Importing the zip file

```
from zipfile import ZipFile
file_name='meat_meat.zip'
with ZipFile(file_name,'r')as zip:
  zip.extractall()
print('Finished')
    Finished
```

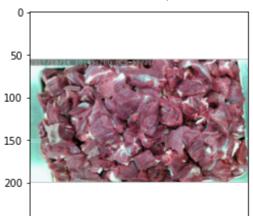
Importing the libraries

```
import keras
import numpy as np
import pandas as pd
from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten
from keras.preprocessing.image import ImageDataGenerator
import matplotlib.image as mpimg
from keras.layers import Conv2D, MaxPooling2D
from tensorflow import keras
import matplotlib.pyplot as plt
```

Fresh Meat

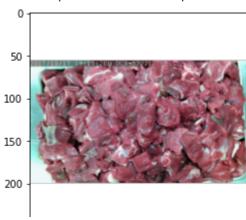
```
print(f" Fresh meat example")
path = '/content/meat_last/Test/Fresh/test_20171016_104521D.png'
img=mpimg.imread(path)
imgplot=plt.imshow(img)
```





Spoiled Meat

Spoiled Meat Example



```
path_to_train = "/content/meat_last/Train"
path_to_test = "/content/meat_last/Test"

Generator = ImageDataGenerator()
train_data = Generator.flow_from_directory(path_to_train, (256, 256), batch_size=32)
test_data = Generator.flow_from_directory(path_to_test, (256, 256), batch_size=32)
    Found 1106 images belonging to 2 classes.
    Found 790 images belonging to 2 classes.
```

2.KISIM: Kendinize özgü bir CNN oluşturunuz.

Creating our Model

```
model=Sequential()
model.add(Conv2D(32, (4, 4), activation='relu', input_shape=(256,256,3)))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))
model.add(Dropout(0.3))
model.add(Conv2D(64, (4, 4), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))
model.add(Dropout(0.3))
model.add(Flatten())
model.add(Dense(64, activation='relu'))
```

```
model.add(Dense(128, activation='relu'))
model.add(Dense(2,activation='sigmoid'))
```

Compiling the model

```
from tensorflow import keras
model.compile(loss=keras.losses.categorical_crossentropy,optimizer=keras.optimizers.Adam(),me
```

4.KISIM: Modelinizi eğitim verisi ile eğitirken, doğrulama verisi ile performansını gözleyecek şekilde history öğesine kaydediniz.

Training the Model

```
history= model.fit_generator(train_data,steps_per_epoch=1000//30,epochs=30,
verbose=1,
validation data=test data, validation steps = 3)
 Epoch 2/30
 Epoch 3/30
 Epoch 4/30
 Epoch 5/30
 33/33 [============= ] - 5s 151ms/step - loss: 0.1511 - accuracy: 0.9
 Epoch 6/30
 Epoch 7/30
 Epoch 8/30
 Epoch 9/30
 Epoch 10/30
 Epoch 11/30
 Epoch 12/30
 Epoch 13/30
 Epoch 14/30
 Epoch 15/30
```

```
Epoch 16/30
Epoch 17/30
Epoch 18/30
Epoch 19/30
Epoch 20/30
Epoch 21/30
Epoch 22/30
Epoch 23/30
Epoch 24/30
Epoch 25/30
Epoch 26/30
33/33 [============= ] - 5s 153ms/step - loss: 0.0593 - accuracy: 0.9
Epoch 27/30
Epoch 28/30
33/33 [=============== ] - 5s 160ms/step - loss: 0.0537 - accuracy: 0.9
Epoch 29/30
```

3. KISIM: CNN modelinizin özetini çıktı olarak alınız (summary).

model.summary()

Model: "sequential 13"

Layer (type)	Output Shape	Param #
conv2d_25 (Conv2D)	(None, 253, 253, 32)	1568
<pre>max_pooling2d_25 (MaxPoolin g2D)</pre>	(None, 126, 126, 32)	0
dropout_24 (Dropout)	(None, 126, 126, 32)	0
conv2d_26 (Conv2D)	(None, 123, 123, 64)	32832
<pre>max_pooling2d_26 (MaxPoolin g2D)</pre>	(None, 61, 61, 64)	0

```
      dropout_25 (Dropout)
      (None, 61, 61, 64)
      0

      flatten_13 (Flatten)
      (None, 238144)
      0

      dense_33 (Dense)
      (None, 64)
      15241280

      dense_34 (Dense)
      (None, 128)
      8320

      dense_35 (Dense)
      (None, 2)
      258

      Total params: 15,284,258

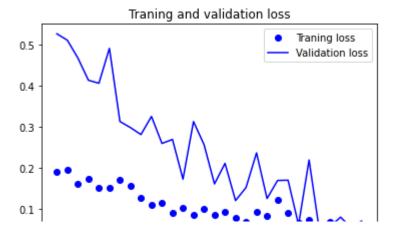
      Trainable params: 15,284,258
```

Non-trainable params: 0

5.KISIM: History'e kaydettiğiniz Eğitim ve doğrulama kaybı (training and validation loss) ve eğitim ve doğrulama başarısının (training and validation accuracy) değişimini grafik olarak çizdiriniz

Ploting the Graph for training and validation accurancy

```
import matplotlib.pyplot as plt
acc=history.history['accuracy']
val acc=history.history['val accuracy']
loss=history.history['loss']
val_loss=history.history['val_loss']
epochs=range(1,len(acc)+1)
plt.plot(epochs,acc,'bo',label='Traning acc')
plt.plot(epochs,val_acc,'b',label='Validation acc')
plt.title('Traning and validation accuracy')
plt.legend()
plt.figure()
plt.plot(epochs,loss,'bo',label='Traning loss')
plt.plot(epochs,val loss,'b',label='Validation loss')
plt.title('Traning and validation loss')
plt.legend()
plt.show()
С→
```



6.KISIM: Overfitting görüyorsanız dropout ve augmentation ekleyerek bunu gidermeye çalışınız.

7.KISIM: Overfitting yok olduysa modelinizin kapasitesini (katman sayısı ve katmanlardaki nöron sayısı) artırınız. Başarınızın önünüzdeki tek engel overfitting kalıncaya kadar 6. KISIM ve 7. KISIM'ı tekrar ediniz.

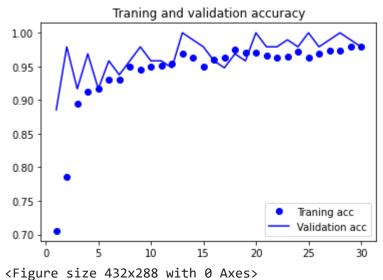
IMPROVING THE MODEL

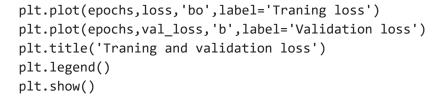
```
model=Sequential()
model.add(Conv2D(32, (5, 5), activation='relu', input_shape=(256,256,3)))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))
model.add(Dropout(0.3))
model.add(Conv2D(64, (5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2),strides=2))
model.add(Dropout(0.3))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dense(256, activation='relu'))
model.add(Dense(2,activation='sigmoid'))
from tensorflow import keras
model.compile(loss=keras.losses.categorical crossentropy,optimizer=keras.optimizers.Adam(),me
history= model.fit generator(train data, steps per epoch=1000//30, epochs=30,
verbose=1,
validation data=test data, validation steps = 3)
```

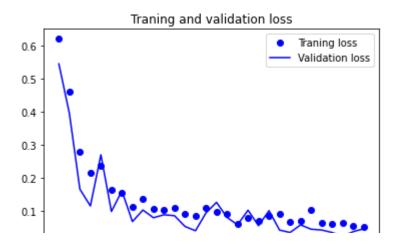
```
This is separate from the ipykernel package so we can avoid doing imports until
Epoch 1/30
33/33 [============== ] - 5s 163ms/step - loss: 0.6215 - accuracy: 0.7
Epoch 2/30
Epoch 3/30
Epoch 4/30
Epoch 5/30
Epoch 6/30
Epoch 7/30
Epoch 8/30
Epoch 9/30
Epoch 10/30
Epoch 11/30
Epoch 12/30
Epoch 13/30
Epoch 14/30
Epoch 15/30
Epoch 16/30
Epoch 17/30
Epoch 18/30
Epoch 19/30
Epoch 20/30
Epoch 21/30
Epoch 22/30
Epoch 23/30
Epoch 24/30
Epoch 25/30
Epoch 26/30
Epoch 27/30
Epoch 28/30
```

```
import matplotlib.pyplot as plt
acc=history.history['accuracy']
val_acc=history.history['val_accuracy']
loss=history.history['loss']
val_loss=history.history['val_loss']
epochs=range(1,len(acc)+1)
plt.plot(epochs,acc,'bo',label='Traning acc')
plt.plot(epochs,val_acc,'b',label='Validation acc')
plt.title('Traning and validation accuracy')
plt.legend()
plt.figure()
```

<Figure size 432x288 with 0 Axes>







8. KISIM: Overfitting'in başladığı noktayı tespit edip buna göre kaç epoch eğitmeniz gerektiğine karar veriniz

The best result I had when I was using 30 epoachs.

→ 9-10-11 Kisimlar

Firstly I uploaded the zip file where we have all our meat datas. The meat photos were very similar to each other. After I imported the libraries and created a model I started training that model. After training the results were not too much satisfying, this can be seen very easily from the graphs. To improve the model I have changed the number of filters and also the size of them. At the same time I increased the number of neurons and because I had just to classes I used Sigmoid output activation. If I will write about epoach number I tried many times different types of epoachs from 5 to 50 (my Pc capasity) and the best result was when I was using 30 epoachs. After retraining the model as it can be seen from the graphs our model had a great impovement.

tamamlanma zamanı: 16:19 ✓ 50 sn.

X

0	33/33	[]	- 5s 152ms/step	- loss:	0.1962 -	accuracy:	0.9175 - val_loss:	0.5113 -	val_accuracy:	0.7812
•	Epoch	3/30								
□.	33/33	[]	- 5s 150ms/step	- loss:	0.1604 -	accuracy:	0.9347 - val_loss:	0.4680 -	val_accuracy:	0.6979
	Epoch	4/30								
	33/33	[]	- 5s 152ms/step	- loss:	0.1732 -	accuracy:	0.9290 - val_loss:	0.4139 -	val_accuracy:	0.9479
	Epoch									
		[======]	- 5s 151ms/step	- loss:	0.1511 -	accuracy:	0.9451 - val_loss:	0.4064 -	val_accuracy:	0.9375
	Epoch	-		-						
		[]	- 5s 152ms/step	- loss:	0.1522 -	accuracy:	0.93/6 - Val_loss:	0.4915 -	val_accuracy:	0./083
	Epoch	[========]	Es 150ms/ston	10551	0 1702	200112000	0 040E - vol loss	0 2122	val accumacu.	0 0006
	Epoch	-	- 33 130IIIS/Step	- 1055.	0.1/02 -	accuracy.	0.9403 - Val_10ss.	0.3133 -	vai_accuracy:	0.9090
		[========]	- 5s 152ms/step	- loss:	0.1564 -	accuracy:	0.9405 - val loss:	0.2984 -	val accuracy:	0.9479
	Epoch	-								
	33/33	[]	- 5s 153ms/step	- loss:	0.1274 -	accuracy:	0.9441 - val_loss:	0.2814 -	val_accuracy:	0.8854
	Epoch	10/30								
	33/33	[]	- 5s 150ms/step	- loss:	0.1092 -	accuracy:	0.9511 - val_loss:	0.3256 -	val_accuracy:	0.9479
	Epoch									
		[=========]	- 5s 152ms/step	- loss:	0.1141 -	accuracy:	0.9530 - val_loss:	0.2598 -	val_accuracy:	0.9271
	Epoch		F- 150/	7	0.0001		0.0055	0.2505		0 0375
	Epoch	13/30	- 55 150ms/step	- loss:	0.0901 -	accuracy:	0.9655 - Val_loss:	0.2695 -	vai_accuracy:	0.93/5
		[========]	- 5s 152ms/sten	- 1055	0 1027 -	accuracy:	0 9539 - val loss:	0 1728 -	val accuracy:	0 9375
	Epoch	-	33 132m3/3ccp	1033.	0.102/	accar acy i	0.5555	0.1/20	var_accaracy.	0.5575
		[======]	- 5s 154ms/step	- loss:	0.0862 -	accuracy:	0.9655 - val_loss:	0.3131 -	val_accuracy:	0.8333
	Epoch	15/30								
		[]	- 5s 152ms/step	- loss:	0.1002 -	accuracy:	0.9655 - val_loss:	0.2571 -	val_accuracy:	0.8958
	Epoch		5 453 ()	-						
		[]	- 55 155MS/Step	- 1oss:	0.005/ -	accuracy:	0.9612 - Val_1055:	0.1611 -	vai_accuracy:	0.9000
	Epoch	[]	- 5s 152ms/sten	- 1055	0 0923 -	accuracy:	0 9616 - val loss:	a 2112 -	val accuracy:	0 9271
	Epoch		33 132m3/3ccp	1033.	0.0323	acca, acy i	0.3010 001_1033.	0.2222	vaz_accar acy .	0.5272
	33/33	[=======]	- 5s 152ms/step	- loss:	0.0777 -	accuracy:	0.9664 - val_loss:	0.1206 -	val_accuracy:	0.9792
	Epoch	19/30								
	33/33	[]	- 5s 152ms/step	- loss:	0.0680 -	accuracy:	0.9645 - val_loss:	0.1523 -	val_accuracy:	0.9479
	Epoch			-						
		[]	- 55 152ms/step	- loss:	0.0939 -	accuracy:	0.9655 - Val_loss:	0.2368 -	vai_accuracy:	0.9688
	Epoch	[========]	- 5c 152mc/cten	- 10551	0 0831 -	accuracy.	0 9655 - val loss:	0 1254 -	val accuracy:	0 0688
	Epoch	-	J3 1J21113/3CCP	1033.	0.0031	accar acy .	0.3033	0.1254	var_accaracy.	0.5000
		[=======]	- 5s 152ms/step	- loss:	0.1218 -	accuracy:	0.9568 - val loss:	0.1696 -	val accuracy:	0.9479
	Epoch	23/30					_		_	
	33/33	[]	- 5s 154ms/step	- loss:	0.0907 -	accuracy:	0.9674 - val_loss:	0.1702 -	val_accuracy:	0.9688
	Epoch									
		[======================================	- 5s 154ms/step	- loss:	0.0653 -	accuracy:	0.9731 - val_loss:	0.0615 -	val_accuracy:	0.9896
	Epoch		Ec. 152ma /at	1	0.0720	2001122011	0 0772 12	0 2106	unl neeumne	0.0702
	Epoch	[=======] 26/30	- 22 123ms/steb	- 1055:	0.0/29 -	accuracy:	0.9//3 - Val_1055:	0.2190 -	var_accuracy:	0.9/92
		[========]	- 5s 153ms/sten	- loss:	0.0593 -	accuracy:	0.9770 - val loss:	0.0443 -	val accuracy:	1.0000
	From h									

Epoch 8/30 Epoch 9/30 Epoch 10/30 Epoch 11/30 Epoch 12/30 Epoch 13/30 Epoch 14/30 Epoch 15/30 Epoch 16/30 Epoch 17/30 Epoch 18/30 Epoch 19/30 Epoch 20/30 Epoch 21/30 Epoch 22/30 Epoch 23/30 Epoch 24/30 Epoch 25/30 Epoch 26/30 Epoch 27/30 Epoch 29/30 Epoch 30/30