        layer.trainable = False

    # add new classifier layers
    flat1 = Flatten()(model.layers[-1].output)
    class1 = Dense(128, activation='relu', kernel_initializer='he_uniform')(flat1)
    output = Dense(1, activation='sigmoid')(class1)

    # define new model
    model = Model(inputs=model.inputs, outputs=output)

    # compile model
    opt = SGD(lr=0.001, momentum=0.9)
    model.compile(optimizer=opt, loss='binary_crossentropy', metrics=['accuracy'])
    model.summary()

    return model
```


Model V: Explore Transfer Learning model is one of the VGG models, such as VGG-16 with 16 layers - Create Data Generation

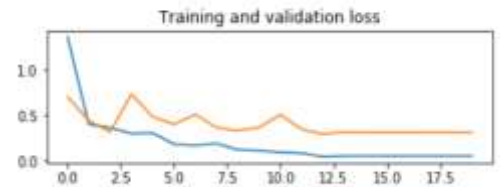
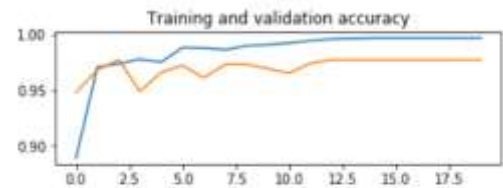
```
[ ] # Create data generator
datagen = ImageDataGenerator(featurewise_center=True)

# specify imagenet mean values for centering
datagen.mean = [123.68, 116.779, 103.939]

# prepare iterator
train_it = datagen.flow_from_directory(train_dir, class_mode='binary', batch_size=64, target_size=(224, 224))
test_it = datagen.flow_from_directory(validation_dir, class_mode='binary', batch_size=64, target_size=(224, 224))
```

Model: "model_8"

Layer (type)	Output Shape	Param #
input_11 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten_61 (Flatten)	(None, 25088)	0
dense_121 (Dense)	(None, 128)	3211392
dense_122 (Dense)	(None, 1)	129
Total params: 17,926,209		
Trainable params: 3,211,521		
Non-trainable params: 14,714,688		



Results

The process of model improvement may continue for as long as we have ideas and the time and resources to test them out. at some point, a final model configuration must be chosen and adopted. In this case, we will keep things simple and use the VGG-16 transfer learning approach as the final model.

First, we will finalize our model by fitting a model on the entire training dataset and saving the model to file for later use. We will then load the saved model and use it to make a prediction on a single image.

```
# load and prepare the image
def load_image(filename):
    # load the image
    img = load_img(filename, target_size=(224, 224))
    # convert to array
    img = img_to_array(img)
    # reshape into a single sample with 3 channels
    img = img.reshape(1, 224, 224, 3)
    # center pixel data
    img = img.astype('float32')
    img = img - [123.68, 116.779, 103.939]
    return img

# load an image and predict the class
def run_example():
    # load the image
    img = load_image(img_path)
    # load model
    model = load_model('final_model.h5')
    # predict the class
    result = model.predict(img)

    if result == 0:
        print ('This is CAT')
    if result == 1 :
        print ('This is DOG')

img_path = train_cats_dir + '/' + 'cat.6.jpg'
img = mpimg.imread(img_path)
plt.imshow(img)

# entry point, run the example
run_example()
```

This is CAT



Conclusion

Model	Echo	Loss	Acc	Val oss	Val acc
Model A	15	0.6932	0.5000	0.6931	0.5010
Model B	15	0.0548	0.9895	0.8607	0.6640
Model C	15	0.1337	0.9605	0.7546	0.6930
Model D	15	0.1987	0.9350	0.5619	0.7560
Model E	15	0.5911	0.6745	0.6199	0.6680
	50	0.1060	0.9630	0.6793	0.7160
Model F	50	0.5104	0.7539	0.5282	0.7260
Model EF	50	0.6673	0.5943	0.6750	0.6080
Model V	20	0.0550	0.9966	0.3134	0.9770

References

- Asirra: A CAPTCHA that Exploits Interest-Aligned Manual Image Categorization, 2007.
- <https://www.microsoft.com/en-us/research/publication/asirra-a-captcha-that-exploits-interest-aligned-manual-image-categorization/>
- Machine Learning Attacks Against the Asirra CAPTCHA, 2007.
- <https://dl.acm.org/doi/10.1145/1455770.1455838>
- OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks, 2013.
- <https://arxiv.org/abs/1312.6229>