In [30]:
```
# Import required packages
import numpy as np
import cv2
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
import time
import tensorflow as tf
from sklearn.model_selection import train_test_split
```

In [2]:
```
tf.config.experimental.list_physical_devices()
```

Out[2]:
```
[PhysicalDevice(name='/physical_device:CPU:0', device_type='CPU')]
```

# 1. Load the datasets

For the project, we provide a training set with 50000 images in the directory `../data/images/` with:

- noisy labels for all images provided in `../data/noisy_label.csv` ;
- clean labels for the first 10000 images provided in `../data/clean_labels.csv` .

In [31]:
```
# [DO NOT MODIFY THIS CELL]

# Load the images
n_img = 50000
n_noisy = 40000
n_clean_noisy = n_img - n_noisy
imgs = np.empty((n_img,32,32,3))
for i in range(n_img):
    img_fn = f'C:/Users/Frank Shi/Desktop/train_data/images/{i+1:05d}.png'
    imgs[i,:,:,:]=cv2.cvtColor(cv2.imread(img_fn),cv2.COLOR_BGR2RGB)

# Load the labels
clean_labels = np.genfromtxt('C:/Users/Frank Shi/Desktop/train_data/clean_labels.
noisy_labels = np.genfromtxt('C:/Users/Frank Shi/Desktop/train_data/noisy_labels.
```

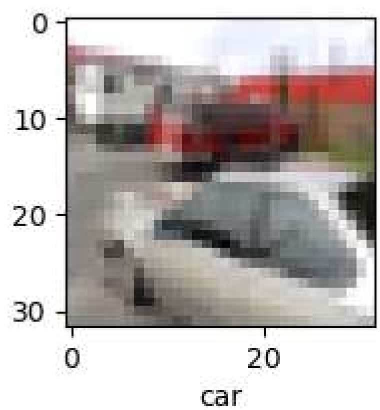
For illustration, we present a small subset (of size 8) of the images with their clean and noisy labels in `clean_noisy_trainset` . You are encouraged to explore more characteristics of the label noises on the whole dataset.

In [32]:
```
# [DO NOT MODIFY THIS CELL]

fig = plt.figure()

ax1 = fig.add_subplot(2,4,1)
ax1.imshow(imgs[0]/255)
ax2 = fig.add_subplot(2,4,2)
ax2.imshow(imgs[1]/255)
ax3 = fig.add_subplot(2,4,3)
ax3.imshow(imgs[2]/255)
ax4 = fig.add_subplot(2,4,4)
ax4.imshow(imgs[3]/255)
ax1 = fig.add_subplot(2,4,5)
ax1.imshow(imgs[4]/255)
ax2 = fig.add_subplot(2,4,6)
ax2.imshow(imgs[5]/255)
ax3 = fig.add_subplot(2,4,7)
ax3.imshow(imgs[6]/255)
ax4 = fig.add_subplot(2,4,8)
ax4.imshow(imgs[7]/255)

# The class-label correspondence
classes = ('plane', 'car', 'bird', 'cat',
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')

# print clean labels
print('Clean labels:')
print(' '.join('%5s' % classes[clean_labels[j]] for j in range(8)))
# print noisy labels
print('Noisy labels:')
print(' '.join('%5s' % classes[noisy_labels[j]] for j in range(8)))
```

```
Clean labels:
 frog truck truck  deer   car   car  bird horse
Noisy labels:
  cat   dog truck  frog   dog  ship  bird  deer
```

In [33]:
```
def show_imgs(X, y, index):
    plt.figure(figsize = (15,2))
    plt.imshow(X[index]/225)
    plt.xlabel(classes[y[index]])

show_imgs(imgs, noisy_labels, 49999)
```

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




## 2. The predictive model

We consider a baseline model directly on the noisy dataset without any label corrections. RGB histogram features are extracted to fit a logistic regression model.

### 2.1. Baseline Model

In [34]:
```
# [DO NOT MODIFY THIS CELL]
# RGB histogram dataset construction
no_bins = 6
bins = np.linspace(0,255,no_bins) # the range of the rgb histogram
target_vec = np.empty(n_img)
feature_mtx = np.empty((n_img,3*(len(bins)-1)))
i = 0
for i in range(n_img):
    # The target vector consists of noisy labels
    target_vec[i] = noisy_labels[i]

    # Use the numbers of pixels in each bin for all three channels as the feature
    feature1 = np.histogram(imgs[i][:,:,0],bins=bins)[0]
    feature2 = np.histogram(imgs[i][:,:,1],bins=bins)[0]
    feature3 = np.histogram(imgs[i][:,:,2],bins=bins)[0]

    # Concatenate three features
    feature_mtx[i,] = np.concatenate((feature1, feature2, feature3), axis=None)
    i += 1
```

In [35]:
```
# [DO NOT MODIFY THIS CELL]
# Train a logistic regression model
clf = LogisticRegression(random_state=0).fit(feature_mtx, target_vec)
```

For the convenience of evaluation, we write the following function `predictive_model` that does the label prediction. **For your predictive model, feel free to modify the function, but make sure the function takes an RGB image of numpy.array format with dimension $32 \times 32 \times 3$ as input, and returns one single label as output.**

In [36]:
```
# [DO NOT MODIFY THIS CELL]
def baseline_model(image):
    '''
    This is the baseline predictive model that takes in the image and returns a l
    '''
    feature1 = np.histogram(image[:,:,0],bins=bins)[0]
    feature2 = np.histogram(image[:,:,1],bins=bins)[0]
    feature3 = np.histogram(image[:,:,2],bins=bins)[0]
    feature = np.concatenate((feature1, feature2, feature3), axis=None).reshape(1
    return clf.predict(feature)
```

## 2.1. Model I

In [37]:
```
X_train_model1, X_test_model1, y_train_model1, y_test_model1 = train_test_split(i


## normalization
X_train_model1 = X_train_model1 / 225
X_test_model1 = X_test_model1/225
print(X_train_model1.shape)
print(X_test_model1.shape)


IMG_SIZE = 32
IMG_SHAPE = (IMG_SIZE, IMG_SIZE, 3)

## model construction
model1 = tf.keras.Sequential([
    ### CNN layers
        tf.keras.layers.Conv2D(32,(3,3),activation ='relu', input_shape=(32,32,3)
        tf.keras.layers.MaxPooling2D((2,2)),
        tf.keras.layers.Dropout(0.2),

        tf.keras.layers.Conv2D(32,(3,3),activation ='relu', input_shape=(32,32,3)
        tf.keras.layers.MaxPooling2D((2,2)),
        tf.keras.layers.Dropout(0.2),

        tf.keras.layers.Conv2D(64,(3,3), activation ='relu'),
        tf.keras.layers.MaxPooling2D((2,2)),
        tf.keras.layers.Dropout(0.2),

        tf.keras.layers.Flatten(),
        tf.keras.layers.Dense(200, activation = 'relu'),
        tf.keras.layers.Dense(100, activation = 'relu'),
        tf.keras.layers.Dropout(0.5),
        tf.keras.layers.Dense(10, activation = 'softmax')
                                ])
    ###################### 21%


model1.compile(optimizer= tf.keras.optimizers.Adam(0.0001),
              ### YOUR CODE HERE ###
              loss= tf.keras.losses.SparseCategoricalCrossentropy(from_logits=Tru
              ######################
              metrics=['sparse_categorical_accuracy'])

### early stop
callback = tf.keras.callbacks.EarlyStopping( patience=4)

start = time.time()
## fit model
history_1 = model1.fit(X_train_model1, y_train_model1, batch_size = 32, epochs=15
end = time.time()


model1.evaluate(X_test_model1, y_test_model1)
```

```
(35000, 32, 32, 3)
```

```
(15000, 32, 32, 3)
Epoch 1/15

C:\Users\Frank Shi\anaconda3\lib\site-packages\keras\backend.py:5582: UserWarni
ng: "`sparse_categorical_crossentropy` received `from_logits=True`, but the `ou
tput` argument was produced by a Softmax activation and thus does not represent
logits. Was this intended?
  output, from_logits = _get_logits(

875/875 [==============================] - 17s 18ms/step - loss: 2.3038 - spa
rse_categorical_accuracy: 0.1027 - val_loss: 2.3002 - val_sparse_categorical_
accuracy: 0.1214
Epoch 2/15
875/875 [==============================] - 17s 19ms/step - loss: 2.2950 - spa
rse_categorical_accuracy: 0.1198 - val_loss: 2.2845 - val_sparse_categorical_
accuracy: 0.1381
Epoch 3/15
875/875 [==============================] - 18s 20ms/step - loss: 2.2834 - spa
rse_categorical_accuracy: 0.1333 - val_loss: 2.2765 - val_sparse_categorical_
accuracy: 0.1497
Epoch 4/15
875/875 [==============================] - 18s 20ms/step - loss: 2.2766 - spa
rse_categorical_accuracy: 0.1420 - val_loss: 2.2706 - val_sparse_categorical_
accuracy: 0.1574
Epoch 5/15
875/875 [==============================] - 19s 21ms/step - loss: 2.2693 - spa
rse_categorical_accuracy: 0.1515 - val_loss: 2.2594 - val_sparse_categorical_
accuracy: 0.1839
Epoch 6/15
875/875 [==============================] - 18s 21ms/step - loss: 2.2629 - spa
rse_categorical_accuracy: 0.1642 - val_loss: 2.2542 - val_sparse_categorical_
accuracy: 0.1857
Epoch 7/15
875/875 [==============================] - 18s 20ms/step - loss: 2.2572 - spa
rse_categorical_accuracy: 0.1702 - val_loss: 2.2494 - val_sparse_categorical_
accuracy: 0.1899
Epoch 8/15
875/875 [==============================] - 18s 20ms/step - loss: 2.2530 - spa
rse_categorical_accuracy: 0.1757 - val_loss: 2.2436 - val_sparse_categorical_
accuracy: 0.1977
Epoch 9/15
875/875 [==============================] - 18s 20ms/step - loss: 2.2499 - spa
rse_categorical_accuracy: 0.1801 - val_loss: 2.2388 - val_sparse_categorical_
accuracy: 0.2034
Epoch 10/15
875/875 [==============================] - 17s 20ms/step - loss: 2.2452 - spa
rse_categorical_accuracy: 0.1839 - val_loss: 2.2361 - val_sparse_categorical_
accuracy: 0.2017
Epoch 11/15
875/875 [==============================] - 17s 20ms/step - loss: 2.2429 - spa
rse_categorical_accuracy: 0.1864 - val_loss: 2.2366 - val_sparse_categorical_
accuracy: 0.2009
Epoch 12/15
875/875 [==============================] - 18s 20ms/step - loss: 2.2394 - spa
rse_categorical_accuracy: 0.1924 - val_loss: 2.2282 - val_sparse_categorical_
accuracy: 0.2100
Epoch 13/15
875/875 [==============================] - 17s 20ms/step - loss: 2.2360 - spa
```

```
rse_categorical_accuracy: 0.1944 - val_loss: 2.2269 - val_sparse_categorical_
accuracy: 0.2037
Epoch 14/15
875/875 [==============================] - 18s 20ms/step - loss: 2.2335 - spa
rse_categorical_accuracy: 0.1984 - val_loss: 2.2225 - val_sparse_categorical_
accuracy: 0.2106
Epoch 15/15
875/875 [==============================] - 19s 22ms/step - loss: 2.2325 - spa
rse_categorical_accuracy: 0.2003 - val_loss: 2.2192 - val_sparse_categorical_
accuracy: 0.2116
469/469 [==============================] - 3s 7ms/step - loss: 2.2231 - spars
e_categorical_accuracy: 0.2134
```

Out[37]:
```
[2.223073720932007, 0.2134000062942505]
```

In [38]:
```
# summarize history for accuracy

print("training time for model 1: " + str((end - start)/60) + 'mins')
```

```
training time for model 1: 4.434418133894602mins
```

In [36]:
```
# [ADD WEAKLY SUPERVISED LEARNING FEATURE TO MODEL I]

# write your code here...

def model_I(image):
    '''
    This function should takes in the image of dimension 32*32*3 as input and ret
    '''
    # write your code here...
    image = image/225
    predictions = model1.predict(image)
    return np.argmax(predictions)
```

In [39]:
```
def model_I(image):
    '''
    This function should takes in the image of dimension 32*32*3 as input and ret
    '''
    # write your code here.
    return np.argmax(model1.predict(image/225), axis = -1)
```

## 2.2. Model II

In [10]:
```
## Base model of model2

#transfer learning model without Image augmentation

#### Image prepreration and nomalization
from sklearn.model_selection import train_test_split
clean_imgs = imgs[0:10000]
noisy_imgs = imgs[10000:]
noisy_labels_400000 =  noisy_labels[10000:]

### split the clean dataset into train and test
X_train_clean, X_test, y_train_clean, y_test = train_test_split(clean_imgs, clear

## combine the clean train dataset with noisy dataset
X_train_combined = np.concatenate((X_train_clean, noisy_imgs))
y_train_combined = np.concatenate((y_train_clean, noisy_labels_400000))


## normalization
X_test = X_test / 225
X_train_combined = X_train_combined / 225
X_train_clean = X_train_clean/225


IMG_SIZE = 32
IMG_SHAPE = (IMG_SIZE, IMG_SIZE, 3)

### loade pretrained model Mobilnet
MobileNet = tf.keras.applications.mobilenet_v2.MobileNetV2(input_shape=IMG_SHAPE,
MobileNet.trainable= True

### construct NN
model = tf.keras.Sequential([
    MobileNet,
    #tf.keras.layers.Conv2D(12,(3,3), activation = 'relu', input_shape = (7, 7, 1
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.2),

    tf.keras.layers.Dense(500, activation = 'relu'),
    tf.keras.layers.Dense(200, activation = 'relu'),

    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(10, activation = 'softmax')
              ])

model.compile(optimizer=tf.keras.optimizers.Adam(0.0001),
              ### YOUR CODE HERE ###
              loss= tf.keras.losses.SparseCategoricalCrossentropy(from_logits=Tru
              ######################
              metrics=['sparse_categorical_accuracy'])

callback = tf.keras.callbacks.EarlyStopping( patience=4)

start = time.time()
history_2_1 =model.fit(X_train_clean, y_train_clean, batch_size = 32, epochs=60,
end = time.time()
```

```
model.evaluate(X_test, y_test)
```

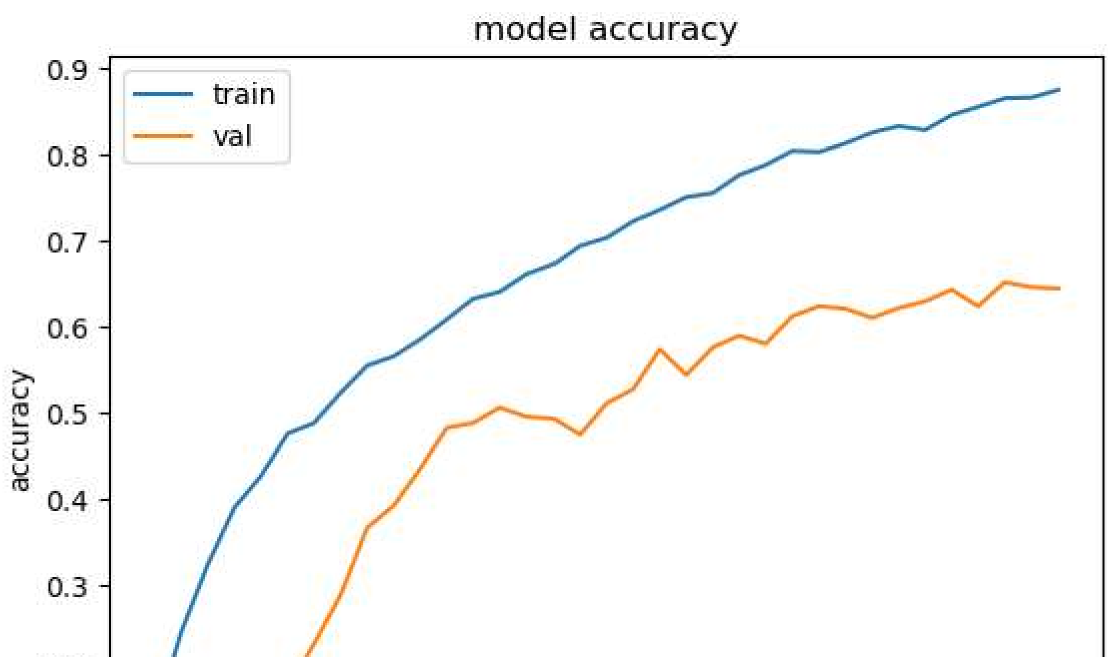
```
WARNING:tensorflow:`input_shape` is undefined or non-square, or `rows` is not
in [96, 128, 160, 192, 224]. Weights for input shape (224, 224) will be loade
d as the default.
Epoch 1/60

C:\Users\Frank Shi\anaconda3\lib\site-packages\keras\backend.py:5582: UserWar
ning: "`sparse_categorical_crossentropy` received `from_logits=True`, but the
`output` argument was produced by a Softmax activation and thus does not repr
esent logits. Was this intended?
  output, from_logits = _get_logits(
```

In [11]:

```
# summarize history for accuracy

print("training time for model 1: " + str((end - start)/60) + 'mins')
```

```
training time for model 1: 11.619206710656483mins
```

In [19]:
```
# model run time
print("training time for model 1: " + str((end - start)/60) + 'mins')

#### plot the acc and loss
plt.plot(history_2_1.history['sparse_categorical_accuracy'])
plt.plot(history_2_1.history['val_sparse_categorical_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()

##plot loss
plt.plot(history_2_1.history['loss'])
plt.plot(history_2_1.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```



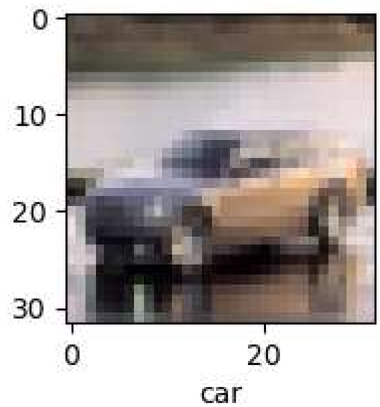
In [80]:

```
### Save the  model
from tensorflow.keras.models import Model
from tensorflow.keras.models import load_model
model_final.save('Model_clean.h5')
print('Model Saved!')
savedModel=load_model('Model_clean.h5')
```

```
Model Saved!
Model: "sequential_19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 mobilenetv2_1.00_224 (Funct  (None, 1, 1, 1280)       2257984   
 ional)                                                          
                                                                 
 global_average_pooling2d_16  (None, 1280)             0         
  (GlobalAveragePooling2D)                                       
                                                                 
 dropout_35 (Dropout)        (None, 1280)              0         
                                                                 
 dense_54 (Dense)            (None, 500)               640500    
                                                                 
 dropout_36 (Dropout)        (None, 500)               0         
                                                                 
 dense_55 (Dense)            (None, 200)               100200    
                                                                 
 dropout_37 (Dropout)        (None, 200)               0         
                                                                 
 dropout_38 (Dropout)        (None, 200)               0         
                                                                 
 dense_56 (Dense)            (None, 10)                2010      
                                                                 
=================================================================
Total params: 3,000,694
Trainable params: 2,966,582
Non-trainable params: 34,112
_________________________________________________________________
```

In [62]:
```
### show ith image prediction
i = 600
print(classes[np.argmax(model.predict(X_test)[i])])

### show ith image in X_test
show_imgs(X_test*225, y_test, i)
```

```
94/94 [==============================] - 3s 31ms/step

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

car
```




## Label Corrrection

In [17]:

```
### label Correction
##Create a empty list capture prob>0.85
confident_imgs = []
model_predict = model.predict(noisy_imgs/225)
for i in range(len(noisy_imgs)):
    if sum(model_predict[i]>0.85) == 1:
        confident_imgs.append(i)

##length of selected noisy labels
print(len(confident_imgs))


### add train_clean date and corrected  noisy labels
X_train_final = np.concatenate((X_train_clean, noisy_imgs[confident_imgs]/225)) #
y_train_final = np.concatenate((y_train_clean, np.argmax(model.predict(noisy_imgs

print(len(X_train_final))
print(len(y_train_final))
print(len(confident_imgs))
```

```
1250/1250 [==============================] - 23s 18ms/step
21744
1250/1250 [==============================] - 23s 18ms/step
28744
28744
21744
```

In [53]:

```
###show how many corrected labels are captured by classes
n = np.argmax(model.predict(noisy_imgs/225),axis=-1)[confident_imgs]
Counter(n)
```

```
1250/1250 [==============================] - 36s 28ms/step
```

Out[53]:

```
Counter({6: 2395,
         8: 1233,
         4: 1073,
         0: 3132,
         3: 1268,
         2: 2216,
         9: 2492,
         1: 2545,
         7: 1673,
         5: 853})
```

## Re-train a new model with corrected labels

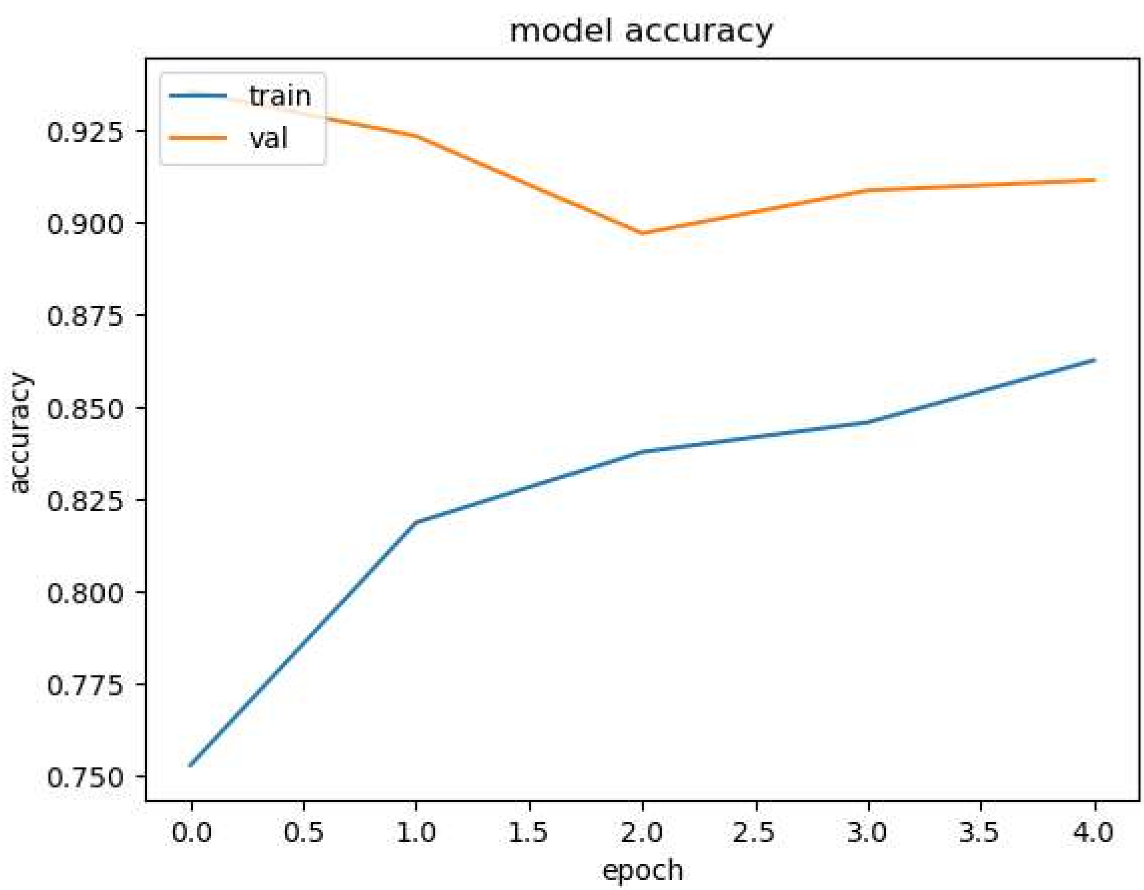
In [20]:
```
## retrain the model with corrected labels
MobileNet.trainable= True
model_final = tf.keras.Sequential([
    MobileNet,
    #tf.keras.layers.Conv2D(12,(3,3), activation = 'relu', input_shape = (7, 7, 1
    tf.keras.layers.GlobalAveragePooling2D(),
    tf.keras.layers.Dropout(0.2),

    tf.keras.layers.Dense(500, activation = 'relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(200, activation = 'relu'),
    tf.keras.layers.Dropout(0.2),

    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(10, activation = 'softmax')
                  ])

model_final.compile(optimizer=tf.keras.optimizers.Adam(0.0001),
              ### YOUR CODE HERE ###
              loss= tf.keras.losses.SparseCategoricalCrossentropy(from_logits=Tru
              ######################
              metrics=['sparse_categorical_accuracy'])

callback = tf.keras.callbacks.EarlyStopping(patience=4)
start = time.time()
history_final = model_final.fit(X_train_final, y_train_final, batch_size = 32, ep
end = time.time()
model_final.evaluate(X_test, y_test)
```

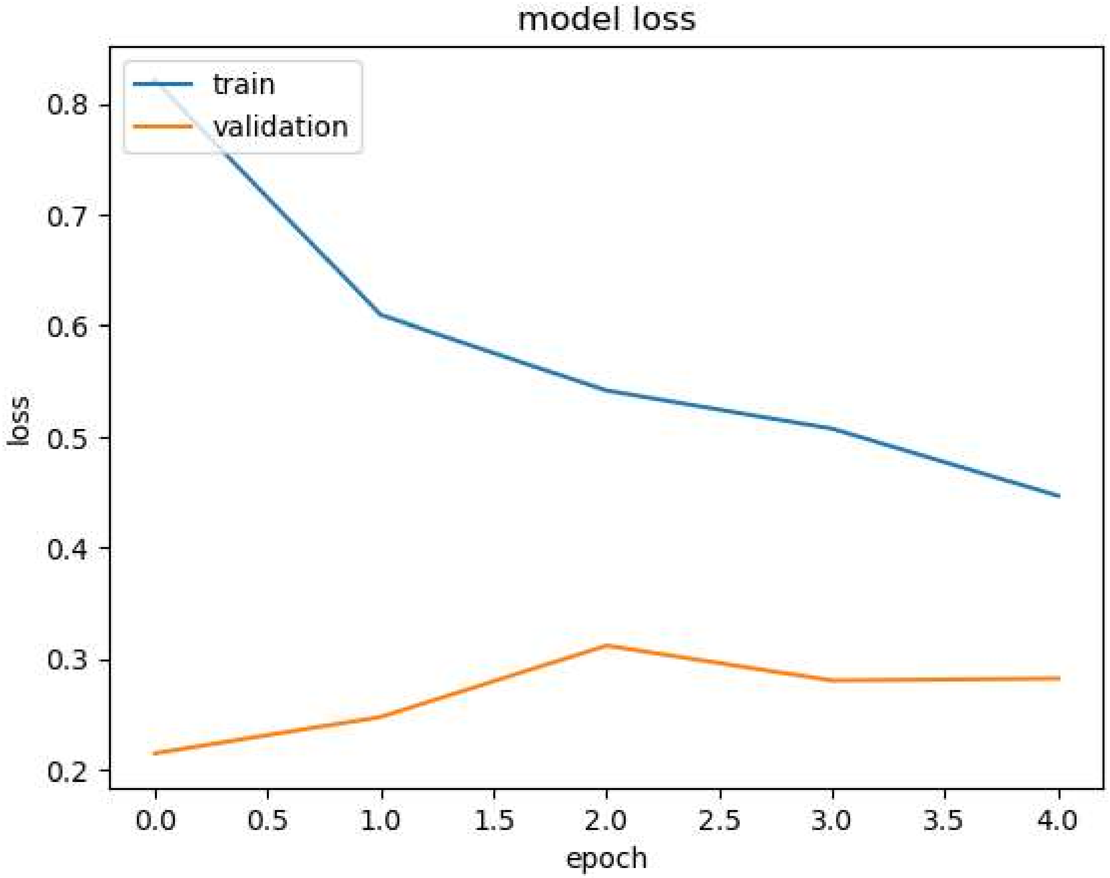
```
Epoch 1/15
719/719 [==============================] - 69s 90ms/step - loss: 0.8212 - spars
e_categorical_accuracy: 0.7529 - val_loss: 0.2147 - val_sparse_categorical_accu
racy: 0.9355
Epoch 2/15
719/719 [==============================] - 72s 101ms/step - loss: 0.6096 - spar
se_categorical_accuracy: 0.8187 - val_loss: 0.2475 - val_sparse_categorical_acc
uracy: 0.9235
Epoch 3/15
719/719 [==============================] - 81s 113ms/step - loss: 0.5417 - spar
se_categorical_accuracy: 0.8379 - val_loss: 0.3119 - val_sparse_categorical_acc
uracy: 0.8970
Epoch 4/15
719/719 [==============================] - 83s 115ms/step - loss: 0.5072 - spar
se_categorical_accuracy: 0.8459 - val_loss: 0.2804 - val_sparse_categorical_acc
uracy: 0.9087
Epoch 5/15
719/719 [==============================] - 84s 118ms/step - loss: 0.4467 - spar
se_categorical_accuracy: 0.8628 - val_loss: 0.2823 - val_sparse_categorical_acc
uracy: 0.9115
94/94 [==============================] - 3s 24ms/step - loss: 1.0752 - sparse_c
ategorical_accuracy: 0.6863
```

Out[20]:
```
[1.0752449035644531, 0.6863333582878113]
```

In [22]:
```
# model run time
print("training time for model 2: " + str((end - start)/60) + 'mins')

#### plot the acc and loss
plt.plot(history_final.history['sparse_categorical_accuracy'])
plt.plot(history_final.history['val_sparse_categorical_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()

##plot loss
plt.plot(history_final.history['loss'])
plt.plot(history_final.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper left')
plt.show()
```

```
training time for model 2: 6.497231590747833mins
```




model loss
train
validation
0.8
0.7
0.6
0.5
0.4
0.3
0.2
loss
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
epoch

In [79]:

```
### Save the final model
from tensorflow.keras.models import Model
from tensorflow.keras.models import load_model
model_final.save('Model_final.h5')
print('Model Saved!')
savedModel=load_model('Model_final.h5')
savedModel.summary()
```

```
Model Saved!
Model: "sequential_19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 mobilenetv2_1.00_224 (Funct  (None, 1, 1, 1280)       2257984   
 ional)                                                          
                                                                 
 global_average_pooling2d_16  (None, 1280)             0         
  (GlobalAveragePooling2D)                                       
                                                                 
 dropout_35 (Dropout)        (None, 1280)              0         
                                                                 
 dense_54 (Dense)            (None, 500)               640500    
                                                                 
 dropout_36 (Dropout)        (None, 500)               0         
                                                                 
 dense_55 (Dense)            (None, 200)               100200    
                                                                 
 dropout_37 (Dropout)        (None, 200)               0         
                                                                 
 dropout_38 (Dropout)        (None, 200)               0         
                                                                 
 dense_56 (Dense)            (None, 10)                2010      
                                                                 
=================================================================
Total params: 3,000,694
Trainable params: 2,966,582
Non-trainable params: 34,112
_________________________________________________________________
```

In [40]:

```
from tensorflow.keras.models import Model
from tensorflow.keras.models import load_model
model_final=load_model('Model_final.h5')
```

In [77]:
```
pip install pyyaml h5py
```

```
Requirement already satisfied: pyyaml in c:\users\frank shi\anaconda3\lib\site-
packages (6.0)
Requirement already satisfied: h5py in c:\users\frank shi\anaconda3\lib\site-pa
ckages (3.7.0)
Requirement already satisfied: numpy>=1.14.5 in c:\users\frank shi\anaconda3\li
b\site-packages (from h5py) (1.21.5)
Note: you may need to restart the kernel to use updated packages.
```

In [55]:
```
# [ADD WEAKLY SUPERVISED LEARNING FEATURE TO MODEL II]

# write your code here...

def model_II(image):
    '''
    This function should takes in the image of dimension 32*32*3 as input and ret
    '''
    # write your code here...
    return np.argmax(model_final.predict(image/225), axis = -1) # take  imgs  dat
```

## 3. Evaluation

For assessment, we will evaluate your final model on a hidden test dataset with clean labels by the `evaluation` function defined as follows. Although you will not have the access to the test set, the function would be useful for the model developments. For example, you can split the small training set, using one portion for weakly supervised learning and the other for validation purpose.

In [50]:
```
##model 2
def evaluation(model, test_labels, test_imgs):  ## take images dataset as input
    y_true = test_labels.reshape(-1)
    y_pred = model(test_imgs)
    print(classification_report(y_true, y_pred))
```

In [51]:
```
# [DO NOT MODIFY THIS CELL]
# This is the code for evaluating the prediction performance on a testset
# You will get an error if running this cell, as you do not have the testset
# Nonetheless, you can create your own validation set to run the evlauation
n_test = 10000

test_images = np.empty((n_test,32,32,3))
for i in range(n_test):
    img_fn = f'C:/Users/Frank Shi/Desktop/train_data/images_test/test{i+1:05d}.pr
    test_imgs[i,:,:,:]=cv2.cvtColor(cv2.imread(img_fn),cv2.COLOR_BGR2RGB)
#evaluation(baseline_model, test_labels, test_imgs)
```

The overall accuracy is $0.24$, which is better than random guess (which should have a accuracy around $0.10$). For the project, you should try to improve the performance by the following strategies:

- Consider a better choice of model architectures, hyperparameters, or training scheme for the predictive model;
- Use both `clean_noisy_trainset` and `noisy_trainset` for model training via **weakly supervised learning** methods. One possible solution is to train a "label-correction" model using the former, correct the labels in the latter, and train the final predictive model using the corrected dataset.
- Apply techniques such as $k$-fold cross validation to avoid overfitting;
- Any other reasonable strategies.

## Save output to CSV file

In [52]:

```
#predicted models from baseline model
baseline_pred = []
for i in test_images:
    baseline_pred.append(baseline_model(i)[0])
print(len(baseline_pred))
```

```
10000
```

In [57]:

```
### predicted labels from model1 and model2
model1_pred = model_I(test_images)
print(len(model1_pred))

model2_pred = model_II(test_images)
print(len(model2_pred))
```

```
313/313 [==============================] - 1s 4ms/step
10000
313/313 [==============================] - 6s 19ms/step
10000
```

In [58]:

```
#Save csv file
import pandas as pd

results = {
    "Baseline": baseline_pred,
    "Model I": model1_pred,
    "Model II": model2_pred
}

results_df = pd.DataFrame(results)
results_df.to_csv("C:/Users/Frank Shi/Desktop/train_data/output/label_prediction.
```

In [59]:
```
sudo apt-get install texlive texlive-latex-extra pandoc
```

```
  File "C:\Users\Frank Shi\AppData\Local\Temp\ipykernel_20588\3908183776.py", l
ine 1
    sudo apt-get install texlive texlive-latex-extra pandoc
         ^
SyntaxError: invalid syntax
```