rueegg_wissiak_optimized

March 7, 2023

1 Optimized Model

This model does not show under- or overfitting and performs well on both, training and testing data. Afterwards, a brief description on how to tackle the challenges of an optimal model complexity.

To address underfitting, one approach is to increase the complexity of the model by adding more layers or increasing the number of filters in each layer. To address overfitting, we can try several approaches. One approach is to simplify the model by removing some layers or decreasing the number of filters in each layer. Another approach is to use less epochs for example.

Adding dropout or weight decay can help to address both of the above mentioned issues. We can also try adjusting the hyperparameters such as learning rate, batch size, or number of epochs.

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[2]:
```
from tensorflow.keras.utils import image_dataset_from_directory

img_size = 150
batch_size = 64
seed = 31

train_ds = image_dataset_from_directory(
    './dataset/seg_train/seg_train',
    validation_split=0.2,
    subset="training",
    labels="inferred",
    seed=seed,
    image_size=(img_size, img_size),
    batch_size=batch_size
)
val_ds = image_dataset_from_directory(
    './dataset/seg_train/seg_train',
    validation_split=0.2,
    subset="validation",
    labels="inferred",
    seed=seed,
    image_size=(img_size, img_size),
    batch_size=batch_size
)
test_ds = image_dataset_from_directory(
    './dataset/seg_test/seg_test',
    labels="inferred",
    seed=seed,
    image_size=(img_size, img_size),
    batch_size=batch_size
)
```

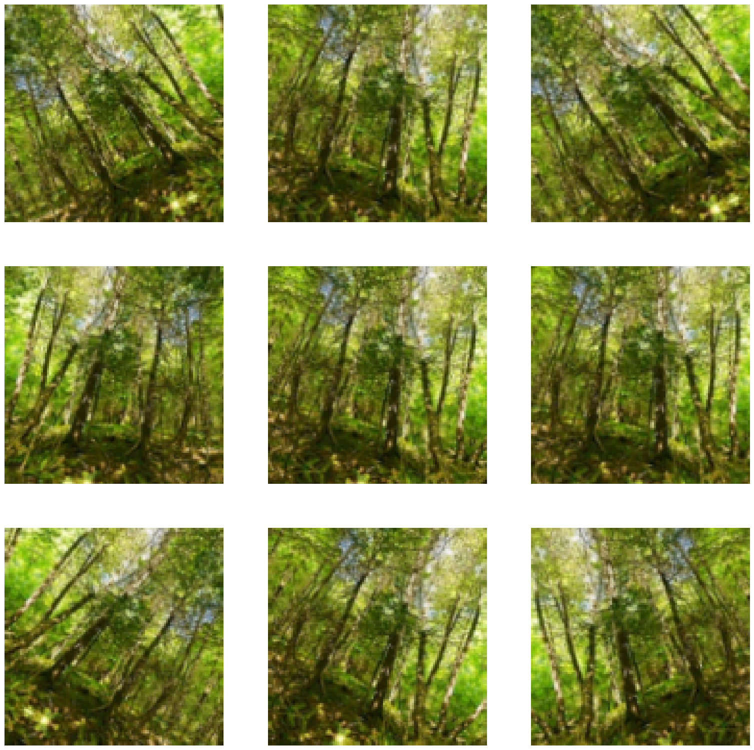
```
Found 2666 files belonging to 5 classes.
Using 2133 files for training.
```

```
2023-03-07 09:01:23.731564: I tensorflow/core/platform/cpu_feature_guard.cc:193]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  SSE4.1 SSE4.2
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
```

```
Found 2666 files belonging to 5 classes.
Using 533 files for validation.
Found 2499 files belonging to 5 classes.
```

[3]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import RandomRotation, RandomZoom, Rescaling,␣
 ↪RandomFlip

data_augmentation = Sequential(
  [
    RandomFlip("horizontal", input_shape=(img_size, img_size, 3)),
    RandomRotation(0.1),
    RandomZoom(0.1),
  ]
)
```

[4]:
```
plt.figure(figsize=(5, 5))
for image, _ in train_ds.take(1):
  for i in range(9):
    augmented_images = data_augmentation(image)
    ax = plt.subplot(3, 3, i + 1)
    plt.imshow(augmented_images[0].numpy().astype("uint8"))
    plt.axis("off")
```



1.1 Building the Model

Here we use the same model as the overfitting one but we add some extras to reduce the overfitting behavior.

1.1.1 Regularization

Regularization is used to reduce the impact impact of the weights. The weights then end up having less impact on the loss function which determines the error between the actual label and predicted label. This reduces complexity of the model and therefore reduces overfitting. We are adding regularization only to those layers which have the largest number of parameters according to the model summary. We are using L2 (Ridge) regularization since it predetermined from the task. We are adding L2 mainly to the layers that add the most parameters to the CNN.

Dropout Layers: The benefit of using dropout is no node in the network will be assigned with high parameter values, as a a result the parameter values will be dispersed and the output of the current layer will not depend on a single node. E.g. Dropout(0.2) drops the input layers at a probability of 0.2.

1.1.2 Generalization

To improve generalization of the model, data augmentation is a useful tool. With data augmentation we can add artificial effects to the images such as shearing, stretching, flipping, rotating and translating. Through these effects, the images always appear differently each time they appear in the training step and therefore the CNN doesn't adapt to the exact images but rather learns about the relative features inside of an image.

1.1.3 Optimizer

For the optimized model we chose Adam over the competitors because it is the most common among SGD. We tried out SGD but it performed very poorly compared to Adam which might be due to insufficient configuration of the learning rate. Adam optimization is a stochastic gradient descent method that is based on adaptive estimation of first-order (mean) and second-order (uncentered variance) moments. Its default implementation already provides a form of annealed learning, beta_1=0.9 for the first-order moment and beta_2=0.999 for the second-order moment.

1.1.4 Activation Function

The following article states that ReLU is the overall the best suited activation function so based on this we decided to use ReLU for our optimized model.

1.1.5 Batch Size

The batch size defines how many samples (images here) run through the Neural Network before the weights get adapted. It is recommended to use mini batches to update the Neural Network multiple times during an epoch. We've tried out differnt batch sizes with the same seed on the image generator TODO

[5]:
```
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,␣
↪Dropout
from tensorflow.keras.regularizers import l2
```

[6]:
```
def create_model(l2_param=0.001, last_dropout_param=0.2):
    model = Sequential()

    model.add(data_augmentation)
    model.add(Rescaling(1./255))

    model.add(Conv2D(32, (3,3), input_shape= (img_size,img_size,3), activation␣
↪= 'relu', padding = 'same')) #padding = same size output
    model.add(MaxPooling2D())

    model.add(Conv2D(64, (3,3), activation = 'relu', padding = 'same'))
    model.add(MaxPooling2D())

    model.add(Conv2D(128, (3,3), activation = 'relu', padding = 'same'))
    model.add(MaxPooling2D())

    model.add(Conv2D(256, (3,3), activation = 'relu', padding = 'same'))
    model.add(MaxPooling2D())

    model.add(Conv2D(512, (3,3), activation = 'relu', padding = 'same',␣
↪kernel_regularizer=l2(l=l2_param)))
```

```
    model.add(MaxPooling2D())
    model.add(Dropout(0.1))

    model.add(Conv2D(1024, (3,3), activation = 'relu', padding = 'same',␣
↪kernel_regularizer=l2(l=l2_param)))
    model.add(MaxPooling2D())
    model.add(Dropout(0.1))

    model.add(Conv2D(512, (3,3), activation = 'relu', padding = 'same',␣
↪kernel_regularizer=l2(l=l2_param)))
    model.add(MaxPooling2D())

    model.add(Dropout(last_dropout_param))
    model.add(Flatten())

    model.add(Dense(256, activation='relu'))
    #model.add(Dense(512, activation='relu'))
    model.add(Dense(5, activation = 'softmax'))

    model.compile(optimizer = 'adam', loss='sparse_categorical_crossentropy',␣
↪metrics=['accuracy'])

    return model
```

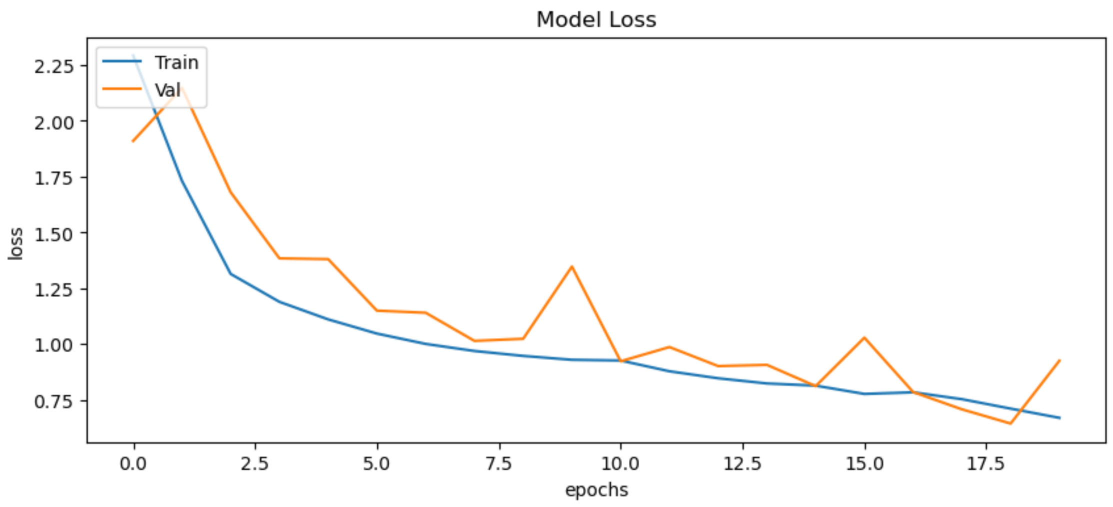
1.2 Cross Validation for L2 Parameter

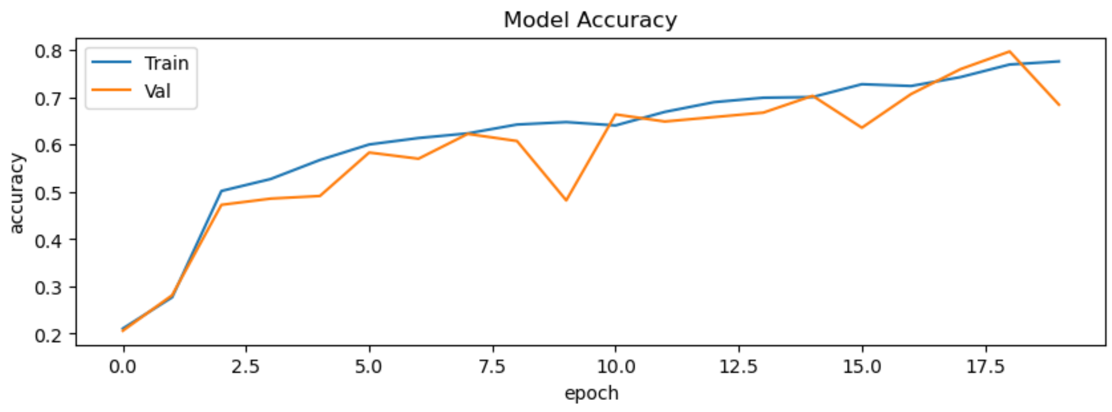
To find the optimal L2 regularization parameter we are using GridSearchCV from sklearn by applying a k=5 Cross Validation. As the to-be-optimized score we use, as per default, the accuracy. To be able to use GridSearchCV we must wrap the model to be compatible with the sklearn ecosystem.

[7]:
```
import itertools
param_grid=dict(
    #
    # l2_param=[0.01, 0.001, 0.0001],
    last_dropout_param=[0.1, 0.2, 0.3],
    #batch_size_param=[16, 32, 128],
    #epochs_param=[10, 20, 30]
)

keys = list(param_grid.keys())
params = list(param_grid.get(x) for x in keys)
param_permutations = list(itertools.product(*params))

model_history = []

for perm in param_permutations:
    model_args = dict()
    for index in range(len(params)):
        key = keys[index]
        value = perm[index]
        model_args[key] = value
    print("CURRENTLY TRAINING THE MODEL WITH THE FOLLOWING PARAMS:")
    print(model_args)
    model = create_model(**model_args)
    history = model.fit(train_ds, validation_data=val_ds, epochs=20)
    %run rueegg_wissiak_model_visualization.ipynb
    eval = model.evaluate(test_ds)
    print(eval)
    model_history.append(dict(history=history, model=model))
```

```
CURRENTLY TRAINING THE MODEL WITH THE FOLLOWING PARAMS:
{'last_dropout_param': 0.1}
Epoch 1/20
34/34 [==============================] - 76s 2s/step - loss: 2.2929 - accuracy:
0.2110 - val_loss: 1.9102 - val_accuracy: 0.2064
Epoch 2/20
34/34 [==============================] - 75s 2s/step - loss: 1.7316 - accuracy:
0.2771 - val_loss: 2.1475 - val_accuracy: 0.2814
Epoch 3/20
34/34 [==============================] - 74s 2s/step - loss: 1.3145 - accuracy:
0.5021 - val_loss: 1.6803 - val_accuracy: 0.4728
Epoch 4/20
34/34 [==============================] - 74s 2s/step - loss: 1.1895 - accuracy:
0.5274 - val_loss: 1.3842 - val_accuracy: 0.4859
Epoch 5/20
34/34 [==============================] - 74s 2s/step - loss: 1.1110 - accuracy:
0.5677 - val_loss: 1.3808 - val_accuracy: 0.4916
Epoch 6/20
34/34 [==============================] - 74s 2s/step - loss: 1.0474 - accuracy:
0.6006 - val_loss: 1.1500 - val_accuracy: 0.5835
Epoch 7/20
34/34 [==============================] - 74s 2s/step - loss: 1.0011 - accuracy:
0.6142 - val_loss: 1.1407 - val_accuracy: 0.5704
Epoch 8/20
34/34 [==============================] - 74s 2s/step - loss: 0.9695 - accuracy:
0.6240 - val_loss: 1.0148 - val_accuracy: 0.6229
Epoch 9/20
34/34 [==============================] - 74s 2s/step - loss: 0.9474 - accuracy:
0.6428 - val_loss: 1.0241 - val_accuracy: 0.6079
Epoch 10/20
34/34 [==============================] - 74s 2s/step - loss: 0.9300 - accuracy:
0.6479 - val_loss: 1.3475 - val_accuracy: 0.4822
Epoch 11/20
34/34 [==============================] - 75s 2s/step - loss: 0.9267 - accuracy:
```

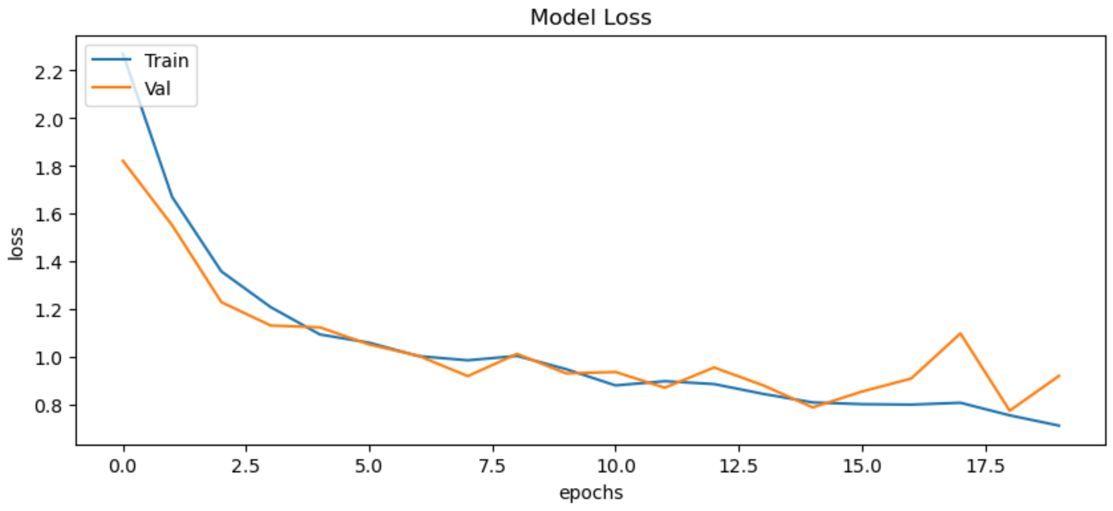
```
0.6409 - val_loss: 0.9234 - val_accuracy: 0.6642
Epoch 12/20
34/34 [==============================] - 74s 2s/step - loss: 0.8786 - accuracy:
0.6695 - val_loss: 0.9871 - val_accuracy: 0.6492
Epoch 13/20
34/34 [==============================] - 74s 2s/step - loss: 0.8472 - accuracy:
0.6901 - val_loss: 0.9019 - val_accuracy: 0.6585
Epoch 14/20
34/34 [==============================] - 75s 2s/step - loss: 0.8241 - accuracy:
0.6995 - val_loss: 0.9073 - val_accuracy: 0.6679
Epoch 15/20
34/34 [==============================] - 75s 2s/step - loss: 0.8143 - accuracy:
0.7009 - val_loss: 0.8120 - val_accuracy: 0.7036
Epoch 16/20
34/34 [==============================] - 74s 2s/step - loss: 0.7771 - accuracy:
0.7281 - val_loss: 1.0291 - val_accuracy: 0.6360
Epoch 17/20
34/34 [==============================] - 74s 2s/step - loss: 0.7843 - accuracy:
0.7243 - val_loss: 0.7855 - val_accuracy: 0.7073
Epoch 18/20
34/34 [==============================] - 74s 2s/step - loss: 0.7536 - accuracy:
0.7431 - val_loss: 0.7082 - val_accuracy: 0.7598
Epoch 19/20
34/34 [==============================] - 74s 2s/step - loss: 0.7113 - accuracy:
0.7698 - val_loss: 0.6444 - val_accuracy: 0.7974
Epoch 20/20
34/34 [==============================] - 74s 2s/step - loss: 0.6701 - accuracy:
0.7764 - val_loss: 0.9259 - val_accuracy: 0.6848
```

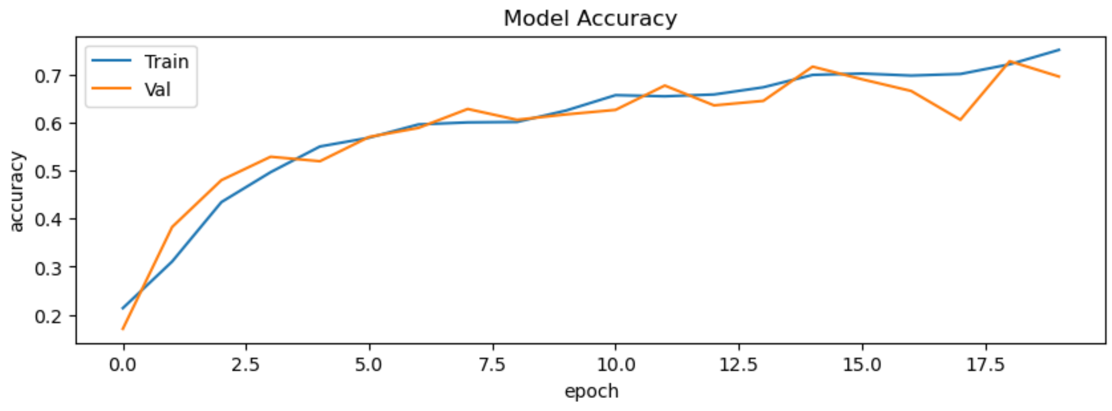




```
40/40 [==============================] - 13s 328ms/step - loss: 0.9742 -
accuracy: 0.6747
[0.9741828441619873, 0.6746698617935181]
CURRENTLY TRAINING THE MODEL WITH THE FOLLOWING PARAMS:
{'last_dropout_param': 0.2}
Epoch 1/20
34/34 [==============================] - 75s 2s/step - loss: 2.2707 - accuracy:
0.2138 - val_loss: 1.8222 - val_accuracy: 0.1707
Epoch 2/20
34/34 [==============================] - 74s 2s/step - loss: 1.6709 - accuracy:
0.3108 - val_loss: 1.5525 - val_accuracy: 0.3827
Epoch 3/20
34/34 [==============================] - 74s 2s/step - loss: 1.3591 - accuracy:
0.4346 - val_loss: 1.2306 - val_accuracy: 0.4803
Epoch 4/20
34/34 [==============================] - 74s 2s/step - loss: 1.2100 - accuracy:
0.4970 - val_loss: 1.1330 - val_accuracy: 0.5291
Epoch 5/20
34/34 [==============================] - 74s 2s/step - loss: 1.0954 - accuracy:
0.5504 - val_loss: 1.1253 - val_accuracy: 0.5197
Epoch 6/20
34/34 [==============================] - 74s 2s/step - loss: 1.0611 - accuracy:
0.5687 - val_loss: 1.0533 - val_accuracy: 0.5704
Epoch 7/20
34/34 [==============================] - 74s 2s/step - loss: 1.0048 - accuracy:
0.5963 - val_loss: 1.0065 - val_accuracy: 0.5891
Epoch 8/20
34/34 [==============================] - 74s 2s/step - loss: 0.9874 - accuracy:
0.6006 - val_loss: 0.9211 - val_accuracy: 0.6285
Epoch 9/20
34/34 [==============================] - 74s 2s/step - loss: 1.0058 - accuracy:
0.6015 - val_loss: 1.0143 - val_accuracy: 0.6060
Epoch 10/20
```

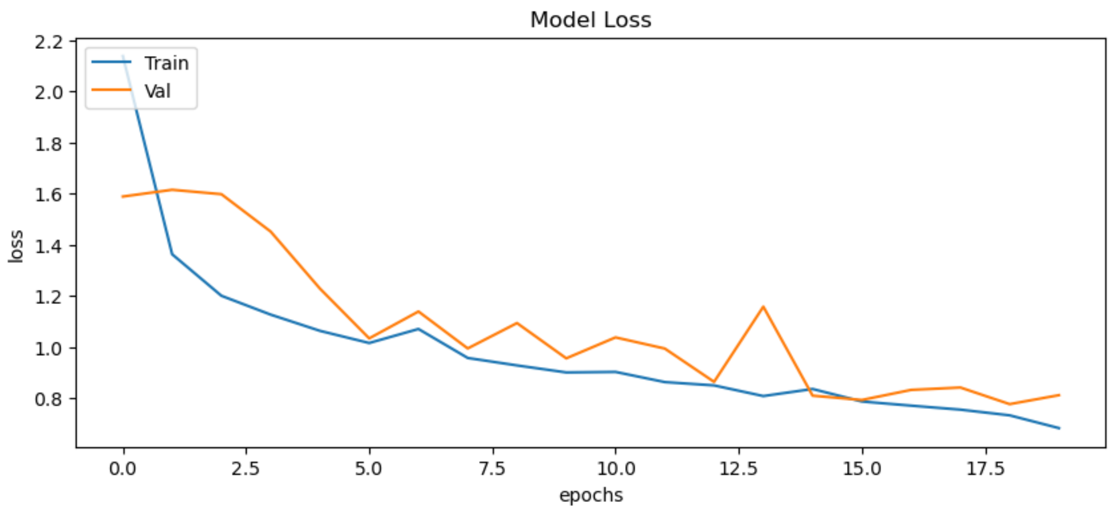
```
34/34 [==============================] - 74s 2s/step - loss: 0.9502 - accuracy:
0.6254 - val_loss: 0.9323 - val_accuracy: 0.6173
Epoch 11/20
34/34 [==============================] - 74s 2s/step - loss: 0.8822 - accuracy:
0.6573 - val_loss: 0.9384 - val_accuracy: 0.6266
Epoch 12/20
34/34 [==============================] - 74s 2s/step - loss: 0.9000 - accuracy:
0.6549 - val_loss: 0.8728 - val_accuracy: 0.6773
Epoch 13/20
34/34 [==============================] - 75s 2s/step - loss: 0.8879 - accuracy:
0.6587 - val_loss: 0.9574 - val_accuracy: 0.6360
Epoch 14/20
34/34 [==============================] - 75s 2s/step - loss: 0.8468 - accuracy:
0.6737 - val_loss: 0.8824 - val_accuracy: 0.6454
Epoch 15/20
34/34 [==============================] - 75s 2s/step - loss: 0.8112 - accuracy:
0.6995 - val_loss: 0.7902 - val_accuracy: 0.7167
Epoch 16/20
34/34 [==============================] - 74s 2s/step - loss: 0.8039 - accuracy:
0.7023 - val_loss: 0.8565 - val_accuracy: 0.6904
Epoch 17/20
34/34 [==============================] - 74s 2s/step - loss: 0.8020 - accuracy:
0.6981 - val_loss: 0.9110 - val_accuracy: 0.6660
Epoch 18/20
34/34 [==============================] - 74s 2s/step - loss: 0.8097 - accuracy:
0.7014 - val_loss: 1.0998 - val_accuracy: 0.6060
Epoch 19/20
34/34 [==============================] - 74s 2s/step - loss: 0.7571 - accuracy:
0.7215 - val_loss: 0.7766 - val_accuracy: 0.7280
Epoch 20/20
34/34 [==============================] - 75s 2s/step - loss: 0.7141 - accuracy:
0.7515 - val_loss: 0.9221 - val_accuracy: 0.6961
```

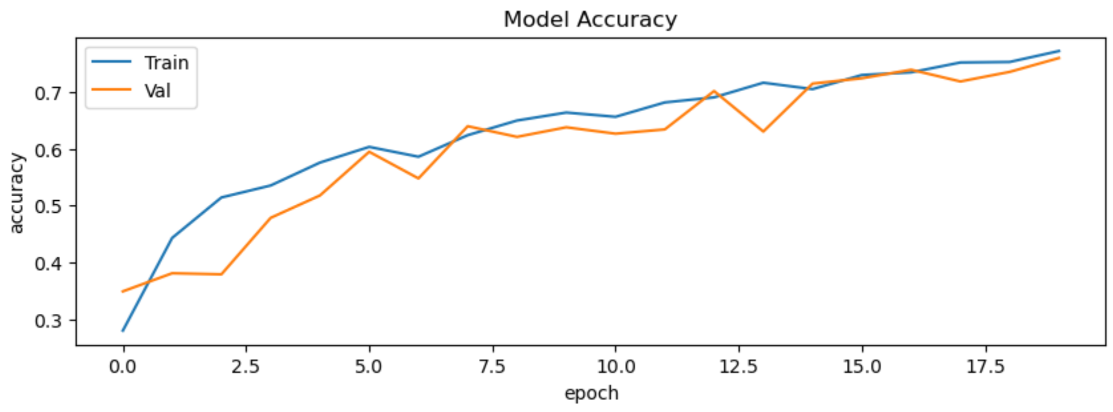




```
40/40 [==============================] - 13s 332ms/step - loss: 0.9308 -
accuracy: 0.6955
[0.9308475255966187, 0.6954782009124756]
CURRENTLY TRAINING THE MODEL WITH THE FOLLOWING PARAMS:
{'last_dropout_param': 0.3}
Epoch 1/20
34/34 [==============================] - 75s 2s/step - loss: 2.1366 - accuracy:
0.2799 - val_loss: 1.5875 - val_accuracy: 0.3490
Epoch 2/20
34/34 [==============================] - 231s 7s/step - loss: 1.3619 - accuracy:
0.4430 - val_loss: 1.6139 - val_accuracy: 0.3809
Epoch 3/20
34/34 [==============================] - 75s 2s/step - loss: 1.1995 - accuracy:
0.5143 - val_loss: 1.5967 - val_accuracy: 0.3790
Epoch 4/20
34/34 [==============================] - 75s 2s/step - loss: 1.1259 - accuracy:
0.5354 - val_loss: 1.4505 - val_accuracy: 0.4784
Epoch 5/20
34/34 [==============================] - 75s 2s/step - loss: 1.0625 - accuracy:
0.5757 - val_loss: 1.2277 - val_accuracy: 0.5178
Epoch 6/20
34/34 [==============================] - 75s 2s/step - loss: 1.0149 - accuracy:
0.6034 - val_loss: 1.0329 - val_accuracy: 0.5947
Epoch 7/20
34/34 [==============================] - 74s 2s/step - loss: 1.0697 - accuracy:
0.5860 - val_loss: 1.1381 - val_accuracy: 0.5478
Epoch 8/20
34/34 [==============================] - 75s 2s/step - loss: 0.9564 - accuracy:
0.6240 - val_loss: 0.9937 - val_accuracy: 0.6398
Epoch 9/20
```

```
34/34 [==============================] - 74s 2s/step - loss: 0.9273 - accuracy:
0.6498 - val_loss: 1.0928 - val_accuracy: 0.6210
Epoch 10/20
34/34 [==============================] - 75s 2s/step - loss: 0.8999 - accuracy:
0.6639 - val_loss: 0.9549 - val_accuracy: 0.6379
Epoch 11/20
34/34 [==============================] - 74s 2s/step - loss: 0.9019 - accuracy:
0.6564 - val_loss: 1.0368 - val_accuracy: 0.6266
Epoch 12/20
34/34 [==============================] - 74s 2s/step - loss: 0.8621 - accuracy:
0.6817 - val_loss: 0.9932 - val_accuracy: 0.6341
Epoch 13/20
34/34 [==============================] - 75s 2s/step - loss: 0.8491 - accuracy:
0.6906 - val_loss: 0.8630 - val_accuracy: 0.7017
Epoch 14/20
34/34 [==============================] - 74s 2s/step - loss: 0.8075 - accuracy:
0.7164 - val_loss: 1.1569 - val_accuracy: 0.6304
Epoch 15/20
34/34 [==============================] - 75s 2s/step - loss: 0.8351 - accuracy:
0.7051 - val_loss: 0.8090 - val_accuracy: 0.7148
Epoch 16/20
34/34 [==============================] - 74s 2s/step - loss: 0.7862 - accuracy:
0.7300 - val_loss: 0.7922 - val_accuracy: 0.7242
Epoch 17/20
34/34 [==============================] - 74s 2s/step - loss: 0.7700 - accuracy:
0.7346 - val_loss: 0.8316 - val_accuracy: 0.7392
Epoch 18/20
34/34 [==============================] - 75s 2s/step - loss: 0.7544 - accuracy:
0.7520 - val_loss: 0.8409 - val_accuracy: 0.7186
Epoch 19/20
34/34 [==============================] - 75s 2s/step - loss: 0.7321 - accuracy:
0.7529 - val_loss: 0.7760 - val_accuracy: 0.7355
Epoch 20/20
34/34 [==============================] - 74s 2s/step - loss: 0.6822 - accuracy:
0.7722 - val_loss: 0.8110 - val_accuracy: 0.7598
```





```
40/40 [==============================] - 13s 333ms/step - loss: 0.7619 -
accuracy: 0.7563
[0.7618743181228638, 0.756302535533905]
```

1.3 Training the Model

[8]:
```
model = create_model()
model.summary()
```

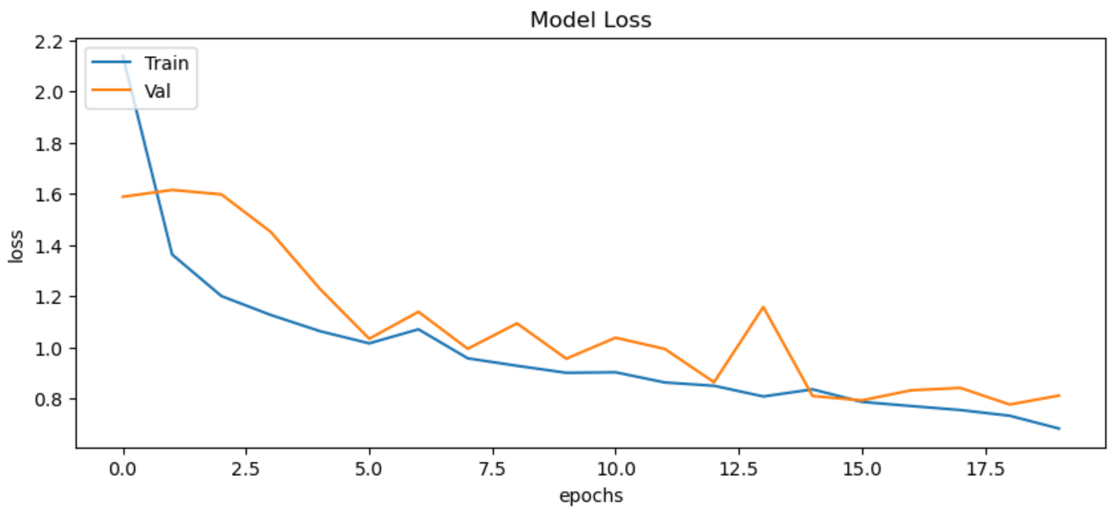
```
Model: "sequential_4"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential (Sequential)     (None, 150, 150, 3)       0
```

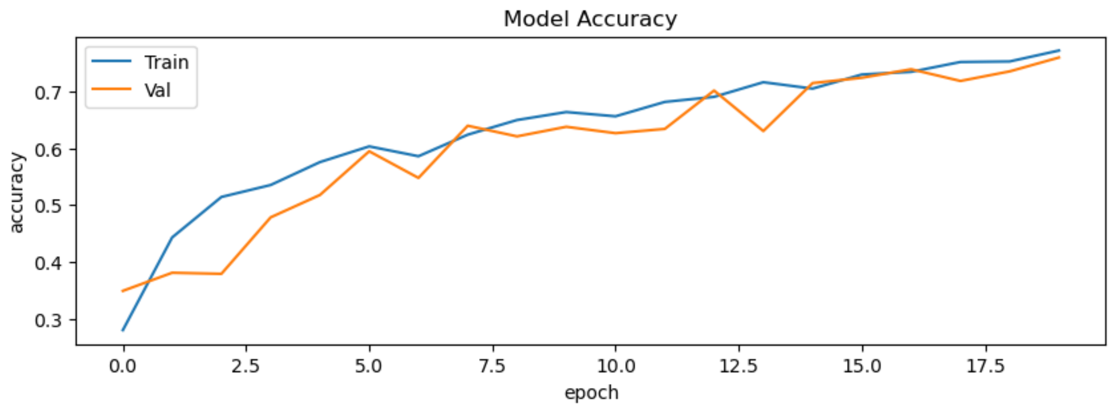
```
rescaling_3 (Rescaling)     (None, 150, 150, 3)       0

conv2d_21 (Conv2D)          (None, 150, 150, 32)      896

max_pooling2d_21 (MaxPoolin  (None, 75, 75, 32)       0
g2D)

conv2d_22 (Conv2D)          (None, 75, 75, 64)        18496

max_pooling2d_22 (MaxPoolin  (None, 37, 37, 64)       0
g2D)

conv2d_23 (Conv2D)          (None, 37, 37, 128)       73856

max_pooling2d_23 (MaxPoolin  (None, 18, 18, 128)      0
g2D)

conv2d_24 (Conv2D)          (None, 18, 18, 256)       295168

max_pooling2d_24 (MaxPoolin  (None, 9, 9, 256)        0
g2D)

conv2d_25 (Conv2D)          (None, 9, 9, 512)         1180160

max_pooling2d_25 (MaxPoolin  (None, 4, 4, 512)        0
g2D)

dropout_9 (Dropout)         (None, 4, 4, 512)         0

conv2d_26 (Conv2D)          (None, 4, 4, 1024)        4719616

max_pooling2d_26 (MaxPoolin  (None, 2, 2, 1024)       0
g2D)

dropout_10 (Dropout)        (None, 2, 2, 1024)        0

conv2d_27 (Conv2D)          (None, 2, 2, 512)         4719104

max_pooling2d_27 (MaxPoolin  (None, 1, 1, 512)        0
g2D)

dropout_11 (Dropout)        (None, 1, 1, 512)         0

flatten_3 (Flatten)         (None, 512)               0

dense_6 (Dense)             (None, 256)               131328

dense_7 (Dense)             (None, 5)                 1285
```

```
=================================================================
Total params: 11,139,909
Trainable params: 11,139,909
Non-trainable params: 0
_________________________________________________________________
```

[9]:
```
#history = model.fit(train_ds, validation_data=val_ds, epochs=10)
```

[10]:
```
%run rueegg_wissiak_model_visualization.ipynb
```





[11]:
```
model.evaluate(test_ds)
```

```
40/40 [==============================] - 14s 339ms/step - loss: 3.3154 -
accuracy: 0.2993
```

```
[11]: [3.31538987159729, 0.29931971430778503]
```