Image Classification

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Intro

This notebook will exploring using deep learning to classify images from the CIFAR100 dataset. The CIFAR100 is a 60,000 RGB dataset of 32x32 images divided into 20 superclasses based on categories such as plants, animals, humans, buildings, objects, and vehicles; each superclass has 5 subclasses of specific entities belonging to each category, bringing a total of 100 classes. Due to confusion and time constraints the CIFAR100 dataset was loaded from within Keras as one of its sample datasets, selecting to classify by the subclasses. The goal is to accurately classify an image into a subclass - ergo it must predict both the category of subject matter and the specific identity of the subject matter.

Load dataset

In [1]:

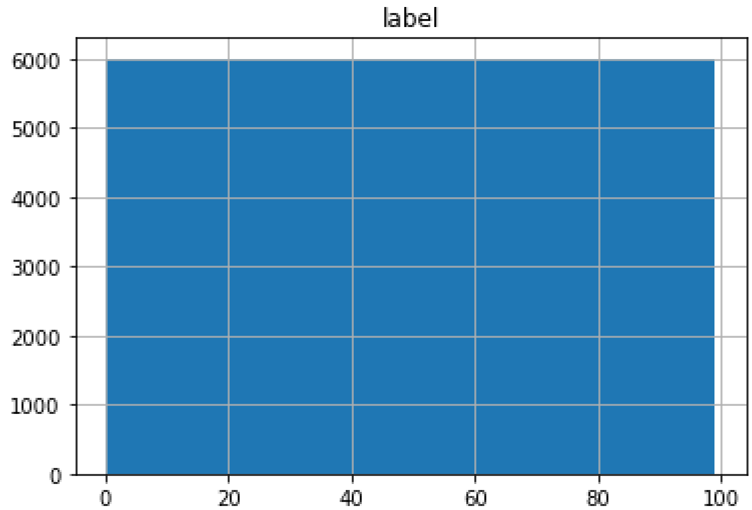
```python
import tensorflow as tf
import numpy as np
import keras

batch_size = 128
num_classes = 100
epochs = 20

(X_train, y_train), (X_test, y_test) = tf.keras.datasets.cifar100.load_data(label

y_train = keras.utils.to_categorical(y_train, num_classes)
y_test = keras.utils.to_categorical(y_test, num_classes)

X_train, X_test = X_train / 255.0, X_test / 255.0

print(X_train[:5])
print('\n')
print("dimensions:", X_train.shape)

print('\n')
print(X_test[:5])
print('\n')
print("dimensions:", X_test.shape)
```

```
[[[[1.         1.         1.        ]
   [1.         1.         1.        ]
   [1.         1.         1.        ]
   ...
   [0.76470588 0.80392157 0.75686275]
   [0.83137255 0.87843137 0.8       ]
   [0.71372549 0.76078431 0.65490196]]

  [[1.         1.         1.        ]
   [0.99607843 0.99607843 0.99607843]
   [0.99607843 0.99607843 0.99607843]
   ...
   [0.66666667 0.69019608 0.58823529]
   [0.63137255 0.65882353 0.50980392]
   [0.57254902 0.60392157 0.44313725]]

  [[1.         1.         1.        ]
   [0.99607843 0.99607843 0.99607843]
   [1.         1.         1.        ]
```

Class distribution

In [2]:
```python
import pandas as pd

df = pd.DataFrame(np.append(np.argmax(y_train, axis=1), np.argmax(y_test, axis=1)
hist = df.hist()
print(hist)
```

```
[[<AxesSubplot:title={'center':'label'}>]]
```



Sequential model

Training

In [3]:
```python
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.optimizers import RMSprop

seq_model = Sequential([
  Flatten(input_shape=(32,32,3)),
  Dense(512, activation='relu'),
  Dropout(0.2),
  Dense(512, activation='relu'),
  Dropout(0.2),
  Dense(num_classes, activation='softmax'),
])

seq_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 flatten (Flatten)           (None, 3072)              0         
                                                                 
 dense (Dense)               (None, 512)               1573376   
                                                                 
 dropout (Dropout)           (None, 512)               0         
                                                                 
 dense_1 (Dense)             (None, 512)               262656    
                                                                 
 dropout_1 (Dropout)         (None, 512)               0         
                                                                 
 dense_2 (Dense)             (None, 100)               51300     
                                                                 
=================================================================
Total params: 1,887,332
Trainable params: 1,887,332
Non-trainable params: 0
_________________________________________________________________
```

Testing

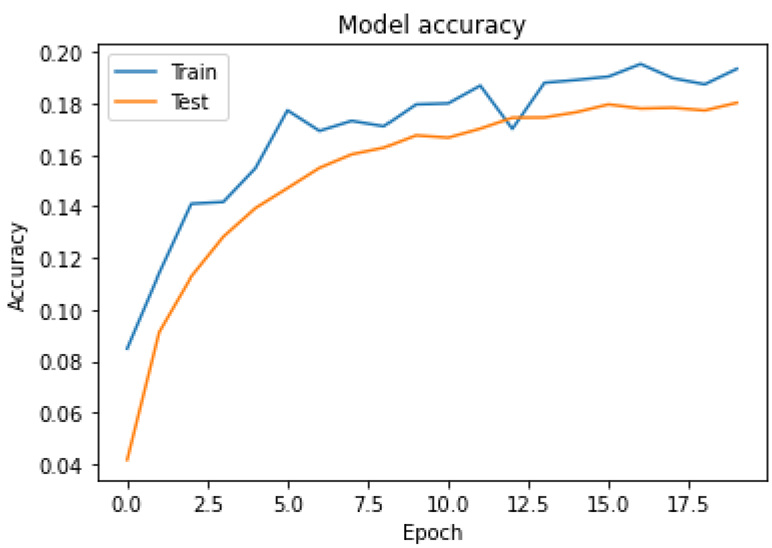
In [4]:
```
seq_model.compile(loss='binary_crossentropy',
              optimizer=RMSprop(),
              metrics=['accuracy'])

seq_history = seq_model.fit(X_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(X_test, y_test))
```

```
Epoch 1/20
391/391 [==============================] - 6s 15ms/step - loss: 0.0673 - accura
cy: 0.0417 - val_loss: 0.0560 - val_accuracy: 0.0849
Epoch 2/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0527 - accura
cy: 0.0913 - val_loss: 0.0498 - val_accuracy: 0.1141
Epoch 3/20
391/391 [==============================] - 6s 15ms/step - loss: 0.0493 - accura
cy: 0.1127 - val_loss: 0.0483 - val_accuracy: 0.1410
Epoch 4/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0483 - accura
cy: 0.1282 - val_loss: 0.0474 - val_accuracy: 0.1417
Epoch 5/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0475 - accura
cy: 0.1393 - val_loss: 0.0468 - val_accuracy: 0.1548
Epoch 6/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0471 - accura
cy: 0.1471 - val_loss: 0.0457 - val_accuracy: 0.1773
Epoch 7/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0467 - accura
cy: 0.1549 - val_loss: 0.0453 - val_accuracy: 0.1693
Epoch 8/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0465 - accura
cy: 0.1602 - val_loss: 0.0455 - val_accuracy: 0.1732
Epoch 9/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0464 - accura
cy: 0.1628 - val_loss: 0.0459 - val_accuracy: 0.1711
Epoch 10/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0462 - accura
cy: 0.1676 - val_loss: 0.0451 - val_accuracy: 0.1796
Epoch 11/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0461 - accura
cy: 0.1667 - val_loss: 0.0452 - val_accuracy: 0.1800
Epoch 12/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0460 - accura
cy: 0.1702 - val_loss: 0.0460 - val_accuracy: 0.1869
Epoch 13/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0459 - accura
cy: 0.1744 - val_loss: 0.0458 - val_accuracy: 0.1701
Epoch 14/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0459 - accura
cy: 0.1745 - val_loss: 0.0448 - val_accuracy: 0.1880
Epoch 15/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0459 - accura
cy: 0.1766 - val_loss: 0.0453 - val_accuracy: 0.1891
Epoch 16/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0458 - accura
```

```
cy: 0.1796 - val_loss: 0.0447 - val_accuracy: 0.1904
Epoch 17/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0457 - accura
cy: 0.1780 - val_loss: 0.0446 - val_accuracy: 0.1953
Epoch 18/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0457 - accura
cy: 0.1783 - val_loss: 0.0442 - val_accuracy: 0.1898
Epoch 19/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0458 - accura
cy: 0.1773 - val_loss: 0.0446 - val_accuracy: 0.1874
Epoch 20/20
391/391 [==============================] - 6s 14ms/step - loss: 0.0457 - accura
cy: 0.1802 - val_loss: 0.0451 - val_accuracy: 0.1934
```

Analysis

In [5]:
```python
import matplotlib.pyplot as plt

plt.plot(seq_history.history['val_accuracy'])
plt.plot(seq_history.history['accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



In [6]:
```python
seq_score = seq_model.evaluate(X_test, y_test, verbose=0)
print('Test loss:', seq_score[0])
print('Test accuracy:', seq_score[1])
```

```
Test loss: 0.04513979330658913
Test accuracy: 0.19339999556541443
```

CNN

Training

In [7]:

```python
from keras import Input
from keras.layers import Conv2D, MaxPooling2D

num_filters = 8
filter_size = 3
pool_size = 2

cnn_model = Sequential(
    [
        Input(shape=(32, 32, 3)),
        Conv2D(32, kernel_size=3, activation="relu"),
        MaxPooling2D(pool_size=2),
        Conv2D(64, kernel_size=3, activation="relu"),
        MaxPooling2D(pool_size=2),
        Flatten(),
        Dropout(0.5),
        Dense(num_classes, activation="softmax"),
    ]
)

cnn_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 conv2d (Conv2D)             (None, 30, 30, 32)        896       
                                                                 
 max_pooling2d (MaxPooling2D  (None, 15, 15, 32)       0         
 )                                                               
                                                                 
 conv2d_1 (Conv2D)           (None, 13, 13, 64)        18496     
                                                                 
 max_pooling2d_1 (MaxPooling  (None, 6, 6, 64)         0         
 2D)                                                             
                                                                 
 flatten_1 (Flatten)         (None, 2304)              0         
                                                                 
 dropout_2 (Dropout)         (None, 2304)              0         
                                                                 
 dense_3 (Dense)             (None, 100)               230500    
                                                                 
=================================================================
Total params: 249,892
Trainable params: 249,892
Non-trainable params: 0
_________________________________________________________________
```

Testing

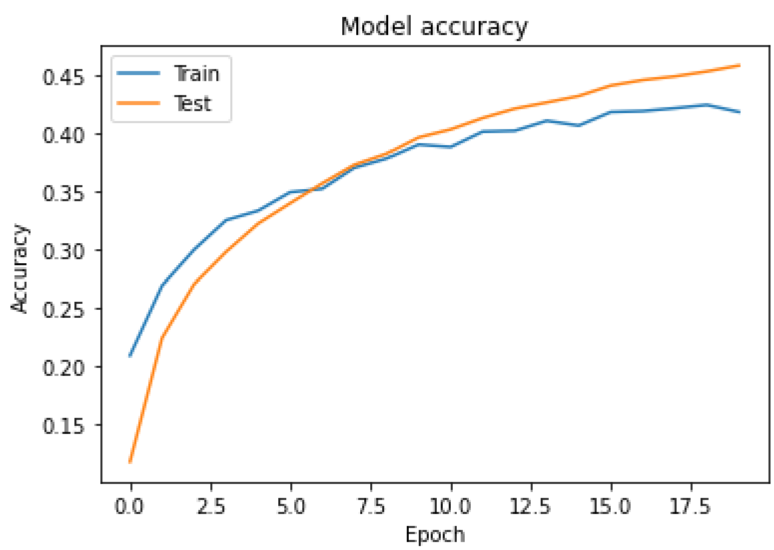
In [8]:
```python
from keras.optimizers import Adam

cnn_model.compile(loss='categorical_crossentropy',
              optimizer=Adam(),
              metrics=['accuracy'])

cnn_history = cnn_model.fit(X_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(X_test, y_test))
```

```
Epoch 1/20
391/391 [==============================] - 13s 33ms/step - loss: 3.9020 - acc
uracy: 0.1180 - val_loss: 3.4041 - val_accuracy: 0.2091
Epoch 2/20
391/391 [==============================] - 13s 32ms/step - loss: 3.2979 - acc
uracy: 0.2241 - val_loss: 3.0982 - val_accuracy: 0.2689
Epoch 3/20
391/391 [==============================] - 13s 33ms/step - loss: 3.0500 - acc
uracy: 0.2701 - val_loss: 2.9242 - val_accuracy: 0.2996
Epoch 4/20
391/391 [==============================] - 13s 32ms/step - loss: 2.9029 - acc
uracy: 0.2978 - val_loss: 2.8290 - val_accuracy: 0.3249
Epoch 5/20
391/391 [==============================] - 12s 32ms/step - loss: 2.7724 - acc
uracy: 0.3219 - val_loss: 2.7461 - val_accuracy: 0.3330
Epoch 6/20
391/391 [==============================] - 13s 32ms/step - loss: 2.6825 - acc
uracy: 0.3394 - val_loss: 2.6743 - val_accuracy: 0.3489
Epoch 7/20
391/391 [==============================] - 13s 32ms/step - loss: 2.6016 - acc
uracy: 0.3564 - val_loss: 2.6322 - val_accuracy: 0.3518
Epoch 8/20
391/391 [==============================] - 13s 32ms/step - loss: 2.5314 - acc
uracy: 0.3724 - val_loss: 2.5574 - val_accuracy: 0.3698
Epoch 9/20
391/391 [==============================] - 13s 33ms/step - loss: 2.4724 - acc
uracy: 0.3818 - val_loss: 2.5034 - val_accuracy: 0.3777
Epoch 10/20
391/391 [==============================] - 13s 33ms/step - loss: 2.4122 - acc
uracy: 0.3959 - val_loss: 2.4755 - val_accuracy: 0.3898
Epoch 11/20
391/391 [==============================] - 13s 33ms/step - loss: 2.3690 - acc
uracy: 0.4028 - val_loss: 2.4595 - val_accuracy: 0.3877
Epoch 12/20
391/391 [==============================] - 13s 33ms/step - loss: 2.3212 - acc
uracy: 0.4126 - val_loss: 2.4131 - val_accuracy: 0.4009
Epoch 13/20
391/391 [==============================] - 13s 33ms/step - loss: 2.2851 - acc
uracy: 0.4206 - val_loss: 2.4093 - val_accuracy: 0.4016
Epoch 14/20
391/391 [==============================] - 13s 33ms/step - loss: 2.2525 - acc
uracy: 0.4259 - val_loss: 2.3722 - val_accuracy: 0.4102
Epoch 15/20
391/391 [==============================] - 13s 33ms/step - loss: 2.2219 - acc
```

```
uracy: 0.4315 - val_loss: 2.3631 - val_accuracy: 0.4061
Epoch 16/20
391/391 [==============================] - 13s 33ms/step - loss: 2.1874 - acc
uracy: 0.4404 - val_loss: 2.3414 - val_accuracy: 0.4177
Epoch 17/20
391/391 [==============================] - 13s 33ms/step - loss: 2.1570 - acc
uracy: 0.4452 - val_loss: 2.3322 - val_accuracy: 0.4185
Epoch 18/20
391/391 [==============================] - 13s 33ms/step - loss: 2.1395 - acc
uracy: 0.4483 - val_loss: 2.3257 - val_accuracy: 0.4210
Epoch 19/20
391/391 [==============================] - 13s 33ms/step - loss: 2.1143 - acc
uracy: 0.4526 - val_loss: 2.3276 - val_accuracy: 0.4238
Epoch 20/20
391/391 [==============================] - 13s 34ms/step - loss: 2.0996 - acc
uracy: 0.4576 - val_loss: 2.3260 - val_accuracy: 0.4178
```

Analysis

In [9]:
```
plt.plot(cnn_history.history['val_accuracy'])
plt.plot(cnn_history.history['accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



In [10]:
```
cnn_score = cnn_model.evaluate(X_test, y_test, verbose=0)
print('Test loss:', cnn_score[0])
print('Test accuracy:', cnn_score[1])
```

```
Test loss: 2.32599139213562
Test accuracy: 0.41780000925064087
```

Pre-trained model (VGG16)

Training

In [11]:
```
from keras import Model
from keras.applications import VGG16
from keras.layers import GlobalAveragePooling2D

X_train, X_test = X_train * 255.0, X_test * 255.0

base_model = VGG16(
    weights='imagenet',
    input_shape=(32, 32, 3),
    include_top=False)

base_model.trainable = False

inputs = Input(shape=(32, 32, 3))
x = base_model(inputs, training=False)
x = GlobalAveragePooling2D()(x)
outputs = Dense(100)(x)
pret_model = Model(inputs, outputs)

pret_model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_3 (InputLayer)        [(None, 32, 32, 3)]       0         
                                                                 
 vgg16 (Functional)          (None, 1, 1, 512)         14714688  
                                                                 
 global_average_pooling2d (G  (None, 512)              0         
 lobalAveragePooling2D)                                          
                                                                 
 dense_4 (Dense)             (None, 100)               51300     
                                                                 
=================================================================
Total params: 14,765,988
Trainable params: 51,300
Non-trainable params: 14,714,688
_________________________________________________________________
```

Testing

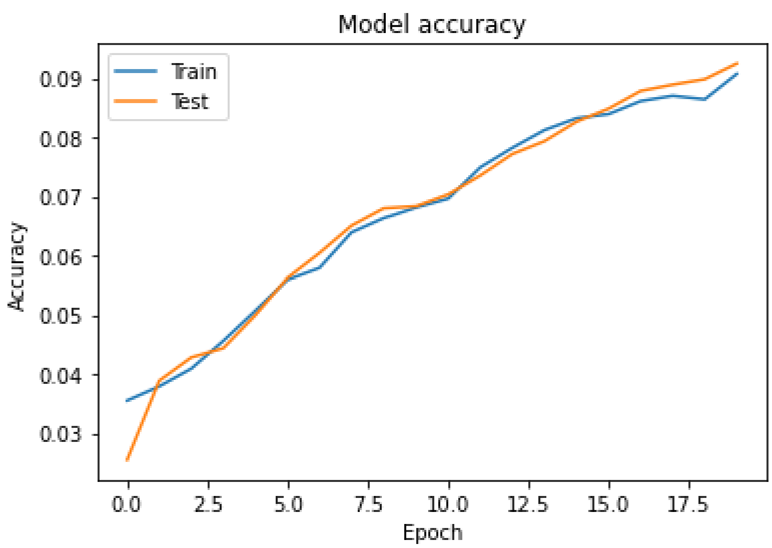
```
In [12]: pret_model.compile(loss='categorical_crossentropy',
                    optimizer=Adam(),
                    metrics=['accuracy'])

pret_history = pret_model.fit(X_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(X_test, y_test))
```

```
Epoch 1/20
391/391 [==============================] - 57s 146ms/step - loss: 8.9790 - accu
racy: 0.0255 - val_loss: 8.8312 - val_accuracy: 0.0355
Epoch 2/20
391/391 [==============================] - 55s 141ms/step - loss: 8.7044 - accu
racy: 0.0389 - val_loss: 8.6733 - val_accuracy: 0.0379
Epoch 3/20
391/391 [==============================] - 55s 142ms/step - loss: 8.5454 - accu
racy: 0.0428 - val_loss: 8.6058 - val_accuracy: 0.0409
Epoch 4/20
391/391 [==============================] - 55s 141ms/step - loss: 8.4708 - accu
racy: 0.0444 - val_loss: 8.2620 - val_accuracy: 0.0456
Epoch 5/20
391/391 [==============================] - 56s 144ms/step - loss: 8.4461 - accu
racy: 0.0499 - val_loss: 8.4399 - val_accuracy: 0.0507
Epoch 6/20
391/391 [==============================] - 57s 146ms/step - loss: 8.3813 - accu
racy: 0.0562 - val_loss: 8.5920 - val_accuracy: 0.0559
Epoch 7/20
391/391 [==============================] - 57s 145ms/step - loss: 8.3800 - accu
racy: 0.0604 - val_loss: 8.5528 - val_accuracy: 0.0579
Epoch 8/20
391/391 [==============================] - 57s 147ms/step - loss: 8.3893 - accu
racy: 0.0650 - val_loss: 8.3382 - val_accuracy: 0.0639
Epoch 9/20
391/391 [==============================] - 58s 147ms/step - loss: 8.4302 - accu
racy: 0.0680 - val_loss: 8.7121 - val_accuracy: 0.0663
Epoch 10/20
391/391 [==============================] - 56s 143ms/step - loss: 8.3344 - accu
racy: 0.0683 - val_loss: 8.2156 - val_accuracy: 0.0681
Epoch 11/20
391/391 [==============================] - 56s 145ms/step - loss: 8.3469 - accu
racy: 0.0703 - val_loss: 8.1798 - val_accuracy: 0.0696
Epoch 12/20
391/391 [==============================] - 57s 145ms/step - loss: 8.3264 - accu
racy: 0.0735 - val_loss: 8.3917 - val_accuracy: 0.0749
Epoch 13/20
391/391 [==============================] - 56s 144ms/step - loss: 8.4681 - accu
racy: 0.0772 - val_loss: 8.4942 - val_accuracy: 0.0782
Epoch 14/20
391/391 [==============================] - 56s 144ms/step - loss: 8.2913 - accu
racy: 0.0793 - val_loss: 8.4078 - val_accuracy: 0.0812
Epoch 15/20
391/391 [==============================] - 56s 144ms/step - loss: 8.2810 - accu
racy: 0.0826 - val_loss: 8.3883 - val_accuracy: 0.0832
Epoch 16/20
391/391 [==============================] - 56s 144ms/step - loss: 8.2514 - accu
```

```
racy: 0.0848 - val_loss: 8.4282 - val_accuracy: 0.0839
Epoch 17/20
391/391 [==============================] - 56s 144ms/step - loss: 8.3596 - accu
racy: 0.0878 - val_loss: 8.5135 - val_accuracy: 0.0861
Epoch 18/20
391/391 [==============================] - 57s 145ms/step - loss: 8.2810 - accu
racy: 0.0889 - val_loss: 8.3794 - val_accuracy: 0.0870
Epoch 19/20
391/391 [==============================] - 56s 144ms/step - loss: 8.2581 - accu
racy: 0.0898 - val_loss: 8.4203 - val_accuracy: 0.0864
Epoch 20/20
391/391 [==============================] - 56s 143ms/step - loss: 8.4792 - accu
racy: 0.0925 - val_loss: 8.5234 - val_accuracy: 0.0907
```

Analysis

In [13]:
```
plt.plot(pret_history.history['val_accuracy'])
plt.plot(pret_history.history['accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.show()
```



In [14]:
```
pret_score = pret_model.evaluate(X_test, y_test, verbose=0)
print('Test loss:', pret_score[0])
print('Test accuracy:', pret_score[1])
```

```
Test loss: 8.523427963256836
Test accuracy: 0.09070000052452087
```

Discussion

Although none are particularly accurate, the results between models are all significantly different and so might more strongly highlight the different capabilities of each model than had the models been trained on a dataset that's easier to classify. The sequential model's accuracy was in the middle of the 3 models at 19.34% accuracy. However, despite having the least test loss at less than 0.05, the sequential model had the quickest running epochs at 6 seconds each. The CNN model produced the most accurate predictions at 41.78% accuracy. The test loss and epoch eras were both in the middle of the 3 model at 2.326 and 13 seconds respectively. Although the ratio of accuracy to combined epoch time is the same between the two former models and the CNN model took twice as long, the roughly doubled accuracy of the CNN model makes it much more appealing to me for image classification. I was not able to learn how to preprocess the dataset for the pre-trained VGG16 model, which might explain why the results of using VGG16 were generally the worst. The test loss was the highest at 8.523, but the accuracy was the lowest at 9.07% and the epoch runtime was the longest at between 55 and 58 seconds per epoch. In addition, the former two models reached the maximum accuracy in fewer epochs than the VGG16 model. Perhaps the pre-trained model would have performed far better had I time to properly learn how to implement the model.