```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tabulate import tabulate
layers = tf.keras.layers
```

The code block below defines a few helper functions to visualize the results. You do not need to touch them.

```
def plot_examples(X, Y, n=10):
    """ Plot the first n examples for each of the 10 classes in the CIFAR dataset X, Y "
    fig, axes = plt.subplots(n, 10, figsize=(10, n))
    for l in range(10):
        axes[0, l].set_title(cifar10_labels[l], fontsize="smaller")
        m = np.squeeze(Y) == l  # boolean mask: True for all images of label l
        for i in range(n):
            image = X[m][i].astype("uint8")  # imshow expects uint8
            ax = axes[i, l]
            ax.imshow(image, origin="upper")
            ax.set(xticks=[], yticks=[])
    return fig, ax


def plot_prediction(X, Y, Y_predict):
    """
    Plot image X along with predicted probabilities Y_predict.
    X: CIFAR image, shape = (32, 32, 3)
    Y: CIFAR label, one-hot encoded, shape = (10)
    Y_predict: predicted probabilities, shape = (10)
    """
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(8, 4))

    # plot image
    ax1.imshow(X.astype("uint8"), origin="upper")
    ax1.set(xticks=[], yticks=[])

    # plot probabilities
    ax2.barh(np.arange(10), Y_predict, align="center")
    ax2.set(xlim=(0, 1), xlabel="Score", yticks=[])
    for i in range(10):
        c = "red" if (i == np.argmax(Y)) else "black"
        ax2.text(0.05, i, cifar10_labels[i].capitalize(), ha="left", va="center", color=


def plot_confusion(Y_true, Y_predict):
    """
    Plot confusion matrix
    Y_true:    array of true classifications (0-9), shape = (N)
    Y_predict: array of predicted classifications (0-9), shape = (N)
    """
```

```
    C = np.histogram2d(Y_true, Y_predict, bins=np.linspace(-0.5, 9.5, 11))[0]
    Cn = C / np.sum(C, axis=1)

    fig = plt.figure()
    plt.imshow(Cn, interpolation="nearest", vmin=0, vmax=1, cmap=plt.cm.YlGnBu)
    plt.colorbar()
    plt.xlabel("prediction")
    plt.ylabel("truth")
    plt.xticks(range(10), cifar10_labels, rotation="vertical")
    plt.yticks(range(10), cifar10_labels)
    for x in range(10):
        for y in range(10):
            plt.annotate("%i" % C[x, y], xy=(y, x), ha="center", va="center")
```

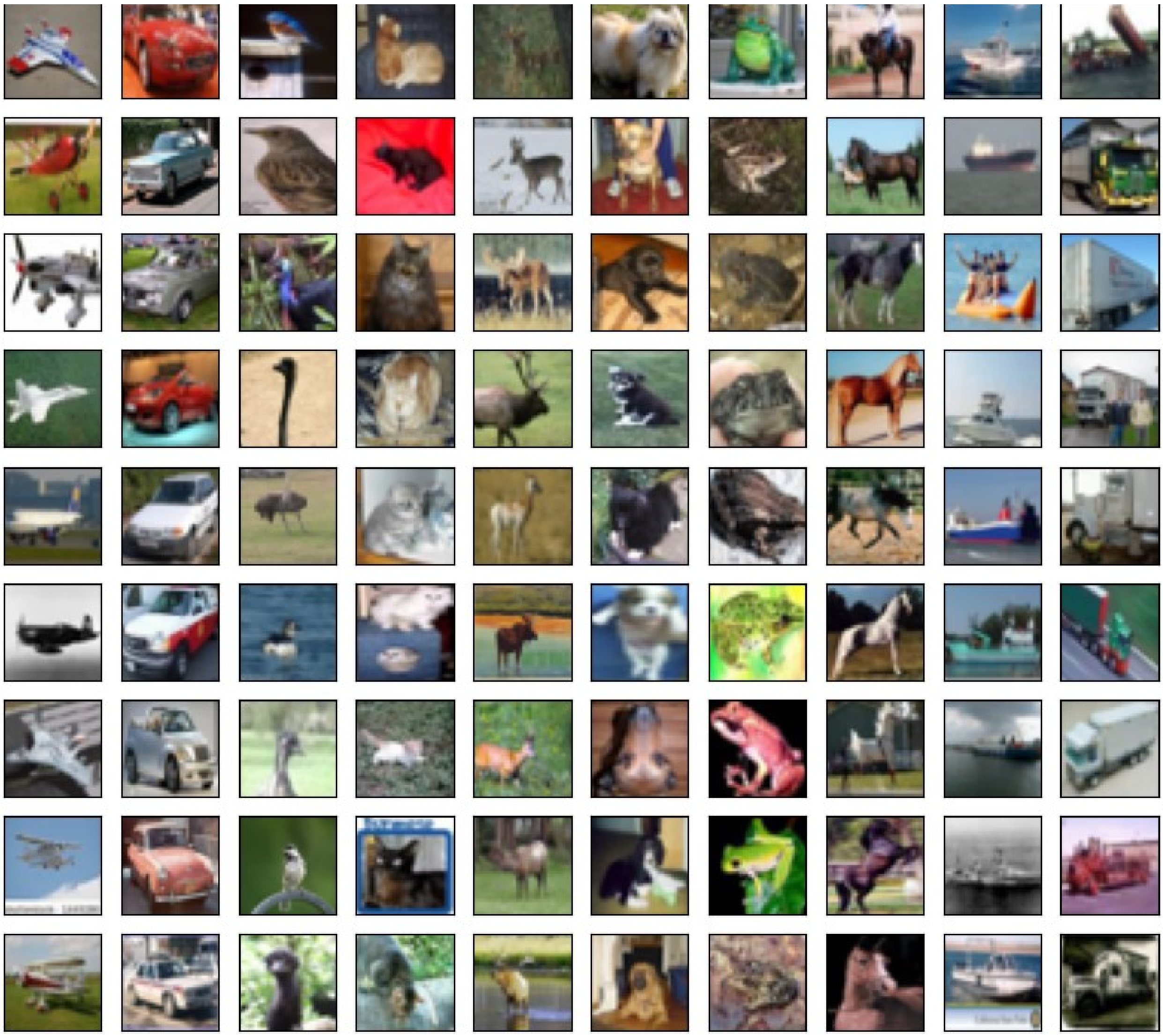
First we load and preprocess CIFAR-10 data. The imagages are 32x32 pixels and have three color channels (red, green blue).

```
# X: images, Y: labels
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()

print("images, shape = ", x_train.shape)
print("labels, shape = ", y_train.shape)

cifar10_labels = np.array([
    'airplane',
    'automobile',
    'bird',
    'cat',
    'deer',
    'dog',
    'frog',
    'horse',
    'ship',
    'truck'])
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 [==============================] - 9s 0us/step
images, shape =  (50000, 32, 32, 3)
labels, shape =  (50000, 1)
```

```
# Hint: To plot example images, you can use the plot examples function
plot_examples(x_train, y_train)
```

```
(<Figure size 1000x1000 with 100 Axes>, <Axes: >)
```



```
print(y_test.shape)
```

```
(10000, 1)
```

```
# convert labels ("0"-"9") to one-hot encodings, "0" = (1, 0, ... 0) and so on
y_train_onehot = tf.keras.utils.to_categorical(y_train, 10)
y_test_onehot = tf.keras.utils.to_categorical(y_test, 10)[:8000]
y_valid_onehot = tf.keras.utils.to_categorical(y_test, 10)[8000:]

# Hint: normalize the data
x_train_norm = (x_train-np.mean(x_train)) / np.std(x_train)
x_test_norm = (x_test-np.mean(x_test)) / np.std(x_test)

# Hint: use 20% of the training data for validation
```

```
x_valid_norm=x_test_norm[8000:]
x_test_norm=x_test_norm[:8000]
```

Define dense network

```
def dense_block(x,n=4, channels=8, convshape=(3,3)):
    xlist=[x]
    for i in range(n):
      xlist.append(layers.Conv2D(channels, convshape, padding="same", activation="relu
      x=layers.concatenate(xlist[:], axis=-1)
    return x
```

```
#Implement the horse example from slide 17 in the notes
x0=tf.keras.Input(shape=(32, 32, 3), name="input")
x=layers.Conv2D(8, kernel_size=(3, 3), padding="valid", activation="relu")(x0)
x=dense_block(x, 4, 16, (4,4))
x=layers.Conv2D(16, kernel_size=(4, 4), padding="valid", activation="relu")(x)
x=layers.MaxPooling2D((2,2), strides=(2,2))(x)

x=dense_block(x, 4, 32, (3,3))
x=layers.Conv2D(32, kernel_size=(3, 3), padding="same", activation="relu")(x)
x=layers.MaxPooling2D((3,3), strides=(3,3))(x)

x=dense_block(x, 4, 64, (2,2))
x=layers.MaxPooling2D((2,2), strides=(2,2))(x)
x=layers.Flatten()(x)
x=layers.Dense(10, activation="softmax")(x)

model = tf.keras.models.Model(
    inputs=[x0],
    outputs=[x],
    name="DenseNet",
)

print(model.summary())
```

```
Model: "DenseNet"
__________________________________________________________________________________
 Layer (type)                Output Shape         Param #     Connected to
==================================================================================
 input (InputLayer)          [(None, 32, 32, 3)]  0           []

 conv2d (Conv2D)             (None, 30, 30, 8)    224         ['input[0][0]']

 conv2d_1 (Conv2D)           (None, 30, 30, 16)   2064        ['conv2d[0][0]']

 concatenate (Concatenate)   (None, 30, 30, 24)   0           ['conv2d[0][0]',
                                                               'conv2d_1[0][0]'

 conv2d_2 (Conv2D)           (None, 30, 30, 16)   6160        ['concatenate[0][

 concatenate_1 (Concatenate) (None, 30, 30, 40)   0           ['conv2d[0][0]',
```

```
                                                                   'conv2d_1[0][0]'
                                                                   'conv2d_2[0][0]'

 conv2d_3 (Conv2D)              (None, 30, 30, 16)   10256       ['concatenate_1[0

 concatenate_2 (Concatenate)    (None, 30, 30, 56)   0           ['conv2d[0][0]',
                                                                  'conv2d_1[0][0]'
                                                                  'conv2d_2[0][0]'
                                                                  'conv2d_3[0][0]'

 conv2d_4 (Conv2D)              (None, 30, 30, 16)   14352       ['concatenate_2[0

 concatenate_3 (Concatenate)    (None, 30, 30, 72)   0           ['conv2d[0][0]',
                                                                  'conv2d_1[0][0]'
                                                                  'conv2d_2[0][0]'
                                                                  'conv2d_3[0][0]'
                                                                  'conv2d_4[0][0]'

 conv2d_5 (Conv2D)              (None, 27, 27, 16)   18448       ['concatenate_3[0

 max_pooling2d (MaxPooling2D)   (None, 13, 13, 16)   0           ['conv2d_5[0][0]'

 conv2d_6 (Conv2D)              (None, 13, 13, 32)   4640        ['max_pooling2d[0

 concatenate_4 (Concatenate)    (None, 13, 13, 48)   0           ['max_pooling2d[0
                                                                  'conv2d_6[0][0]'

 conv2d_7 (Conv2D)              (None, 13, 13, 32)   13856       ['concatenate_4[0

 concatenate_5 (Concatenate)    (None, 13, 13, 80)   0           ['max_pooling2d[0
                                                                  'conv2d_6[0][0]'
                                                                  'conv2d_7[0][0]'

 conv2d_8 (Conv2D)              (None, 13, 13, 32)   23072       ['concatenate_5[0

 concatenate_6 (Concatenate)    (None, 13, 13, 112)  0           ['max_pooling2d[0
                                                                  'conv2d_6[0][0]'
                                                                  'conv2d_7[0][0]'
                                                                  'conv2d_8[0][0]'

 conv2d_9 (Conv2D)              (None, 13, 13, 32)   32288       ['concatenate_6[0
```

```
# ------------------------------------------------------------
# Training
# ------------------------------------------------------------
model.compile(
    loss='categorical_crossentropy',
    optimizer="adam",
    metrics=["accuracy"]
)

model.fit(
    x_train_norm, y_train_onehot,
    batch_size=1000,
    epochs=20, # train at least for 20 epochs
    verbose=1,
    validation_data=(x_valid_norm, y_valid_onehot),
```

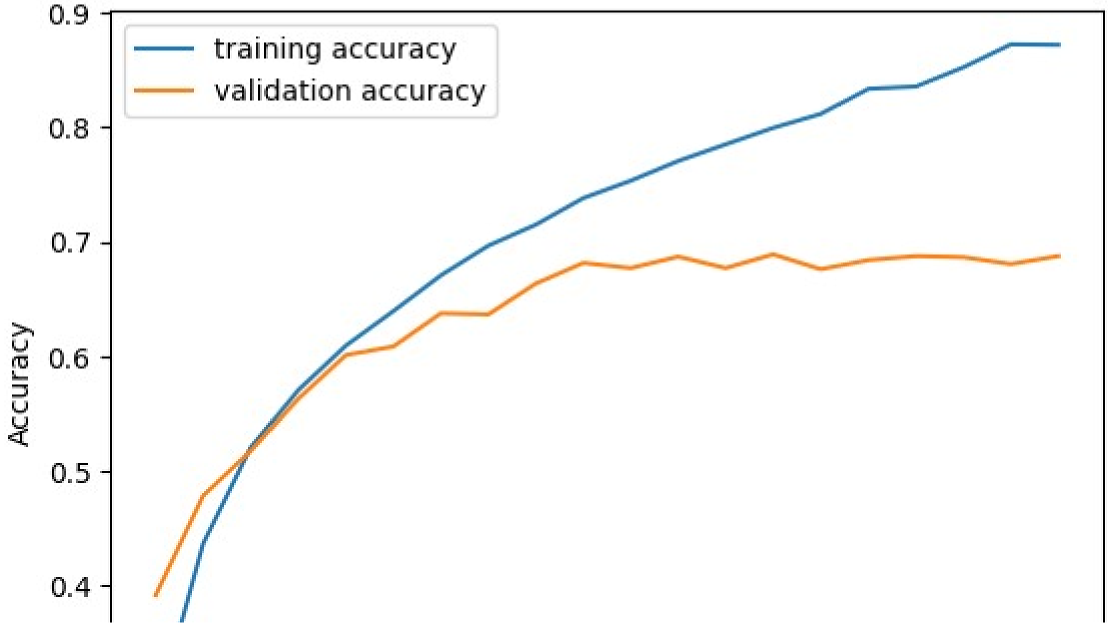
```
    validation_data=(X_valid_norm, y_valid_onehot),
    callbacks=[tf.keras.callbacks.CSVLogger("history_{}.csv".format(model.name))],
)
```

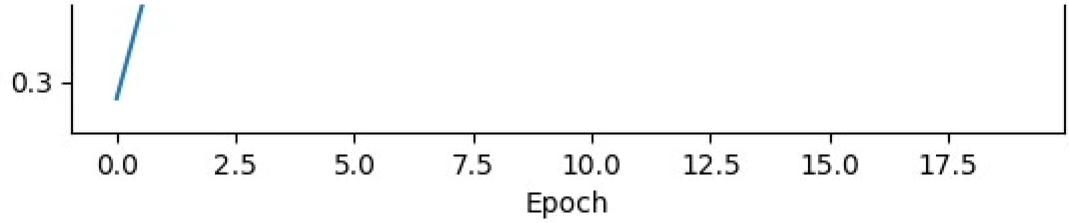
```
Epoch 1/20
50/50 [==============================] - 49s 719ms/step - loss: 1.9764 - accuracy:
Epoch 2/20
50/50 [==============================] - 13s 256ms/step - loss: 1.5586 - accuracy:
Epoch 3/20
50/50 [==============================] - 13s 253ms/step - loss: 1.3427 - accuracy:
Epoch 4/20
50/50 [==============================] - 13s 252ms/step - loss: 1.2093 - accuracy:
Epoch 5/20
50/50 [==============================] - 12s 246ms/step - loss: 1.1043 - accuracy:
Epoch 6/20
50/50 [==============================] - 12s 246ms/step - loss: 1.0235 - accuracy:
Epoch 7/20
50/50 [==============================] - 12s 248ms/step - loss: 0.9392 - accuracy:
Epoch 8/20
50/50 [==============================] - 12s 248ms/step - loss: 0.8757 - accuracy:
Epoch 9/20
50/50 [==============================] - 12s 248ms/step - loss: 0.8196 - accuracy:
Epoch 10/20
50/50 [==============================] - 12s 248ms/step - loss: 0.7555 - accuracy:
Epoch 11/20
50/50 [==============================] - 12s 249ms/step - loss: 0.7115 - accuracy:
Epoch 12/20
50/50 [==============================] - 12s 248ms/step - loss: 0.6614 - accuracy:
Epoch 13/20
50/50 [==============================] - 12s 249ms/step - loss: 0.6224 - accuracy:
Epoch 14/20
50/50 [==============================] - 15s 310ms/step - loss: 0.5737 - accuracy:
Epoch 15/20
50/50 [==============================] - 31s 614ms/step - loss: 0.5397 - accuracy:
Epoch 16/20
50/50 [==============================] - 13s 251ms/step - loss: 0.4854 - accuracy:
Epoch 17/20
50/50 [==============================] - 12s 248ms/step - loss: 0.4716 - accuracy:
Epoch 18/20
50/50 [==============================] - 12s 248ms/step - loss: 0.4265 - accuracy:
Epoch 19/20
50/50 [==============================] - 12s 249ms/step - loss: 0.3676 - accuracy:
Epoch 20/20
50/50 [==============================] - 12s 249ms/step - loss: 0.3656 - accuracy:
<keras.callbacks.History at 0x222cc0a1250>
```

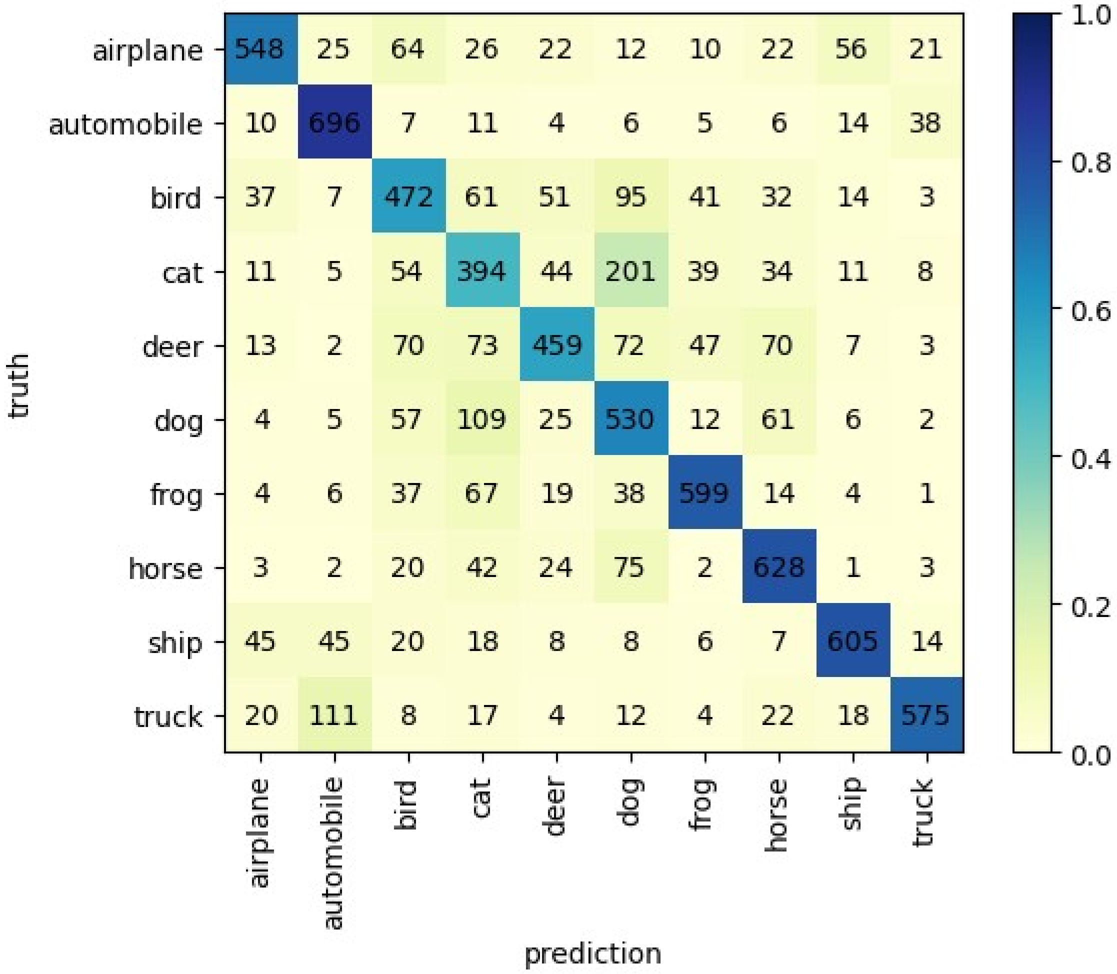
```
# ------------------------------------------------------------
# Plots
# ------------------------------------------------------------
# training curves
history = np.genfromtxt("history_{}.csv".format(model.name), delimiter=",", names=True

plt.figure()
plt.plot(history["epoch"], history["accuracy"], label="training accuracy")
plt.plot(history["epoch"], history["val_accuracy"], label="validation accuracy")
plt.legend()
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
```

```
plt.ylabel('Accuracy')

# Hint: this is how you can plot the confusion matrix.
# calculate predictions for test set
y_predict = model.predict(x_test_norm, batch_size=128)

# convert back to class labels (0-9)
y_predict_cl = np.argmax(y_predict, axis=1)
y_test_cl = np.argmax(y_test_onehot, axis=1)

# plot confusion matrix
plot_confusion(y_test_cl, y_predict_cl)

#
test_acc=np.mean(np.equal(y_predict_cl, y_test_cl))
print(test_acc)

# Task: plot a few examples of correctly and incorrectly classified images.
# Hint: First find the indices of correctly and incorrectly classified images:
i0 = np.argwhere(y_predict_cl != y_test_cl)  # misclassified images
i1 = np.argwhere(y_predict_cl == y_test_cl)  # correctly classified images


# original (unnormalized) test images
x_test = x_test[:8000]

# Hint: Now you can use the `plot_prediction` function to plot the images:
# plot first 3 false classifications
for i in i0[0:3,0]:
    plot_prediction(x_test[i], y_test_onehot[i], y_predict[i])

#Plot correct classifications:
for i in i1[0:3,0]:
    plot_prediction(x_test[i], y_test_onehot[i], y_predict[i])
```

```
63/63 [==============================] - 4s 47ms/step
0.68825
```

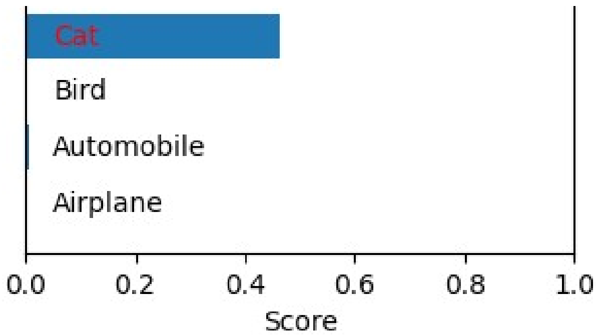


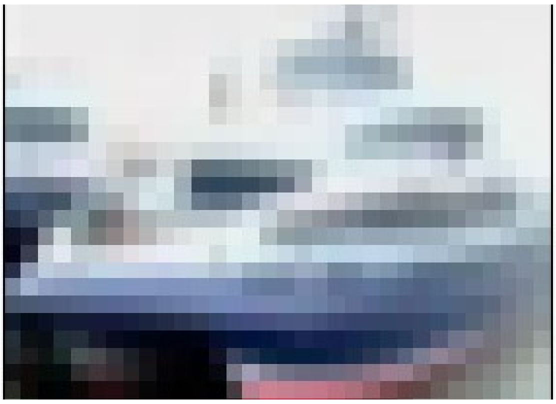




Note

train accuracy: 87%, validation accuracy: 69%, test accuracy: 72%. Much better test accuracy now=better model with DenseNet. Although it is a bit overfitted (high generalization error), we could use some regularization or similar to improve performance.






Ship
Horse
Frog
Dog
Deer
Cat
Bird