In [16]:

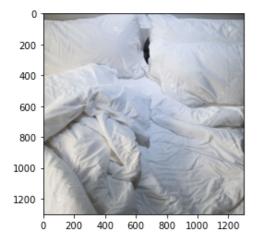
```
import tensorflow as tf
from tensorflow.keras import datasets, layers, models
from keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
import numpy as np
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D
from keras.layers import Activation, Dropout, Flatten, Dense
from keras.preprocessing import image
import keras
import cv2
from PIL import ImageFile
from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
%matplotlib inline
from keras.utils import to categorical
from sklearn.model selection import train test split
import pandas as pd
```

In [17]:

```
ImageFile.LOAD_TRUNCATED_IMAGES = True
img = image.load_img("Datasets/HumanActivityDataset/train/Control/24905349-close-up-of-me
ssy-bedding-sheets-and-pillow.jpg")
plt.imshow(img)

cv2.imread("Datasets/HumanActivityDataset/train/Control/24905349-close-up-of-messy-beddin
g-sheets-and-pillow.jpg").shape

train = ImageDataGenerator(rescale = 1/255)
validation = ImageDataGenerator(rescale = 1/255)
```



In [25]:

Found 4273 images belonging to 6 classes. Found 58 images belonging to 6 classes.

```
In [26]:
train dataset.class indices
train dataset.classes
Out[26]:
array([0, 0, 0, ..., 5, 5, 5])
In [27]:
validation dataset.class indices
validation dataset.classes
Out[27]:
array([0, 0, 0, 0, 1, 1, 2, 2, 2, 2, 2, 2, 3, 3, 3, 3, 3, 4, 5, 5, 5, 5,
     5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5])
In [28]:
cnn = models.Sequential([
  tf.keras.layers.Conv2D(32,(3,3),activation="relu",input shape=(32,32,3)),
  tf.keras.layers.MaxPool2D(2,2),
   tf.keras.layers.Conv2D(32,(3,3),activation="relu"),
   tf.keras.layers.MaxPool2D(2,2),
   tf.keras.layers.Conv2D(64,(3,3),activation="relu"),
   tf.keras.layers.MaxPool2D(2,2),
   tf.keras.layers.Flatten(),
   tf.keras.layers.Dense(64,activation="relu"),
   tf.keras.layers.Dense(6,activation="softmax")
])
In [29]:
cnn.compile(optimizer="adam",
          loss='sparse categorical crossentropy',
          metrics=['accuracy'])
In [30]:
history1 =cnn.fit(train dataset,
     steps_per_epoch = 50,
     batch size = 3,
     epochs = 100,
     validation data = validation dataset
Epoch 1/100
50/50 [============== ] - 2s 41ms/step - loss: 1.8083 - accuracy: 0.1933 -
val loss: 1.7079 - val accuracy: 0.6897
Epoch 2/100
val loss: 1.6646 - val accuracy: 0.6897
Epoch 3/100
val loss: 1.7100 - val accuracy: 0.6897
Epoch 4/100
val_loss: 1.6560 - val_accuracy: 0.6897
Epoch 5/100
val_loss: 1.6705 - val_accuracy: 0.6897
Epoch 6/100
val loss: 1.6854 - val accuracy: 0.6897
Epoch 7/100
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```

```
val loss: 1.6584 - val accuracy: 0.6034
Epoch 8/100
val loss: 1.6819 - val accuracy: 0.5345
Epoch 9/100
val loss: 1.7344 - val accuracy: 0.3103
Epoch 10/100
val_loss: 1.6322 - val_accuracy: 0.6724
Epoch 11/100
val loss: 1.9702 - val accuracy: 0.0172
Epoch 12/100
val loss: 1.5192 - val accuracy: 0.3621
Epoch 13/100
50/50 [============= ] - 2s 37ms/step - loss: 1.6799 - accuracy: 0.2838 -
val loss: 1.6752 - val accuracy: 0.0862
Epoch 14/100
val loss: 1.5264 - val accuracy: 0.2586
Epoch 15/100
val loss: 1.4987 - val accuracy: 0.2586
Epoch 16/100
val_loss: 1.5880 - val_accuracy: 0.3103
Epoch 17/100
val loss: 1.6499 - val accuracy: 0.1379
Epoch 18/100
val loss: 1.5067 - val accuracy: 0.2414
Epoch 19/100
val loss: 1.7026 - val accuracy: 0.1724
Epoch 20/100
val loss: 1.8586 - val accuracy: 0.1034
Epoch 21/100
val loss: 1.7378 - val accuracy: 0.0690
Epoch 22/100
val loss: 1.6230 - val accuracy: 0.2586
Epoch 23/100
val loss: 1.3907 - val accuracy: 0.5000
Epoch 24/100
val loss: 1.5795 - val accuracy: 0.3276
Epoch 25/100
50/50 [============= ] - 1s 27ms/step - loss: 1.5221 - accuracy: 0.3667 -
val loss: 1.5722 - val accuracy: 0.3448
Epoch 26/100
val loss: 1.4183 - val accuracy: 0.5000
Epoch 27/100
val loss: 1.4356 - val accuracy: 0.4310
Epoch 28/100
val_loss: 1.4300 - val_accuracy: 0.4138
Epoch 29/100
val_loss: 1.8508 - val_accuracy: 0.1379
Epoch 30/100
val loss: 1.3862 - val accuracy: 0.5000
Epoch 31/100
```

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```
val loss: 1.5708 - val accuracy: 0.2586
Epoch 32/100
val loss: 1.4585 - val accuracy: 0.3966
Epoch 33/100
val loss: 1.5243 - val accuracy: 0.1724
Epoch 34/100
val_loss: 2.0111 - val_accuracy: 0.1207
Epoch 35/100
val loss: 1.5958 - val accuracy: 0.2759
Epoch 36/100
val loss: 1.5965 - val accuracy: 0.2586
Epoch 37/100
50/50 [============= ] - 3s 55ms/step - loss: 1.4782 - accuracy: 0.4333 -
val loss: 1.6451 - val accuracy: 0.1552
Epoch 38/100
val loss: 1.7533 - val accuracy: 0.1207
Epoch 39/100
val loss: 1.4317 - val accuracy: 0.3621
Epoch 40/100
val_loss: 1.6077 - val_accuracy: 0.2931
Epoch 41/100
val loss: 1.5382 - val accuracy: 0.3966
Epoch 42/100
val loss: 1.4707 - val accuracy: 0.3621
Epoch 43/100
val loss: 1.4716 - val accuracy: 0.4310
Epoch 44/100
val loss: 1.3684 - val accuracy: 0.4828
Epoch 45/100
val loss: 1.6778 - val accuracy: 0.3621
Epoch 46/100
val loss: 1.6391 - val accuracy: 0.2586
Epoch 47/100
val loss: 1.3508 - val accuracy: 0.5345
Epoch 48/100
50/50 [============ ] - 0s 7ms/step - loss: 1.4617 - accuracy: 0.4533 -
val loss: 1.7648 - val accuracy: 0.2414
Epoch 49/100
50/50 [============= ] - 2s 36ms/step - loss: 1.3582 - accuracy: 0.4200 -
val loss: 1.3652 - val accuracy: 0.4828
Epoch 50/100
val loss: 1.3937 - val accuracy: 0.4655
Epoch 51/100
val loss: 1.6358 - val accuracy: 0.3276
Epoch 52/100
val_loss: 1.3467 - val_accuracy: 0.4310
Epoch 53/100
val_loss: 1.3714 - val_accuracy: 0.4828
Epoch 54/100
val loss: 1.5614 - val accuracy: 0.3448
Epoch 55/100
```

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```
val loss: 1.4555 - val accuracy: 0.4483
Epoch 56/100
50/50 [============= ] - 1s 28ms/step - loss: 1.3444 - accuracy: 0.4600 -
val loss: 1.3545 - val accuracy: 0.5172
Epoch 57/100
val loss: 1.3270 - val accuracy: 0.5000
Epoch 58/100
val loss: 1.4939 - val accuracy: 0.3793
Epoch 59/100
val loss: 1.9373 - val accuracy: 0.1897
Epoch 60/100
50/50 [============ ] - 2s 31ms/step - loss: 1.3480 - accuracy: 0.5200 -
val loss: 1.4473 - val accuracy: 0.3966
Epoch 61/100
val loss: 1.4654 - val accuracy: 0.3966
Epoch 62/100
val loss: 1.7702 - val accuracy: 0.1724
Epoch 63/100
val loss: 1.4625 - val accuracy: 0.3966
Epoch 64/100
val_loss: 1.9994 - val_accuracy: 0.1897
Epoch 65/100
val loss: 1.4833 - val accuracy: 0.3448
Epoch 66/100
val loss: 1.8510 - val accuracy: 0.1897
Epoch 67/100
val loss: 1.8843 - val accuracy: 0.1552
Epoch 68/100
val loss: 1.8354 - val accuracy: 0.1552
Epoch 69/100
val loss: 1.8359 - val accuracy: 0.2414
Epoch 70/100
val loss: 1.5089 - val accuracy: 0.4138
Epoch 71/100
val loss: 1.4522 - val accuracy: 0.4138
Epoch 72/100
val loss: 1.2666 - val accuracy: 0.5690
Epoch 73/100
val loss: 1.8619 - val accuracy: 0.2931
Epoch 74/100
val loss: 1.7583 - val accuracy: 0.3793
Epoch 75/100
val loss: 2.1321 - val accuracy: 0.1897
Epoch 76/100
val_loss: 1.6017 - val_accuracy: 0.4483
Epoch 77/100
val_loss: 1.7248 - val_accuracy: 0.3276
Epoch 78/100
50/50 [============ ] - 2s 34ms/step - loss: 1.2896 - accuracy: 0.5000 -
val loss: 1.5425 - val accuracy: 0.3276
Epoch 79/100
```

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```
val loss: 1.4101 - val accuracy: 0.4138
Epoch 80/100
50/50 [============= ] - 1s 10ms/step - loss: 1.0221 - accuracy: 0.5933 -
val loss: 2.1509 - val accuracy: 0.1897
Epoch 81/100
val loss: 1.3856 - val accuracy: 0.4483
Epoch 82/100
val_loss: 1.6539 - val_accuracy: 0.2931
Epoch 83/100
val loss: 1.7232 - val accuracy: 0.2414
Epoch 84/100
50/50 [============= ] - 1s 14ms/step - loss: 0.9719 - accuracy: 0.6467 -
val loss: 1.7175 - val accuracy: 0.2586
Epoch 85/100
50/50 [============ ] - 0s 9ms/step - loss: 1.0825 - accuracy: 0.5800 -
val loss: 1.6805 - val accuracy: 0.2586
Epoch 86/100
val loss: 1.4243 - val accuracy: 0.4655
Epoch 87/100
val loss: 1.5494 - val accuracy: 0.3448
Epoch 88/100
val_loss: 1.6603 - val_accuracy: 0.3966
Epoch 89/100
val loss: 1.5413 - val accuracy: 0.4483
Epoch 90/100
val loss: 1.4950 - val accuracy: 0.4655
Epoch 91/100
val loss: 1.6449 - val accuracy: 0.3621
Epoch 92/100
val loss: 1.7189 - val accuracy: 0.3276
Epoch 93/100
val loss: 2.1982 - val accuracy: 0.1897
Epoch 94/100
val_loss: 1.5905 - val_accuracy: 0.3793
Epoch 95/100
val loss: 1.6064 - val accuracy: 0.4138
Epoch 96/100
50/50 [===========] - 2s 42ms/step - loss: 0.8614 - accuracy: 0.6800 -
val loss: 1.7350 - val accuracy: 0.4310
Epoch 97/100
50/50 [============ ] - 5s 91ms/step - loss: 1.0111 - accuracy: 0.6067 -
val loss: 1.6299 - val accuracy: 0.3621
Epoch 98/100
val loss: 1.7067 - val accuracy: 0.3103
Epoch 99/100
val loss: 1.2862 - val accuracy: 0.5172
Epoch 100/100
val loss: 1.4589 - val accuracy: 0.4655
In [31]:
cnn.summary()
```

Model: "sequential 3"

Layer (type)	Output Snape	Param #
conv2d_9 (Conv2D)	(None, 30, 30, 32)	896
max_pooling2d_9 (MaxPooling2	(None, 15, 15, 32)	0
conv2d_10 (Conv2D)	(None, 13, 13, 32)	9248
max_pooling2d_10 (MaxPooling	(None, 6, 6, 32)	0
conv2d_11 (Conv2D)	(None, 4, 4, 64)	18496
max_pooling2d_11 (MaxPooling	(None, 2, 2, 64)	0
flatten_3 (Flatten)	(None, 256)	0
dense_6 (Dense)	(None, 64)	16448
dense_7 (Dense)	(None, 6)	390
Total params: 45,478		

Total params: 45,478
Trainable params: 45,478
Non-trainable params: 0

In [32]:

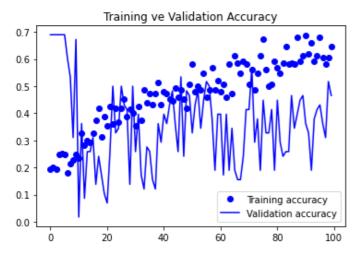
```
import matplotlib.pyplot as plt
%matplotlib inline

accuracy = history1.history['accuracy']
val_accuracy = history1.history['val_accuracy']
loss = history1.history['loss']
val_loss = history1.history['val_loss']
epochs = range(len(accuracy))

plt.plot(epochs, accuracy, 'bo', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training ve Validation Accuracy')
plt.legend()
plt.figure()
```

Out[32]:

<Figure size 432x288 with 0 Axes>



<Figure size 432x288 with 0 Axes>

In []: