
AIN433 Introduction to Computer Vision Lab.

Practical 4 - Image Classification Using CNN & VGG16

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Overview

The aim of this assignment is training CNN for image classification using TensorFlow and fine tuning a pretrained VGG16 on ImageNet data using transfer learning.

1 Dataset

The dataset is Indoor Scene Recognition Dataset from Computer Vision and Pattern Recognition Conference 2019, containing 15620 images in 67 categories. Due to computational and time limitations and assignment restrictions, a subset of this dataset (15 category, each of which has more than or equal to 300 images) has been selected to be used in training/validation/testing. That is 7701 images of 15 category.

These categories are the following:

- kitchen: 734 images
- livingroom: 705 images
- bedroom: 662 images
- airport_inside: 608 images
- bar: 603 images
- subway: 539 images
- casino: 515 images
- restaurant: 513 images
- warehouse: 506 images
- inside_subway: 457 images
- bakery: 405 images
- pantry: 384 images
- bookstore: 380 images
- toystore: 347 images
- corridor: 343 images

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv2d_10 (Conv2D)	(None, 100, 100, 16)	448
max_pooling2d_10 (MaxPooling)	(None, 50, 50, 16)	0
conv2d_11 (Conv2D)	(None, 50, 50, 8)	1160
max_pooling2d_11 (MaxPooling)	(None, 25, 25, 8)	0
flatten_5 (Flatten)	(None, 5000)	0
dense_10 (Dense)	(None, 32)	160032
dense_11 (Dense)	(None, 15)	495
Total params: 162,135		
Trainable params: 162,135		
Non-trainable params: 0		

Figure 1: Topology of CNN without Dropout.

Train / test / validation splits has been done such that, 80% of the data is train data, 10% is test data and 10% is validation data. In numbers, there are 6160 images in training data, 770 images in test data and 771 images in validation data. Also, all images were resized to shape of (100, 100, 3) (channels last notation) and intensity values were scaled to 0 - 1. Note that images are not grayscale, instead, they are RGB.

2 CNN Part

There are two different topologies for CNN, one with dropout layers and one with no dropout layers.

2.1 CNN with no Dropouts

The topology of this CNN is shown in 1. Code snippet to create that topology can be seen in 1.

Each convolution layer is followed by a max pooling layer where pooling window size is 2x2. That choice was arbitrary. First convolution layer has 16 kernels, seconds has 8 kernels. Those choices were arbitrary too. Kernel sizes are 3x3, which is also an arbitrary choice. All activation functions except output layer's are ReLU, output layer's activation function is Softmax. Output layer's activation function choice was intentional, to make output values ranging from 0 to 1 (since they are probabilities), Softmax should be used. But other choices were arbitrary. Actually not arbitrary but more like because of the convention. I mean, if everyone uses it that way, there must be some wisdom there I guess. Number of convolution layers (2) and dense layers (3, including output) are also results of arbitrary choices. Loss choice was "categorical cross entropy" and this was also due to convention. Everyone uses that way. Model does not yield that good results but that will be discussed later.

Listing 1: Code of CNN with no dropout

```

1 model = tf.keras.Sequential()
2 model.add(layers.InputLayer(input_shape=(HEIGHT, WIDTH, CHANNELS)))
3
4 model.add(layers.Conv2D(16, kernel_size=(3,3), padding='same', activation=
   = 'relu'))
5 model.add(layers.MaxPool2D(pool_size=(2,2)))
6
7 model.add(layers.Conv2D(8, kernel_size=(3,3), padding='same', activation=
   'relu'))

```

Train Accuracies and Losses

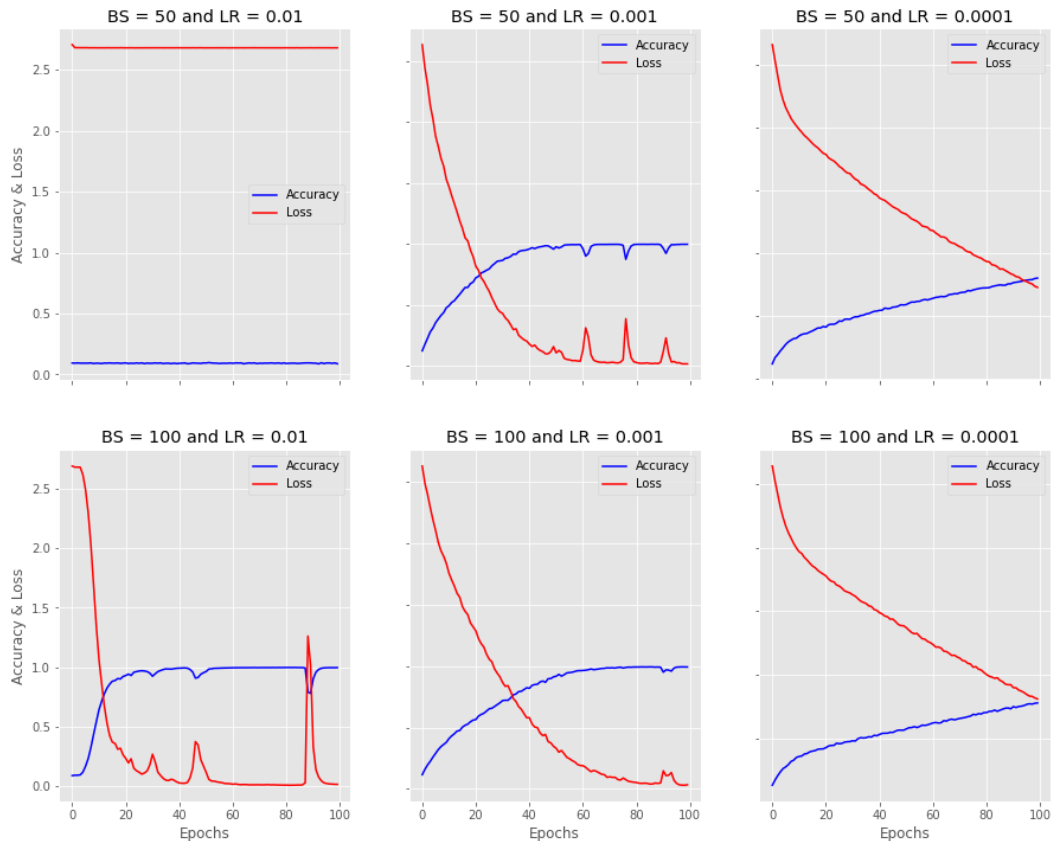


Figure 2: Train accuracies and losses of CNN models.

```

8 model.add(layers.MaxPool2D(pool_size=(2,2)))
9
10 model.add(layers.Flatten())
11 model.add(layers.Dense(32, activation='relu'))
12 model.add(layers.Dense(NUM_CLASSES, activation='softmax'))
13
14 model.compile(loss='categorical_crossentropy', optimizer=Adam(
15     learning_rate=LEARNING_RATE), metrics=['accuracy'])
15 history = model.fit(X_train, y_train, batch_size=BATCH_SIZE, epochs=
    EPOCH_SIZE, validation_data = (X_validation, y_validation), shuffle=
    True)

```

Using epoch size as 100 (mendated), 2 different batch sizes (50 and 100) and 3 different learning rates (0.01, 0.001 and 0.0001) were tested in every possible combinations. That yields 6 different models, from a model with batch size of 50 and learning rate of 0.01 to a model with batch size of 100 and learning rate of 0.0001.

See the train accuracies and losses in [2](#) and validation accuracies and losses in [3](#) and test accuracies in [4](#).

See confusion matrices of the models in [5](#).

Confusion matrices says a lot about how model behaves. Looking at validation accuracy & loss graph, you can't tell if model just says random stuff, or as in current sample, just says everything is class "x". Model 0 thinks that every image belongs to a certain class. This happened probably due to learning

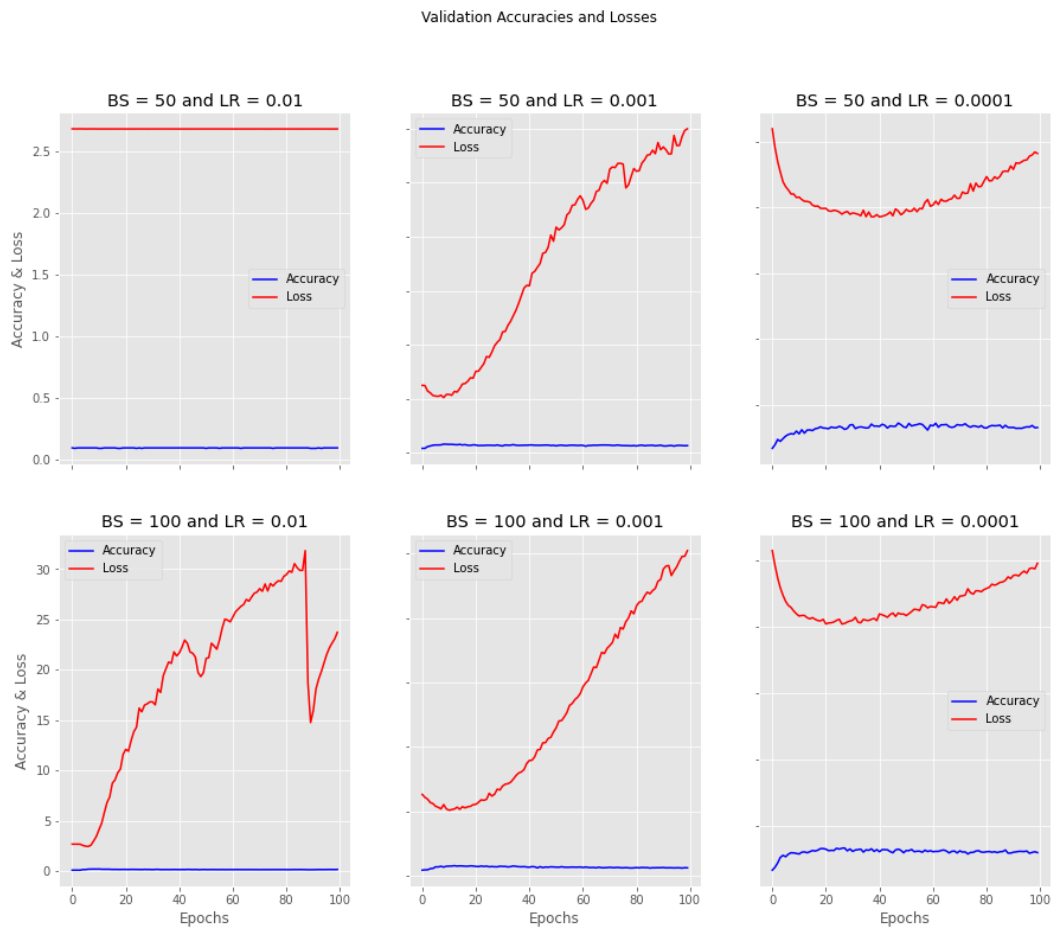


Figure 3: Validation accuracies and losses of CNN models.

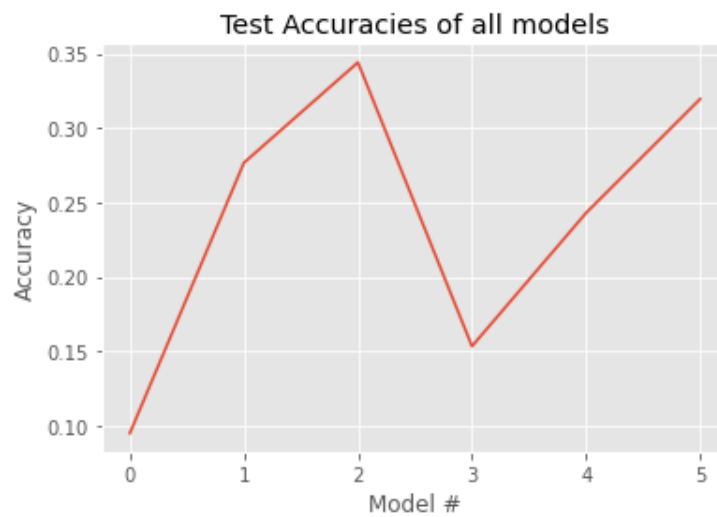


Figure 4: Test accuracies of CNN models.

Figure 5: Confusion Matrices of models without dropout.

2.2 CNN with Dropouts

Also, dropout layer has been implemented to this topology because it was mandated in assignment instructions. Dropout layer added to end of every convolution layer and every dense layer except output layer. Resulting topology can be seen in 6.

Code snippet to create that topology can be seen in 2.

Listing 2: Code of CNN with dropout

```
1 model_ = tf.keras.Sequential()
2 model_.add(layers.InputLayer(input_shape=(HEIGHT, WIDTH, CHANNELS)))
3
4 model_.add(layers.Conv2D(16, kernel_size=(3,3), padding='same',
5                           activation='relu'))
6 model_.add(layers.MaxPool2D(pool_size=(2,2)))
```

Model: "sequential_11"

Layer (type)	Output Shape	Param #
conv2d_22 (Conv2D)	(None, 100, 100, 16)	448
max_pooling2d_22 (MaxPooling)	(None, 50, 50, 16)	0
dropout_15 (Dropout)	(None, 50, 50, 16)	0
conv2d_23 (Conv2D)	(None, 50, 50, 8)	1160
max_pooling2d_23 (MaxPooling)	(None, 25, 25, 8)	0
dropout_16 (Dropout)	(None, 25, 25, 8)	0
flatten_11 (Flatten)	(None, 5000)	0
dense_22 (Dense)	(None, 32)	160032
dropout_17 (Dropout)	(None, 32)	0
dense_23 (Dense)	(None, 15)	495
Total params: 162,135		
Trainable params: 162,135		
Non-trainable params: 0		

Figure 6: Topology of CNN with Dropout.

```

6 model_.add(layers.Dropout(DROPOUT))
7
8 model_.add(layers.Conv2D(8, kernel_size=(3,3), padding='same', activation
  ='relu'))
9 model_.add(layers.MaxPool2D(pool_size=(2,2)))
10 model_.add(layers.Dropout(DROPOUT))
11
12 model_.add(layers.Flatten())
13 model_.add(layers.Dense(32, activation='relu'))
14 model_.add(layers.Dropout(DROPOUT))
15 model_.add(layers.Dense(NUM_CLASSES, activation='softmax'))
16
17 model_.compile(loss='categorical_crossentropy', optimizer=Adam(
  learning_rate=LEARNING_RATE), metrics=['accuracy'])
18
19 history_ = model_.fit(X_train, y_train, batch_size=BATCH_SIZE, epochs=
  EPOCH_SIZE, validation_data = (X_validation, y_validation), shuffle=
  True)

```

See the train / test / validation accuracy & loss graphs in 7, in 8 and in 9.

See their confusion matrices in 10.

Dropout was added after every layer part, because all of them are being trained and all of them may overfit. Using 4 different dropout rates (0.1, 0.25, 0.50 and 0.75) model has been tested. Test accuracies were same, and that is suprising. Human error was checked on that and seemed none, but this is always a possibility. Dropout didn't change much, actually different rates of dropout also didn't change much and this is probably due to lack of learning of the base model. I mean, add dropout or not, if model didn't learn anything, then what would that change?

Train Accuracies and Losses of model with Dropout

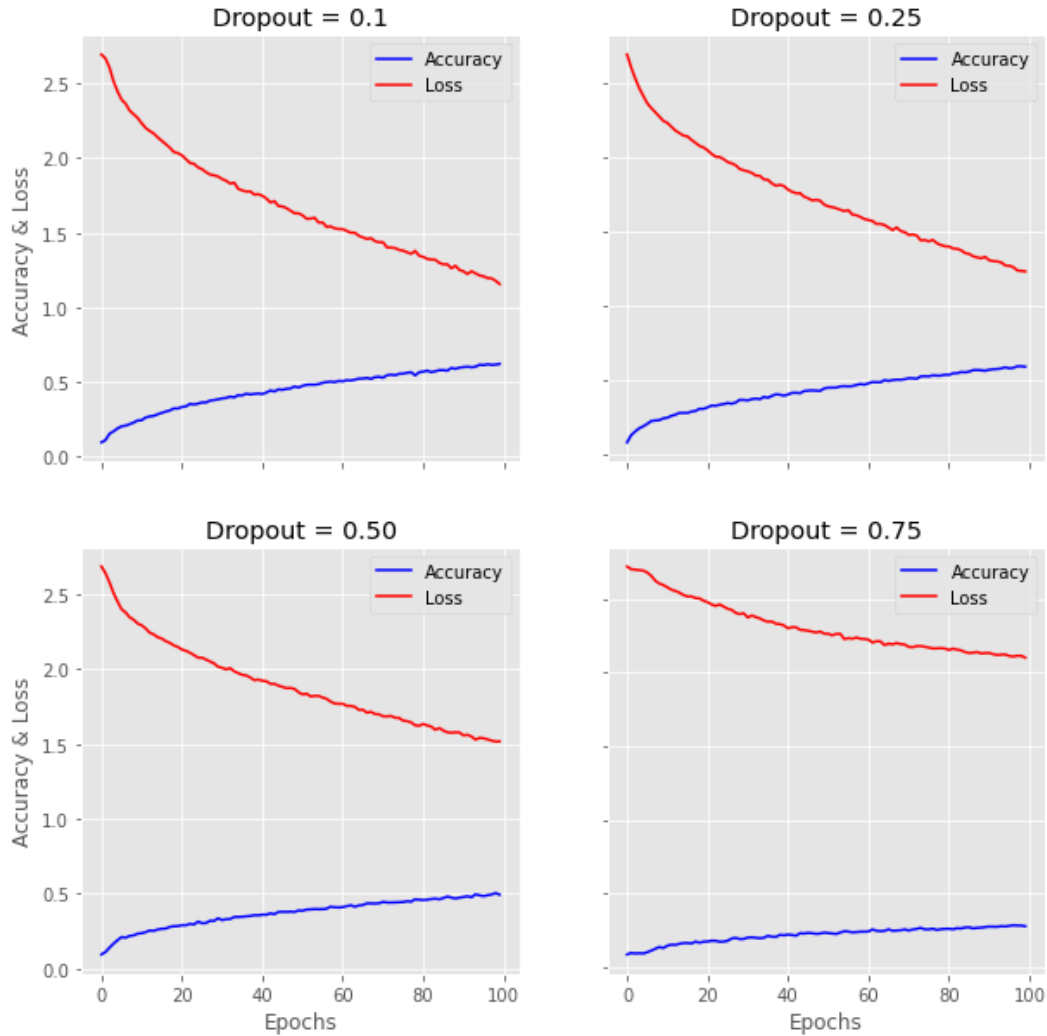


Figure 7: Train accuracies and losses of CNN models with dropout.

3 VGG Part

Fine tuning is a form of training in which, weights of a model are being fine tuned. These models usually were trained on large datasets such as ImageNet dataset. Taking the already trained model and tuning it for the dataset on hand, makes the learning faster than training a brand new neural network, and probably more robust to different kind of data samples. In general, last layers of the model (classification part of the models, see CNNs online for basic understanding) are being trained since all the thing that rest of the network do is extracting features. But in some cases, last few feature extraction layers also trained.

In this assignment, VGG16 that trained on ImageNet dataset has been used in two different configuration. In the first configuration, classification part of the VGG16 has been altered, such that last 3 Dense layers (classification part of the model) has 64, 32 and 15 neurons respectively (original VGG has different number of neurons in these layers) and unlike other layers, their weights has been initialized randomly. Layers other than classification part are freezed meaning that they will not be

Validation Accuracies and Losses of model with Dropout

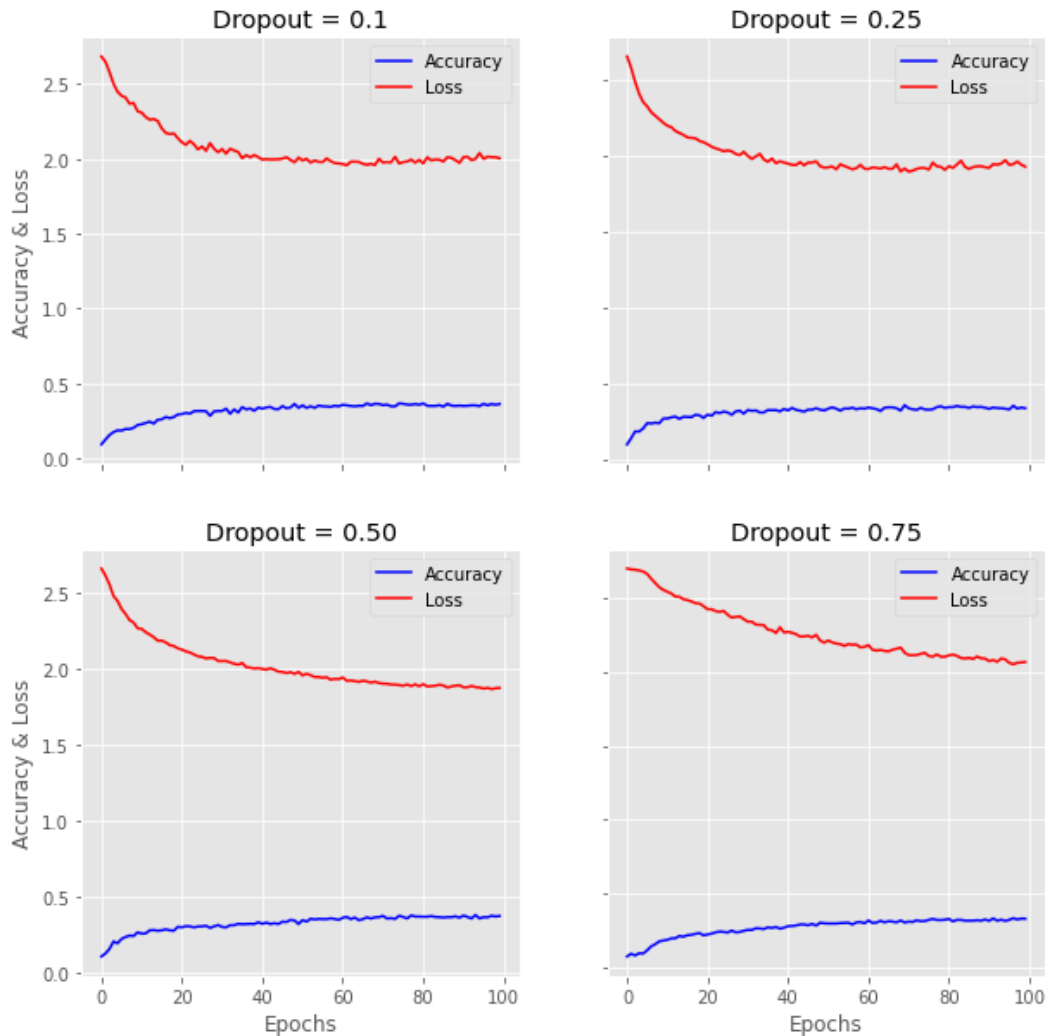


Figure 8: Validation accuracies and losses of CNN models with dropout.

trained. In the second configuration, on top of the first configuration, also last convolution layer is trainable however it's weights are not randomly initialized but initialized with VGG16 weights.

3.1 Configuration 1

Code to create the configuration 1 model can be seen in 3.

Listing 3: Code of VGG Configuration 1

```
1 vgg = VGG16(weights='imagenet', include_top=False, input_shape = (HEIGHT,
    WIDTH, CHANNELS))
2
3 for layer in vgg.layers:
4     layer.trainable = False
5
6 model_vgg = tf.keras.Sequential([
7     vgg,
8     layers.Flatten(),
```




Figure 9: Test accuracies of CNN models with dropout.

Confusion matrix of model 0 with dropout of 0.1

```
[[24 0 3 2 3 2 1 4 3 2 1 1 6 4 5]
 [ 1 4 2 4 7 1 1 0 6 3 1 5 3 1 2]
 [ 1 1 12 0 5 9 2 1 5 6 1 12 3 2 0]
 [ 0 0 1 38 0 0 2 0 8 7 1 5 0 1 3]
 [ 1 2 2 1 9 4 0 1 2 1 1 7 1 2 4]
 [ 5 1 7 1 3 21 0 3 0 1 0 3 5 0 1]
 [ 1 0 1 3 0 0 22 0 2 1 1 1 1 0 2]
 [ 2 1 1 2 2 3 2 16 1 2 1 3 6 0 4]
 [ 1 1 1 17 0 1 6 1 23 9 0 5 4 1 3]
 [ 0 1 3 27 1 1 2 2 12 15 0 1 1 0 4]
 [ 2 2 2 1 1 1 2 0 8 1 9 3 2 1 4]
 [ 2 1 2 8 6 10 0 1 2 2 0 12 1 0 4]
 [ 4 1 0 3 5 3 1 2 3 2 1 4 16 1 8]
 [ 3 2 1 1 8 4 0 2 0 2 2 4 0 3 3]
 [ 5 0 0 4 2 4 1 1 3 2 2 1 3 0 22]]
```

(a) Model 0

Confusion matrix of model 1 with dropout of 0.25

```
[[24 0 3 2 3 2 1 4 3 2 1 1 6 4 5]
 [ 1 4 2 4 7 1 1 0 6 3 1 5 3 1 2]
 [ 1 1 12 0 5 9 2 1 5 6 1 12 3 2 0]
 [ 0 0 1 38 0 0 2 0 8 7 1 5 0 1 3]
 [ 1 2 2 1 9 4 0 1 2 1 1 7 1 2 4]
 [ 5 1 7 1 3 21 0 3 0 1 0 3 5 0 1]
 [ 1 0 1 3 0 0 22 0 2 1 1 1 1 0 2]
 [ 2 1 1 2 2 3 2 16 1 2 1 3 6 0 4]
 [ 1 1 1 17 0 1 6 1 23 9 0 5 4 1 3]
 [ 0 1 3 27 1 1 2 2 12 15 0 1 1 0 4]
 [ 2 2 2 1 1 1 2 0 8 1 9 3 2 1 4]
 [ 2 1 2 8 6 10 0 1 2 2 0 12 1 0 4]
 [ 4 1 0 3 5 3 1 2 3 2 1 4 16 1 8]
 [ 3 2 1 1 8 4 0 2 0 2 2 4 0 3 3]
 [ 5 0 0 4 2 4 1 1 3 2 2 1 3 0 22]]
```

(b) Model 1

Confusion matrix of model 2 with dropout of 0.5

```
[[24 0 3 2 3 2 1 4 3 2 1 1 6 4 5]
 [ 1 4 2 4 7 1 1 0 6 3 1 5 3 1 2]
 [ 1 1 12 0 5 9 2 1 5 6 1 12 3 2 0]
 [ 0 0 1 38 0 0 2 0 8 7 1 5 0 1 3]
 [ 1 2 2 1 9 4 0 1 2 1 1 7 1 2 4]
 [ 5 1 7 1 3 21 0 3 0 1 0 3 5 0 1]
 [ 1 0 1 3 0 0 22 0 2 1 1 1 1 0 2]
 [ 2 1 1 2 2 3 2 16 1 2 1 3 6 0 4]
 [ 1 1 1 17 0 1 6 1 23 9 0 5 4 1 3]
 [ 0 1 3 27 1 1 2 2 12 15 0 1 1 0 4]
 [ 2 2 2 1 1 1 2 0 8 1 9 3 2 1 4]
 [ 2 1 2 8 6 10 0 1 2 2 0 12 1 0 4]
 [ 4 1 0 3 5 3 1 2 3 2 1 4 16 1 8]
 [ 3 2 1 1 8 4 0 2 0 2 2 4 0 3 3]
 [ 5 0 0 4 2 4 1 1 3 2 2 1 3 0 22]]
```

(c) Model 2

Confusion matrix of model 3 with dropout of 0.75

```
[[24 0 3 2 3 2 1 4 3 2 1 1 6 4 5]
 [ 1 4 2 4 7 1 1 0 6 3 1 5 3 1 2]
 [ 1 1 12 0 5 9 2 1 5 6 1 12 3 2 0]
 [ 0 0 1 38 0 0 2 0 8 7 1 5 0 1 3]
 [ 1 2 2 1 9 4 0 1 2 1 1 7 1 2 4]
 [ 5 1 7 1 3 21 0 3 0 1 0 3 5 0 1]
 [ 1 0 1 3 0 0 22 0 2 1 1 1 1 0 2]
 [ 2 1 1 2 2 3 2 16 1 2 1 3 6 0 4]
 [ 1 1 1 17 0 1 6 1 23 9 0 5 4 1 3]
 [ 0 1 3 27 1 1 2 2 12 15 0 1 1 0 4]
 [ 2 2 2 1 1 1 2 0 8 1 9 3 2 1 4]
 [ 2 1 2 8 6 10 0 1 2 2 0 12 1 0 4]
 [ 4 1 0 3 5 3 1 2 3 2 1 4 16 1 8]
 [ 3 2 1 1 8 4 0 2 0 2 2 4 0 3 3]
 [ 5 0 0 4 2 4 1 1 3 2 2 1 3 0 22]]
```

(d) Model 3

Figure 10: Confusion Matrices of models without dropout.

Model: "vgg16"

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 100, 100, 3)]	0
block1_conv1 (Conv2D)	(None, 100, 100, 64)	1792
block1_conv2 (Conv2D)	(None, 100, 100, 64)	36928
block1_pool (MaxPooling2D)	(None, 50, 50, 64)	0
block2_conv1 (Conv2D)	(None, 50, 50, 128)	73856
block2_conv2 (Conv2D)	(None, 50, 50, 128)	147584
block2_pool (MaxPooling2D)	(None, 25, 25, 128)	0
block3_conv1 (Conv2D)	(None, 25, 25, 256)	295168
block3_conv2 (Conv2D)	(None, 25, 25, 256)	590080
block3_conv3 (Conv2D)	(None, 25, 25, 256)	590080
block3_pool (MaxPooling2D)	(None, 12, 12, 256)	0
block4_conv1 (Conv2D)	(None, 12, 12, 512)	1180160
block4_conv2 (Conv2D)	(None, 12, 12, 512)	2359808
block4_conv3 (Conv2D)	(None, 12, 12, 512)	2359808
block4_pool (MaxPooling2D)	(None, 6, 6, 512)	0
block5_conv1 (Conv2D)	(None, 6, 6, 512)	2359808
block5_conv2 (Conv2D)	(None, 6, 6, 512)	2359808
block5_conv3 (Conv2D)	(None, 6, 6, 512)	2359808
block5_pool (MaxPooling2D)	(None, 3, 3, 512)	0
Total params: 14,714,688		
Trainable params: 0		
Non-trainable params: 14,714,688		

Figure 11: Topology of imported VGG.

```

9     layers.Dense(64, activation="relu"),
10    layers.Dense(32, activation="relu"),
11    layers.Dense(NUM_CLASSES, activation="softmax")
12 ])
13
14
15 model_vgg.compile(loss='categorical_crossentropy', optimizer="Adam",
16                  metrics=['accuracy'])
17 history_vgg = model_vgg.fit(X_train, y_train, batch_size=100, epochs=100,
18                             validation_data = (X_validation, y_validation), shuffle=True)

```

Also topology of imported VGG can be seen in 11 and topology of configuration 1 model can be seen in 12.

Number of neuron selection here highly affected by runtime because even with that number of neurons, training took 5 - 6 hours.

Train / validation / test accuracies and losses can be seen in 13, in 14 and in 15.

Model: "sequential_2"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 3, 3, 512)	14714688
flatten_2 (Flatten)	(None, 4608)	0
dense_6 (Dense)	(None, 64)	294976
dense_7 (Dense)	(None, 32)	2080
dense_8 (Dense)	(None, 15)	495
Total params: 15,012,239		
Trainable params: 297,551		
Non-trainable params: 14,714,688		

Figure 12: Topology of configuration 1 model.

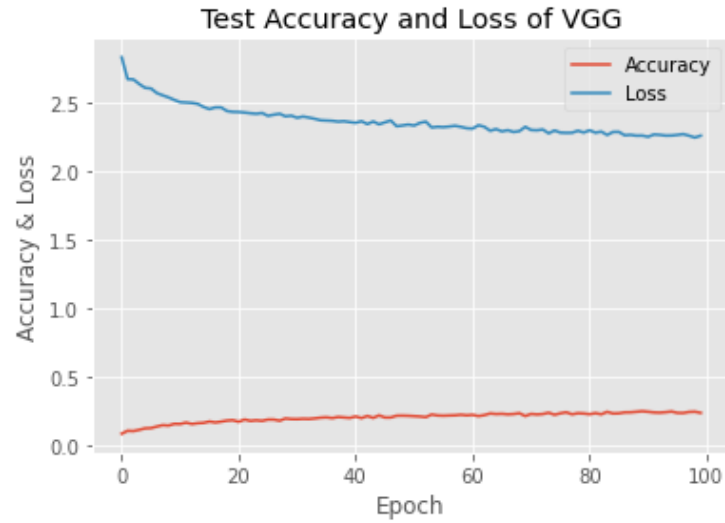


Figure 13: Train accuracy and loss of VGG Configuration 1.

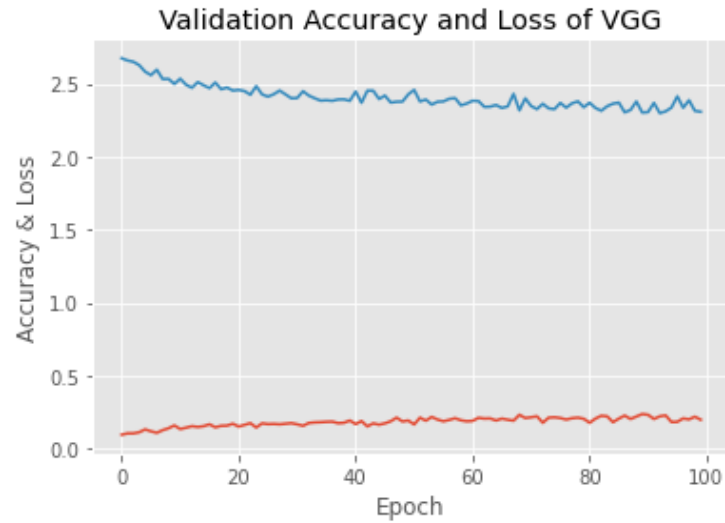


Figure 14: Validation accuracy and loss of VGG Configuration 1.

```
In [26]: y_pred_vgg = model_vgg.predict(X_test)
y_pred_classes_vgg = np.argmax(y_pred_vgg, axis=1)
y_test_classes = np.argmax(y_test, axis=1)

vgg_accuracy_fc = accuracy_score(y_test_classes, y_pred_classes_vgg)

print("VGG that only Dense layers trained has accuracy of", vgg_accuracy_fc)

VGG that only Dense layers trained has accuracy of 0.22467532467532467
```

Figure 15: Test accuracy of VGG Configuration 1.

```
Confusion matrix of VGG that only Dense layers trained
[[14  0  0  5  1  0  2  7  1  3  6  4  8  5  5]
 [ 7  4  0  1  2  0  0  1  1  3 12  2  0  6  2]
 [17  1  3  0  1  1  3  7  1  7  8  3  2  1  5]
 [ 2  0  0 34  0  0 10  1  1 13  1  1  2  0  1]
 [ 8  2  1  1  1  1  0  4  0  1 10  1  2  4  2]
 [14  0  1  2  0  0  0  7  0  3  8  6  2  4  4]
 [ 1  0  0  3  0  0 23  3  0  1  2  0  1  0  1]
 [ 5  0  0  0  0  1  3 21  0  0  5  3  2  0  6]
 [10  0  0 18  0  0  7  1  7 15  4  4  2  1  4]
 [ 5  1  1 18  0  1  3  4  5 15  4  5  3  0  5]
 [ 5  1  1  1  0  0  1  6  1  3 13  3  0  2  2]
 [ 9  0  0  5  0  1  0  3  1  8 13  9  1  0  1]
 [ 7  1  0  3  0  1  9  4  0  2  3  0 12  1 11]
 [ 6  3  0  1  2  1  0  2  0  1  8  0  0  6  5]
 [10  0  0  3  1  0  1  2  0  2 11  2  5  2 11]]
```

Figure 16: Confusion matrix of VGG Configuration 1.

Also, confusion matrix can be seen in 16.

Well, it didn't do a good job. That may be due to bad number of weights. Train accuracy is low too, meaning that no learning happened actually. Or this accuracy score might be a good accuracy score for this problem. I don't really know. Looking at the confusion matrix at 16, it can be seen that model has lots of incorrect predictions which make it seem like no learning happened during training.

3.2 Configuration 2

Code to create the configuration 1 model can be seen in 4.

Listing 4: Code of VGG Configuration 2

```
1 vgg = VGG16(weights='imagenet', include_top=False, input_shape = (HEIGHT,
    WIDTH, CHANNELS))
2
3 for layer in vgg.layers:
4     layer.trainable = False
5
6 vgg.layers[-1].trainable = True
7 vgg.layers[-2].trainable = True
8
9 model_vgg_ = tf.keras.Sequential([
10     vgg,
11     layers.Flatten(),
12     layers.Dense(64, activation="relu"),
13     layers.Dense(32, activation="relu"),
14     layers.Dense(NUM_CLASSES, activation="softmax")
15 ])
16 model_vgg_.summary()
17
18 model_vgg_.compile(loss='categorical_crossentropy', optimizer="Adam",
    metrics=['accuracy'])
```

Model: "sequential"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 3, 3, 512)	14714688
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 64)	294976
dense_1 (Dense)	(None, 32)	2080
dense_2 (Dense)	(None, 15)	495
Total params: 15,012,239		
Trainable params: 2,657,359		
Non-trainable params: 12,354,880		

Figure 17: Topology of configuration 2 model.

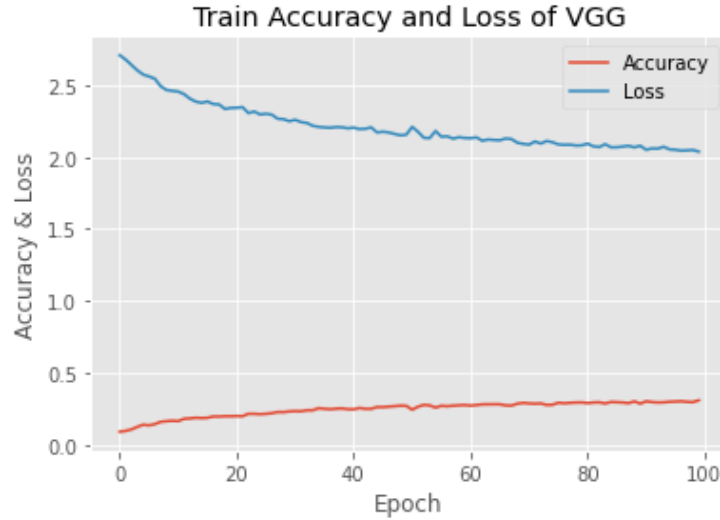


Figure 18: Train accuracy and loss of VGG Configuration 2.

```

19
20 history_vgg = model_vgg.fit(X_train, y_train, batch_size=100, epochs=100,
    validation_data = (X_validation, y_validation), shuffle=True)

```

Topology of configuration 1 model can be seen in 17.

Train / validation / test accuracies and losses can be seen in 18, in 19 and in 20.

Also, confusion matrix can be seen in 21.

Again, results are not promising but configuration 2 did better! So, a conclusion might be that, ImageNet classes are not aligned with the used dataset. Because when the last convolution layer trained (which is a feature extraction layer), the accuracy increased.

Being said these, one of the proposed models (model 2, batch size = 50 and learning rate = 0.0001) did better than fine tuning. Also training of the proposed models were way faster than fine tuning VGG16, in numbers training 6 different models took in total 43515 seconds and fine tuning VGG16 configuration 2 took 174807 seconds which is about 4x more. Also, altering CNN to get better results is much easier than fine tuning VGG16 because of the both runtime, and that we have entire

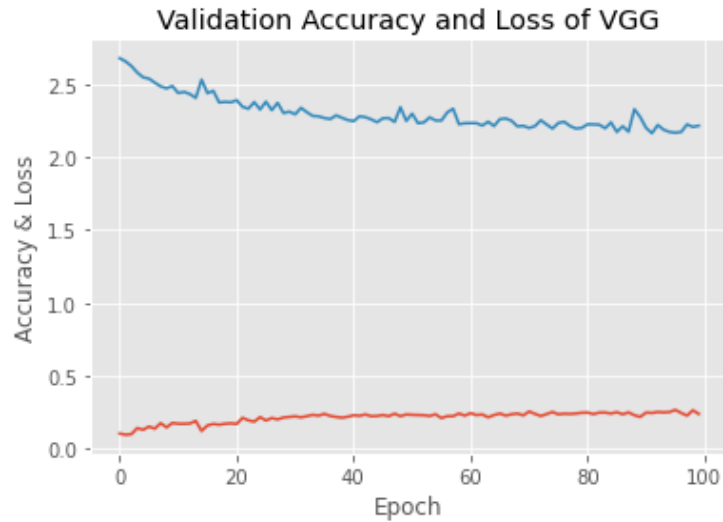


Figure 19: Validation accuracy and loss of VGG Configuration 2.

```
In [25]: y_pred_vgg_ = model_vgg_.predict(X_test)
y_pred_classes_vgg_ = np.argmax(y_pred_vgg_, axis=1)
y_test_classes = np.argmax(y_test, axis=1)

vgg_accuracy_fc_conf2 = accuracy_score(y_test_classes, y_pred_classes_vgg_)

print("VGG that Dense layers & last Convolution layer trained has accuracy of", vgg_accuracy_fc_conf2)

VGG that Dense layers & last Convolution layer trained has accuracy of 0.24675324675324675
```

Figure 20: Test accuracy of VGG Configuration 2.

```
Confusion matrix of VGG that Dense layers & last Convolution layer trained
[[ 0  0  2  6  4 10  0 14  2  1  0  7  8  2  5]
 [ 3  0  4  1  9  4  0  2  0  1  7  2  1  5  2]
 [ 2  0  2  0  8 17  3 11  2  1  2  6  2  2  2]
 [ 0  0  2 32  0  3 14  0  1  8  0  2  4  0  0]
 [ 0  0  2  0 11  8  0  6  0  0  2  4  2  3  0]
 [ 0  0  2  2  6 17  0 12  0  2  1  3  2  3  1]
 [ 1  0  0  5  0  1 21  3  0  0  0  1  3  0  0]
 [ 0  1  0  0  1  1  3 33  0  0  0  2  5  0  0]
 [ 1  0  6 22  1  2  7  4 10  8  1  9  0  0  2]
 [ 0  0  5 23  0  4  3  6  8 11  1  8  0  0  1]
 [ 1  0  3  0  6  2  1  7  2  1 11  1  0  2  2]
 [ 0  1  1  5  3 11  2  8  2  4  0 13  1  0  0]
 [ 0  1  1  1  2  7 12  6  2  1  0  0 17  0  4]
 [ 2  0  1  0  7  7  0  4  0  1  3  1  0  9  0]
 [ 1  1  5  1  7  9  3  5  0  2  1  2  8  2  3]]
```

Figure 21: Confusion matrix of VGG Configuration 2.

control of CNN while VGG16 comes with number of imported layers which is impossible (if not, hard) to alter.