

Codes for the Model

```
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Activation, Dense, Flatten, BatchNormalization, Conv2D,
MaxPool2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import categorical_crossentropy
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import itertools
import os
import shutil
import random
import glob
import matplotlib.pyplot as plt
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
%matplotlib inline
```

```
train_path = r"C:\Users\kemi\Desktop\opencv\aug\data\train"
valid_path = r"C:\Users\kemi\Desktop\opencv\aug\data\valid"
test_path = r"C:\Users\kemi\Desktop\opencv\aug\data\test"
```

```
train_batches =
ImageDataGenerator(preprocessing_function=tf.keras.applications.vgg16.preprocess_input) \
    .flow_from_directory(directory=train_path, target_size=(224,224),
classes=['looselyChained', 'tightlyChained', 'unchained'], batch_size=10)
valid_batches =
ImageDataGenerator(preprocessing_function=tf.keras.applications.vgg16.preprocess_input) \
    .flow_from_directory(directory=valid_path, target_size=(224,224),
classes=['looselyChained', 'tightlyChained', 'unchained'], batch_size=10)
test_batches =
ImageDataGenerator(preprocessing_function=tf.keras.applications.vgg16.preprocess_input) \
    .flow_from_directory(directory=test_path, target_size=(224,224),
classes=['looselyChained', 'tightlyChained', 'unchained'], batch_size=10, shuffle=False)
```

Result:

```
Found 3000 images belonging to 3 classes.
Found 600 images belonging to 3 classes.
Found 300 images belonging to 3 classes.
```

```
imgs, labels = next(train_batches)
```

```
def plotImages(images_arr):  
    fig, axes = plt.subplots(1, 10, figsize=(20,20))  
    axes = axes.flatten()  
    for img, ax in zip( images_arr, axes):  
        ax.imshow(img)  
        ax.axis('off')  
    plt.tight_layout()  
    plt.show()
```

```
plotImages(imgs)  
print(labels)
```

Result:

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

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Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).

Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).



```
[1.  0.  0.]  
[1.  0.  0.]  
[0.  0.  1.]
```

```

[0. 1. 0.]
[1. 0. 0.]
[1. 0. 0.]
[0. 0. 1.]
[0. 1. 0.]
[0. 1. 0.]
[0. 1. 0.]]

```

#build a fine-tuned pre-trained model

```

mobile = tf.keras.applications.mobilenet.MobileNet()
mobile.summary()

```

Result:

Model: "mobilenet_1.00_224"

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 224, 224, 3)]	0
conv1 (Conv2D)	(None, 112, 112, 32)	864
conv1_bn (BatchNormalization)	(None, 112, 112, 32)	128
conv1_relu (ReLU)	(None, 112, 112, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, 112, 112, 32)	288
conv_dw_1_bn (BatchNormaliza	(None, 112, 112, 32)	128
conv_dw_1_relu (ReLU)	(None, 112, 112, 32)	0
conv_pw_1 (Conv2D)	(None, 112, 112, 64)	2048
conv_pw_1_bn (BatchNormaliza	(None, 112, 112, 64)	256
conv_pw_1_relu (ReLU)	(None, 112, 112, 64)	0
conv_pad_2 (ZeroPadding2D)	(None, 113, 113, 64)	0
conv_dw_2 (DepthwiseConv2D)	(None, 56, 56, 64)	576
conv_dw_2_bn (BatchNormaliza	(None, 56, 56, 64)	256

conv_dw_2_relu (ReLU)	(None, 56, 56, 64)	0
conv_pw_2 (Conv2D)	(None, 56, 56, 128)	8192
conv_pw_2_bn (BatchNormaliza	(None, 56, 56, 128)	512
conv_pw_2_relu (ReLU)	(None, 56, 56, 128)	0
conv_dw_3 (DepthwiseConv2D)	(None, 56, 56, 128)	1152
conv_dw_3_bn (BatchNormaliza	(None, 56, 56, 128)	512
conv_dw_3_relu (ReLU)	(None, 56, 56, 128)	0
conv_pw_3 (Conv2D)	(None, 56, 56, 128)	16384
conv_pw_3_bn (BatchNormaliza	(None, 56, 56, 128)	512
conv_pw_3_relu (ReLU)	(None, 56, 56, 128)	0
conv_pad_4 (ZeroPadding2D)	(None, 57, 57, 128)	0
conv_dw_4 (DepthwiseConv2D)	(None, 28, 28, 128)	1152
conv_dw_4_bn (BatchNormaliza	(None, 28, 28, 128)	512
conv_dw_4_relu (ReLU)	(None, 28, 28, 128)	0
conv_pw_4 (Conv2D)	(None, 28, 28, 256)	32768
conv_pw_4_bn (BatchNormaliza	(None, 28, 28, 256)	1024
conv_pw_4_relu (ReLU)	(None, 28, 28, 256)	0
conv_dw_5 (DepthwiseConv2D)	(None, 28, 28, 256)	2304
conv_dw_5_bn (BatchNormaliza	(None, 28, 28, 256)	1024
conv_dw_5_relu (ReLU)	(None, 28, 28, 256)	0
conv_pw_5 (Conv2D)	(None, 28, 28, 256)	65536
conv_pw_5_bn (BatchNormaliza	(None, 28, 28, 256)	1024
conv_pw_5_relu (ReLU)	(None, 28, 28, 256)	0
conv_pad_6 (ZeroPadding2D)	(None, 29, 29, 256)	0

conv_dw_6 (DepthwiseConv2D)	(None, 14, 14, 256)	2304
conv_dw_6_bn (BatchNormaliza	(None, 14, 14, 256)	1024
conv_dw_6_relu (ReLU)	(None, 14, 14, 256)	0
conv_pw_6 (Conv2D)	(None, 14, 14, 512)	131072
conv_pw_6_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_pw_6_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_7 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_7_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_dw_7_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_7 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_7_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_pw_7_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_8 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_8_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_dw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_8 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_8_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_pw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_9 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_9_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_dw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_9 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_9_bn (BatchNormaliza	(None, 14, 14, 512)	2048

conv_pw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_10 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_10_bn (BatchNormaliz	(None, 14, 14, 512)	2048
conv_dw_10_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_10 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_10_bn (BatchNormaliz	(None, 14, 14, 512)	2048
conv_pw_10_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_11 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_11_bn (BatchNormaliz	(None, 14, 14, 512)	2048
conv_dw_11_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_11 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_11_bn (BatchNormaliz	(None, 14, 14, 512)	2048
conv_pw_11_relu (ReLU)	(None, 14, 14, 512)	0
conv_pad_12 (ZeroPadding2D)	(None, 15, 15, 512)	0
conv_dw_12 (DepthwiseConv2D)	(None, 7, 7, 512)	4608
conv_dw_12_bn (BatchNormaliz	(None, 7, 7, 512)	2048
conv_dw_12_relu (ReLU)	(None, 7, 7, 512)	0
conv_pw_12 (Conv2D)	(None, 7, 7, 1024)	524288
conv_pw_12_bn (BatchNormaliz	(None, 7, 7, 1024)	4096
conv_pw_12_relu (ReLU)	(None, 7, 7, 1024)	0
conv_dw_13 (DepthwiseConv2D)	(None, 7, 7, 1024)	9216
conv_dw_13_bn (BatchNormaliz	(None, 7, 7, 1024)	4096
conv_dw_13_relu (ReLU)	(None, 7, 7, 1024)	0
conv_pw_13 (Conv2D)	(None, 7, 7, 1024)	1048576

conv_pw_13_bn (BatchNormaliz	(None, 7, 7, 1024)	4096
conv_pw_13_relu (ReLU)	(None, 7, 7, 1024)	0
global_average_pooling2d_1 ((None, 1024)	0
reshape_1 (Reshape)	(None, 1, 1, 1024)	0
dropout (Dropout)	(None, 1, 1, 1024)	0
conv_preds (Conv2D)	(None, 1, 1, 1000)	1025000
reshape_2 (Reshape)	(None, 1000)	0
predictions (Activation)	(None, 1000)	0
=====		
Total params: 4,253,864		
Trainable params: 4,231,976		
Non-trainable params: 21,888		

```
x = mobile.layers[-6].output
```

```
output = Dense(units=3, activation='softmax')(x)
```

```
from tensorflow.keras.models import Model
model = Model(inputs=mobile.input, outputs=output)
```

```
for layer in model.layers[:-23]:
    layer.trainable = True
```

```
model.summary()
```

Result:

```
Model: "model_1"
```

Layer (type)	Output Shape	Param #
=====		
input_2 (InputLayer)	[(None, 224, 224, 3)]	0

conv1 (Conv2D)	(None, 112, 112, 32)	864
conv1_bn (BatchNormalization)	(None, 112, 112, 32)	128
conv1_relu (ReLU)	(None, 112, 112, 32)	0
conv_dw_1 (DepthwiseConv2D)	(None, 112, 112, 32)	288
conv_dw_1_bn (BatchNormaliza	(None, 112, 112, 32)	128
conv_dw_1_relu (ReLU)	(None, 112, 112, 32)	0
conv_pw_1 (Conv2D)	(None, 112, 112, 64)	2048
conv_pw_1_bn (BatchNormaliza	(None, 112, 112, 64)	256
conv_pw_1_relu (ReLU)	(None, 112, 112, 64)	0
conv_pad_2 (ZeroPadding2D)	(None, 113, 113, 64)	0
conv_dw_2 (DepthwiseConv2D)	(None, 56, 56, 64)	576
conv_dw_2_bn (BatchNormaliza	(None, 56, 56, 64)	256
conv_dw_2_relu (ReLU)	(None, 56, 56, 64)	0
conv_pw_2 (Conv2D)	(None, 56, 56, 128)	8192
conv_pw_2_bn (BatchNormaliza	(None, 56, 56, 128)	512
conv_pw_2_relu (ReLU)	(None, 56, 56, 128)	0
conv_dw_3 (DepthwiseConv2D)	(None, 56, 56, 128)	1152
conv_dw_3_bn (BatchNormaliza	(None, 56, 56, 128)	512
conv_dw_3_relu (ReLU)	(None, 56, 56, 128)	0
conv_pw_3 (Conv2D)	(None, 56, 56, 128)	16384
conv_pw_3_bn (BatchNormaliza	(None, 56, 56, 128)	512
conv_pw_3_relu (ReLU)	(None, 56, 56, 128)	0
conv_pad_4 (ZeroPadding2D)	(None, 57, 57, 128)	0

conv_dw_4 (DepthwiseConv2D)	(None, 28, 28, 128)	1152
conv_dw_4_bn (BatchNormaliza	(None, 28, 28, 128)	512
conv_dw_4_relu (ReLU)	(None, 28, 28, 128)	0
conv_pw_4 (Conv2D)	(None, 28, 28, 256)	32768
conv_pw_4_bn (BatchNormaliza	(None, 28, 28, 256)	1024
conv_pw_4_relu (ReLU)	(None, 28, 28, 256)	0
conv_dw_5 (DepthwiseConv2D)	(None, 28, 28, 256)	2304
conv_dw_5_bn (BatchNormaliza	(None, 28, 28, 256)	1024
conv_dw_5_relu (ReLU)	(None, 28, 28, 256)	0
conv_pw_5 (Conv2D)	(None, 28, 28, 256)	65536
conv_pw_5_bn (BatchNormaliza	(None, 28, 28, 256)	1024
conv_pw_5_relu (ReLU)	(None, 28, 28, 256)	0
conv_pad_6 (ZeroPadding2D)	(None, 29, 29, 256)	0
conv_dw_6 (DepthwiseConv2D)	(None, 14, 14, 256)	2304
conv_dw_6_bn (BatchNormaliza	(None, 14, 14, 256)	1024
conv_dw_6_relu (ReLU)	(None, 14, 14, 256)	0
conv_pw_6 (Conv2D)	(None, 14, 14, 512)	131072
conv_pw_6_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_pw_6_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_7 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_7_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_dw_7_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_7 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_7_bn (BatchNormaliza	(None, 14, 14, 512)	2048

conv_pw_7_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_8 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_8_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_dw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_8 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_8_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_pw_8_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_9 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_9_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_dw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_9 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_9_bn (BatchNormaliza	(None, 14, 14, 512)	2048
conv_pw_9_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_10 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_10_bn (BatchNormaliz	(None, 14, 14, 512)	2048
conv_dw_10_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_10 (Conv2D)	(None, 14, 14, 512)	262144
conv_pw_10_bn (BatchNormaliz	(None, 14, 14, 512)	2048
conv_pw_10_relu (ReLU)	(None, 14, 14, 512)	0
conv_dw_11 (DepthwiseConv2D)	(None, 14, 14, 512)	4608
conv_dw_11_bn (BatchNormaliz	(None, 14, 14, 512)	2048
conv_dw_11_relu (ReLU)	(None, 14, 14, 512)	0
conv_pw_11 (Conv2D)	(None, 14, 14, 512)	262144

conv_pw_11_bn	(BatchNormaliz (None, 14, 14, 512)	2048
conv_pw_11_relu	(ReLU) (None, 14, 14, 512)	0
conv_pad_12	(ZeroPadding2D) (None, 15, 15, 512)	0
conv_dw_12	(DepthwiseConv2D) (None, 7, 7, 512)	4608
conv_dw_12_bn	(BatchNormaliz (None, 7, 7, 512)	2048
conv_dw_12_relu	(ReLU) (None, 7, 7, 512)	0
conv_pw_12	(Conv2D) (None, 7, 7, 1024)	524288
conv_pw_12_bn	(BatchNormaliz (None, 7, 7, 1024)	4096
conv_pw_12_relu	(ReLU) (None, 7, 7, 1024)	0
conv_dw_13	(DepthwiseConv2D) (None, 7, 7, 1024)	9216
conv_dw_13_bn	(BatchNormaliz (None, 7, 7, 1024)	4096
conv_dw_13_relu	(ReLU) (None, 7, 7, 1024)	0
conv_pw_13	(Conv2D) (None, 7, 7, 1024)	1048576
conv_pw_13_bn	(BatchNormaliz (None, 7, 7, 1024)	4096
conv_pw_13_relu	(ReLU) (None, 7, 7, 1024)	0
global_average_pooling2d_1	((None, 1024)	0
dense_1	(Dense) (None, 3)	3075

```

=====
Total params: 3,231,939
Trainable params: 3,210,051
Non-trainable params: 21,888

```

```

model.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy',
metrics=['accuracy'])

```

```
model.fit(x=train_batches,  
          steps_per_epoch=len(train_batches),  
          validation_data=valid_batches,  
          validation_steps=len(valid_batches),  
          epochs=45,  
          verbose=2  
)
```

Result:

```
Epoch 1/45  
300/300 - 446s - loss: 0.8082 - accuracy: 0.6523 - val_loss: 0.6368 -  
val_accuracy: 0.7483  
Epoch 2/45  
300/300 - 490s - loss: 0.3411 - accuracy: 0.8737 - val_loss: 0.6650 -  
val_accuracy: 0.7317  
Epoch 3/45  
300/300 - 459s - loss: 0.1986 - accuracy: 0.9327 - val_loss: 0.5288 -  
val_accuracy: 0.8067  
Epoch 4/45  
300/300 - 402s - loss: 0.1275 - accuracy: 0.9600 - val_loss: 0.7433 -  
val_accuracy: 0.7017  
Epoch 5/45  
300/300 - 411s - loss: 0.0929 - accuracy: 0.9750 - val_loss: 0.6221 -  
val_accuracy: 0.8117  
Epoch 6/45  
300/300 - 405s - loss: 0.0819 - accuracy: 0.9757 - val_loss: 0.5439 -  
val_accuracy: 0.8200  
Epoch 7/45  
300/300 - 40786s - loss: 0.0727 - accuracy: 0.9750 - val_loss: 0.7493 -  
val_accuracy: 0.7583  
Epoch 8/45  
300/300 - 320s - loss: 0.0749 - accuracy: 0.9733 - val_loss: 1.0464 -  
val_accuracy: 0.7183  
Epoch 9/45  
300/300 - 313s - loss: 0.0644 - accuracy: 0.9780 - val_loss: 1.0688 -  
val_accuracy: 0.7350  
Epoch 10/45  
300/300 - 309s - loss: 0.0697 - accuracy: 0.9770 - val_loss: 0.7255 -  
val_accuracy: 0.8117  
Epoch 11/45  
300/300 - 319s - loss: 0.0699 - accuracy: 0.9733 - val_loss: 0.5891 -  
val_accuracy: 0.8283  
Epoch 12/45  
300/300 - 309s - loss: 0.0694 - accuracy: 0.9767 - val_loss: 0.8485 -  
val_accuracy: 0.8083
```

Epoch 13/45
300/300 - 309s - loss: 0.0883 - accuracy: 0.9680 - val_loss: 0.8734 - val_accuracy: 0.7883

Epoch 14/45
300/300 - 310s - loss: 0.0810 - accuracy: 0.9730 - val_loss: 0.8160 - val_accuracy: 0.8267

Epoch 15/45
300/300 - 308s - loss: 0.0668 - accuracy: 0.9753 - val_loss: 0.7841 - val_accuracy: 0.8200

Epoch 16/45
300/300 - 314s - loss: 0.0377 - accuracy: 0.9887 - val_loss: 0.7425 - val_accuracy: 0.8350

Epoch 17/45
300/300 - 311s - loss: 0.0632 - accuracy: 0.9777 - val_loss: 1.3885 - val_accuracy: 0.7733

Epoch 18/45
300/300 - 310s - loss: 0.0848 - accuracy: 0.9697 - val_loss: 0.8897 - val_accuracy: 0.7967

Epoch 19/45
300/300 - 310s - loss: 0.0478 - accuracy: 0.9833 - val_loss: 0.9696 - val_accuracy: 0.8117

Epoch 20/45
300/300 - 310s - loss: 0.0506 - accuracy: 0.9807 - val_loss: 0.8710 - val_accuracy: 0.8183

Epoch 21/45
300/300 - 308s - loss: 0.0678 - accuracy: 0.9793 - val_loss: 0.7148 - val_accuracy: 0.8500

Epoch 22/45
300/300 - 2775s - loss: 0.0554 - accuracy: 0.9827 - val_loss: 0.5984 - val_accuracy: 0.8317

Epoch 23/45
300/300 - 312s - loss: 0.0341 - accuracy: 0.9897 - val_loss: 0.5455 - val_accuracy: 0.8733

Epoch 24/45
300/300 - 311s - loss: 0.0572 - accuracy: 0.9820 - val_loss: 0.7362 - val_accuracy: 0.8150

Epoch 25/45
300/300 - 310s - loss: 0.0679 - accuracy: 0.9783 - val_loss: 0.9251 - val_accuracy: 0.8250

Epoch 26/45
300/300 - 309s - loss: 0.0372 - accuracy: 0.9890 - val_loss: 0.8609 - val_accuracy: 0.8517

Epoch 27/45
300/300 - 310s - loss: 0.0432 - accuracy: 0.9860 - val_loss: 1.2711 - val_accuracy: 0.7583

Epoch 28/45

300/300 - 312s - loss: 0.0293 - accuracy: 0.9893 - val_loss: 1.2968 -
val_accuracy: 0.8117
Epoch 29/45
300/300 - 311s - loss: 0.0566 - accuracy: 0.9820 - val_loss: 0.8950 -
val_accuracy: 0.8117
Epoch 30/45
300/300 - 311s - loss: 0.0416 - accuracy: 0.9867 - val_loss: 0.6869 -
val_accuracy: 0.8567
Epoch 31/45
300/300 - 310s - loss: 0.0269 - accuracy: 0.9920 - val_loss: 0.7906 -
val_accuracy: 0.8450
Epoch 32/45
300/300 - 310s - loss: 0.0326 - accuracy: 0.9897 - val_loss: 0.8588 -
val_accuracy: 0.7867
Epoch 33/45
300/300 - 311s - loss: 0.0425 - accuracy: 0.9857 - val_loss: 0.8502 -
val_accuracy: 0.8133
Epoch 34/45
300/300 - 320s - loss: 0.0315 - accuracy: 0.9900 - val_loss: 0.8716 -
val_accuracy: 0.8433
Epoch 35/45
300/300 - 311s - loss: 0.0219 - accuracy: 0.9923 - val_loss: 0.8566 -
val_accuracy: 0.8500
Epoch 36/45
300/300 - 309s - loss: 0.0323 - accuracy: 0.9927 - val_loss: 0.8248 -
val_accuracy: 0.8417
Epoch 37/45
300/300 - 309s - loss: 0.0198 - accuracy: 0.9933 - val_loss: 1.1241 -
val_accuracy: 0.8350
Epoch 38/45
300/300 - 311s - loss: 0.0132 - accuracy: 0.9967 - val_loss: 0.8218 -
val_accuracy: 0.8533
Epoch 39/45
300/300 - 311s - loss: 0.0223 - accuracy: 0.9927 - val_loss: 0.8927 -
val_accuracy: 0.8383
Epoch 40/45
300/300 - 309s - loss: 0.0636 - accuracy: 0.9823 - val_loss: 0.9921 -
val_accuracy: 0.8300
Epoch 41/45
300/300 - 309s - loss: 0.0558 - accuracy: 0.9837 - val_loss: 0.7282 -
val_accuracy: 0.8517
Epoch 42/45
300/300 - 309s - loss: 0.0240 - accuracy: 0.9910 - val_loss: 1.0447 -
val_accuracy: 0.8317
Epoch 43/45
300/300 - 311s - loss: 0.0352 - accuracy: 0.9900 - val_loss: 0.6196 -
val_accuracy: 0.8533

```
Epoch 44/45
300/300 - 311s - loss: 0.0318 - accuracy: 0.9883 - val_loss: 0.7156 -
val_accuracy: 0.8383
Epoch 45/45
300/300 - 311s - loss: 0.0291 - accuracy: 0.9900 - val_loss: 0.7501 -
val_accuracy: 0.8267
```

Out[22]:

```
<keras.callbacks.History at 0x2a8c5a26f10>
```

```
test_imgs, test_labels = next(test_batches)
plotImages(test_imgs)
print(test_labels)
```

Results:

```
Clipping input data to the valid range for imshow with RGB data ([0..1]
for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1]
for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1]
for floats or [0..255] for integers).
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for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1]
for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1]
for floats or [0..255] for integers).
```



```
[[1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
 [1. 0. 0.]
```

```
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
[1. 0. 0.]
```

In [43]:

```
predictions = model.predict(x=test_batches, steps=len(test_batches), verbose=0)

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_true=test_batches.classes, y_pred=np.argmax(predictions, axis=-1))

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)
```



```

thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, cm[i, j],
             horizontalalignment="center",
             color="white" if cm[i, j] > thresh else "black")

plt.tight_layout()
plt.ylabel('True label')
plt.xlabel('Predicted label')

```

Test_batches.class_indices

Result:

```
{'looselyChained': 0, 'tightlyChained': 1, 'unchained': 2}
```

```
cm_plot_labels = ['looselyChained', 'tightlyChained', 'unchained']
```

```
plot_confusion_matrix(cm=cm, classes=cm_plot_labels, title='Confusion Matrix')
```

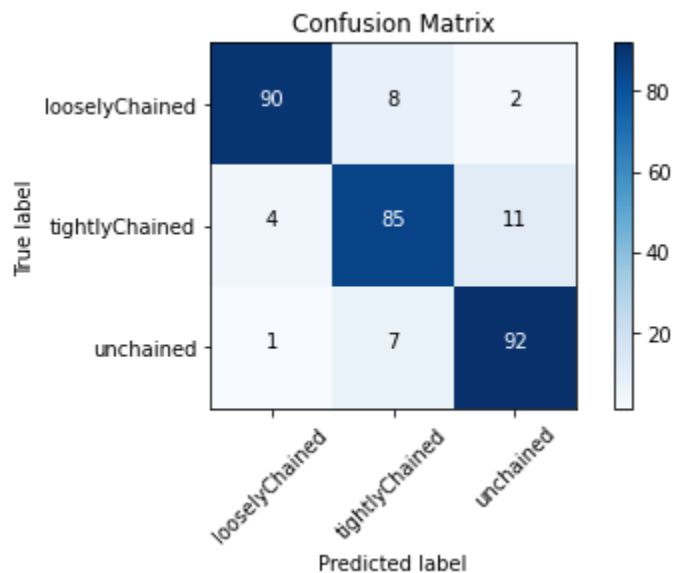
Result:

Confusion matrix, without normalization

```

[[90  8  2]
 [ 4 85 11]
 [ 1  7 92]]

```



```
from sklearn.metrics import precision_recall_fscore_support
print(precision_recall_fscore_support(y_true=test_batches.classes,
y_pred=np.argmax(predictions, axis=-1), average='micro'))
```

Result:

```
(0.89, 0.89, 0.89, None)
```