

REPORT

Assignment 3:

Building your own convolutional neural networks

MR.CHALERMKIAT CHANAHCHAN

ID: 62070701602

King Mongkut's University of Technology Thonburi
Faculty of Engineering, Department of Computer Engineering
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Assignment 3: Building your own convolutional neural networks

Due: 7 November 2019. Please submit your report in PDF to LEB2

Introduction

In this assignment, we will design and implement the convolutional neural network to classify CIFAR10. An initial guide can be found in the Keras documentation, but **students are encouraged to come up with their own design or** modify the success case.

Tasks

1. Load and explore CIFAR10 data.
2. Design the convolutional neural networks.
3. Justify and explain your design.
4. Train the model.
5. Evaluate the results.

Tasks 1: Load and explore CIFAR10 data.

Load CIFAR10 data

Code:

```
# The data, split between train and test sets:
(x_train, y_train), (x_test, y_test) = cifar10.load_data()
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
```

Output:

```
x_train shape: (50000, 32, 32, 3)
50000 train samples
10000 test samples
```

Example of Training data each:

```
[[[ 59  62  63]
  [ 43  46  45]
  [ 50  48  43]
  ...
  [158 132 108]
  [152 125 102]
  [148 124 103]]

 [[ 16  20  20]
  [  0  0  0]
  [ 18  8  0]
  ...
```

Example figure of traing data:

```
from matplotlib import pyplot
sample_id = 10000
pyplot.imshow(X_train[sample_id])
pyplot.show()
```

Figure ID = 1000

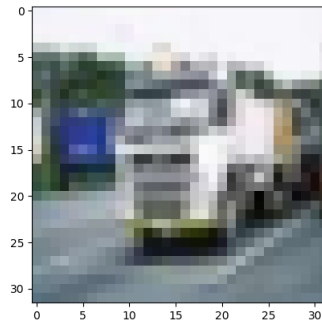


Figure ID = 3000

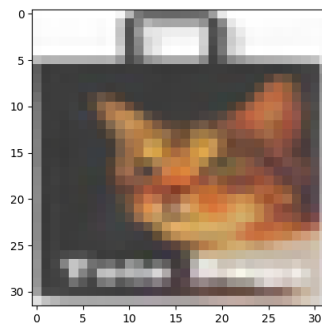
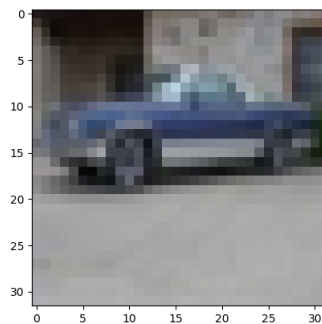
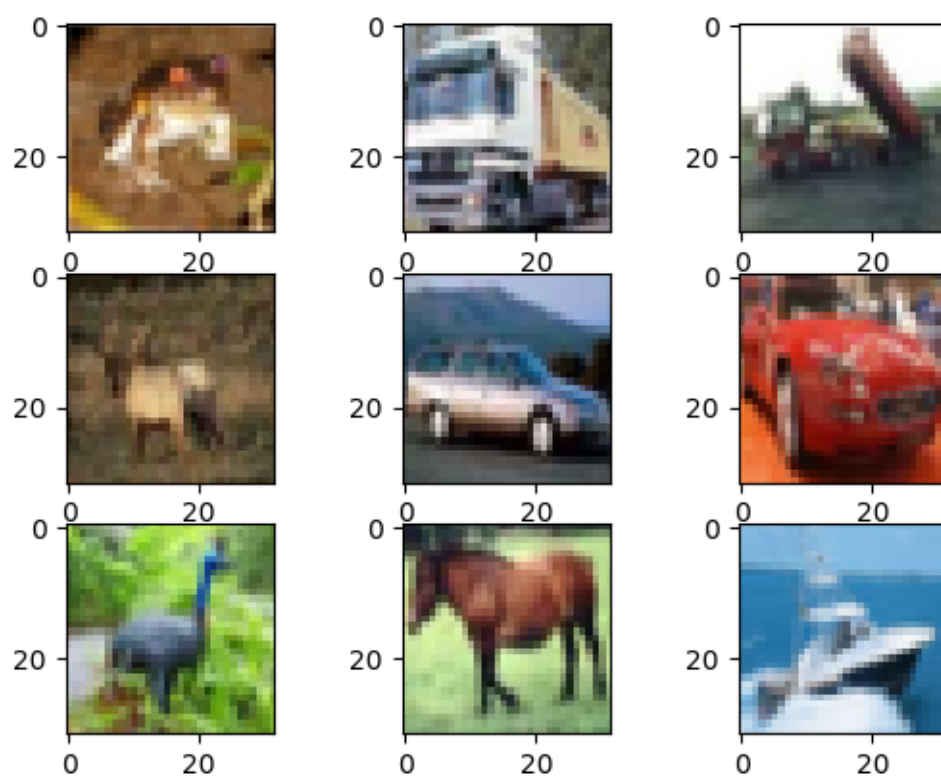


Figure ID = 10000

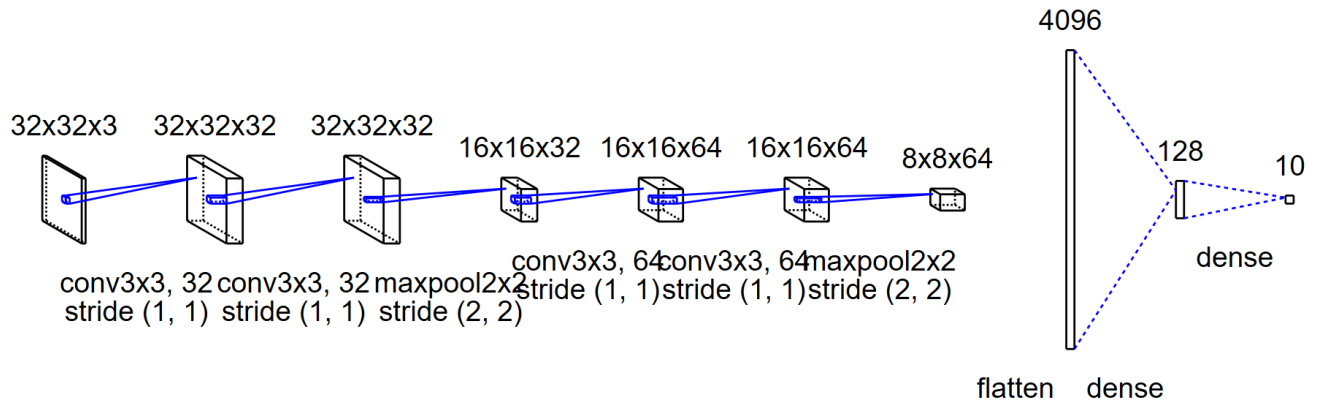


Example Figure ID 0 to 8 in 3x3 grid plot:



Tasks 2: Design the convolutional neural networks.

My design Model:



Drawn by Mr.Chalermkiat Chanachan using convet-drawer (<https://github.com/yu4u/convnet-drawer>)

Tasks 3: Justify and explain your design.

I think if CNN is not reducing matrix in the model what it happens then I try to design model with the same matrix in Layers (1, 2, 3 and 4, 5).

My model has 2 parts. First part is 7 convolutional layers and second part is 3 connected layers. At convolutional layers in the first- and second-layer use activation function with ReLU function. the third Layer use is pooling layer with max-pooling 2x2 dimension. the fourth- and fifth-layer use activation function with tanh function. the sixth layer is pooling layer with max-pooling 2x2 dimension. After flattening into one dimensional (vector) use sigmoid function and the last layer use SoftMax function. My model optimizes ADAM and calculate loss function with cross-entropy or log loss.

Tasks 4: Train the model.

Code:

```
model = Sequential()

model.add(Conv2D(32, (3, 3), activation='relu', padding='same', input_shape=(32, 32, 3)))
model.add(Conv2D(32, (3, 3), activation='relu', padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Conv2D(64, (3, 3), activation='tanh', padding='same'))
model.add(Conv2D(64, (3, 3), activation='tanh', padding='same'))
model.add(MaxPooling2D(pool_size=(2, 2)))

model.add(Flatten())
model.add(Dense(128, activation='sigmoid', kernel_initializer='he_uniform'))
model.add(Dense(10, activation='softmax'))
opt = keras.optimizers.Adam(learning_rate=0.001, beta_1=0.9, beta_2=0.999, amsgrad=False)

# Let's train the model using RMSprop
model.compile(loss='categorical_crossentropy',
              optimizer=opt,
              metrics=['accuracy'])
```

Output:

No Color = calculating times with full performance (CPU compute) = ~ 180 s

Yellow Color = Calculating times with better performance = ~400 s

Red Color = Calculating times when I am sleeping my computer = > 500

Using real-time data augmentation.

Epoch 1/100

1563/1563 [=====] - 197s 126ms/step - loss: 1.4489 - accuracy: 0.4747 - val_loss: 1.2016 - val_accuracy

Epoch 2/100

1563/1563 [=====] - 196s 125ms/step - loss: 1.0718 - accuracy: 0.6207 - val_loss: 0.9462 - val_accuracy

Epoch 3/100

1563/1563 [=====] - 194s 124ms/step - loss: 0.9474 - accuracy: 0.6653 - val_loss: 0.8820 - val_accuracy

Epoch 4/100

1563/1563 [=====] - 187s 120ms/step - loss: 0.8703 - accuracy: 0.6950 - val_loss: 0.7765 - val_accuracy

Epoch 5/100

1563/1563 [=====] - 183s 117ms/step - loss: 0.8175 - accuracy: 0.7139 - val_loss: 0.8358 - val_accuracy

Epoch 6/100

1563/1563 [=====] - 252s 161ms/step - loss: 0.7906 - accuracy: 0.7241 - val_loss: 0.7268 - val_accuracy

Epoch 7/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.7475 - accuracy: 0.7364 - val_loss: 0.7746 - val_accuracy

Epoch 8/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.7236 - accuracy: 0.7470 - val_loss: 0.7360 - val_accuracy

Epoch 9/100
1563/1563 [=====] - 406s 260ms/step - loss: 0.7042 - accuracy: 0.7541 - val_loss: 0.7263 - val_accuracy

Epoch 10/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.6875 - accuracy: 0.7605 - val_loss: 0.7206 - val_accuracy

Epoch 11/100
1563/1563 [=====] - 405s 259ms/step - loss: 0.6792 - accuracy: 0.7626 - val_loss: 0.6916 - val_accuracy

Epoch 12/100
1563/1563 [=====] - 404s 259ms/step - loss: 0.6612 - accuracy: 0.7685 - val_loss: 0.6788 - val_accuracy

Epoch 13/100
1563/1563 [=====] - 403s 258ms/step - loss: 0.6464 - accuracy: 0.7723 - val_loss: 0.6684 - val_accuracy

Epoch 14/100
1563/1563 [=====] - 404s 258ms/step - loss: 0.6422 - accuracy: 0.7745 - val_loss: 0.7059 - val_accuracy

Epoch 15/100
1563/1563 [=====] - 404s 259ms/step - loss: 0.6315 - accuracy: 0.7795 - val_loss: 0.6757 - val_accuracy

Epoch 16/100
1563/1563 [=====] - 404s 259ms/step - loss: 0.6219 - accuracy: 0.7842 - val_loss: 0.6772 - val_accuracy

Epoch 17/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.6114 - accuracy: 0.7874 - val_loss: 0.6287 - val_accuracy

Epoch 18/100
1563/1563 [=====] - 406s 260ms/step - loss: 0.6127 - accuracy: 0.7869 - val_loss: 0.6659 - val_accuracy

Epoch 19/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.5997 - accuracy: 0.7905 - val_loss: 0.6503 - val_accuracy

Epoch 20/100
1563/1563 [=====] - 403s 258ms/step - loss: 0.5913 - accuracy: 0.7917 - val_loss: 0.6479 - val_accuracy

Epoch 21/100
1563/1563 [=====] - 405s 259ms/step - loss: 0.5910 - accuracy: 0.7934 - val_loss: 0.6140 - val_accuracy

Epoch 22/100
1563/1563 [=====] - 406s 260ms/step - loss: 0.5831 - accuracy: 0.7956 - val_loss: 0.6340 - val_accuracy

Epoch 23/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.5821 - accuracy: 0.7959 - val_loss: 0.6825 - val_accuracy

Epoch 24/100
1563/1563 [=====] - 404s 259ms/step - loss: 0.5741 - accuracy: 0.8004 - val_loss: 0.6572 - val_accuracy

Epoch 25/100
1563/1563 [=====] - 411s 263ms/step - loss: 0.5743 - accuracy: 0.7968 - val_loss: 0.6550 - val_accuracy

Epoch 26/100
1563/1563 [=====] - 410s 262ms/step - loss: 0.5723 - accuracy: 0.8004 - val_loss: 0.6567 - val_accuracy

Epoch 27/100
1563/1563 [=====] - 404s 259ms/step - loss: 0.5623 - accuracy: 0.8033 - val_loss: 0.6638 - val_accuracy

Epoch 28/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.5605 - accuracy: 0.8027 - val_loss: 0.6266 - val_accuracy

Epoch 29/100
1563/1563 [=====] - 405s 259ms/step - loss: 0.5510 - accuracy: 0.8068 - val_loss: 0.6606 - val_accuracy

Epoch 30/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.5596 - accuracy: 0.8022 - val_loss: 0.6460 - val_accuracy

Epoch 31/100
1563/1563 [=====] - 403s 258ms/step - loss: 0.5559 - accuracy: 0.8042 - val_loss: 0.6567 - val_accuracy

Epoch 32/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.5509 - accuracy: 0.8073 - val_loss: 0.6221 - val_accuracy

Epoch 33/100
1563/1563 [=====] - 404s 259ms/step - loss: 0.5505 - accuracy: 0.8071 - val_loss: 0.6248 - val_accuracy

Epoch 34/100
1563/1563 [=====] - 401s 257ms/step - loss: 0.5375 - accuracy: 0.8106 - val_loss: 0.6391 - val_accuracy

Epoch 35/100
1563/1563 [=====] - 402s 257ms/step - loss: 0.5377 - accuracy: 0.8115 - val_loss: 0.6416 - val_accuracy

Epoch 36/100

1563/1563 [=====] - 404s 259ms/step - loss: 0.5404 - accuracy: 0.8127 - val_loss: 0.6468 - val_accuracy

Epoch 37/100

1563/1563 [=====] - 402s 257ms/step - loss: 0.5390 - accuracy: 0.8121 - val_loss: 0.6314 - val_accuracy

Epoch 38/100

1563/1563 [=====] - 404s 258ms/step - loss: 0.5377 - accuracy: 0.8101 - val_loss: 0.6460 - val_accuracy

Epoch 39/100

1563/1563 [=====] - 405s 259ms/step - loss: 0.5331 - accuracy: 0.8134 - val_loss: 0.6623 - val_accuracy

Epoch 40/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.5331 - accuracy: 0.8135 - val_loss: 0.6279 - val_accuracy

Epoch 41/100

1563/1563 [=====] - 402s 257ms/step - loss: 0.5272 - accuracy: 0.8163 - val_loss: 0.6553 - val_accuracy

Epoch 42/100

1563/1563 [=====] - 405s 259ms/step - loss: 0.5307 - accuracy: 0.8149 - val_loss: 0.6570 - val_accuracy

Epoch 43/100

1563/1563 [=====] - 405s 259ms/step - loss: 0.5248 - accuracy: 0.8153 - val_loss: 0.6487 - val_accuracy

Epoch 44/100

1563/1563 [=====] - 402s 257ms/step - loss: 0.5265 - accuracy: 0.8147 - val_loss: 0.6328 - val_accuracy

Epoch 45/100

1563/1563 [=====] - 404s 259ms/step - loss: 0.5206 - accuracy: 0.8173 - val_loss: 0.6524 - val_accuracy

Epoch 46/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.5170 - accuracy: 0.8209 - val_loss: 0.6661 - val_accuracy

Epoch 47/100

1563/1563 [=====] - 406s 260ms/step - loss: 0.5187 - accuracy: 0.8158 - val_loss: 0.6338 - val_accuracy

Epoch 48/100

1563/1563 [=====] - 404s 259ms/step - loss: 0.5284 - accuracy: 0.8134 - val_loss: 0.6234 - val_accuracy

Epoch 49/100

1563/1563 [=====] - 404s 259ms/step - loss: 0.5195 - accuracy: 0.8186 - val_loss: 0.6892 - val_accuracy

Epoch 50/100

1563/1563 [=====] - 402s 257ms/step - loss: 0.5156 - accuracy: 0.8185 - val_loss: 0.6136 - val_accuracy

Epoch 51/100

1563/1563 [=====] - 406s 259ms/step - loss: 0.5101 - accuracy: 0.8215 - val_loss: 0.6170 - val_accuracy

Epoch 52/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.5091 - accuracy: 0.8204 - val_loss: 0.6165 - val_accuracy

Epoch 53/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.5135 - accuracy: 0.8198 - val_loss: 0.6020 - val_accuracy

Epoch 54/100

1563/1563 [=====] - 404s 258ms/step - loss: 0.5099 - accuracy: 0.8217 - val_loss: 0.6276 - val_accuracy

Epoch 55/100

1563/1563 [=====] - 401s 257ms/step - loss: 0.5057 - accuracy: 0.8218 - val_loss: 0.6090 - val_accuracy

Epoch 56/100

1563/1563 [=====] - 404s 259ms/step - loss: 0.5043 - accuracy: 0.8240 - val_loss: 0.6234 - val_accuracy

Epoch 57/100

1563/1563 [=====] - 406s 259ms/step - loss: 0.5055 - accuracy: 0.8241 - val_loss: 0.6287 - val_accuracy

Epoch 58/100

1563/1563 [=====] - 406s 260ms/step - loss: 0.5109 - accuracy: 0.8213 - val_loss: 0.6554 - val_accuracy

Epoch 59/100

1563/1563 [=====] - 404s 258ms/step - loss: 0.5033 - accuracy: 0.8240 - val_loss: 0.6129 - val_accuracy

Epoch 60/100

1563/1563 [=====] - 405s 259ms/step - loss: 0.5059 - accuracy: 0.8226 - val_loss: 0.6299 - val_accuracy

Epoch 61/100

1563/1563 [=====] - 405s 259ms/step - loss: 0.5066 - accuracy: 0.8222 - val_loss: 0.6217 - val_accuracy

Epoch 62/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.5031 - accuracy: 0.8238 - val_loss: 0.6430 - val_accuracy

Epoch 63/100

1563/1563 [=====] - 402s 257ms/step - loss: 0.5042 - accuracy: 0.8224 - val_loss: 0.6317 - val_accuracy

Epoch 64/100

1563/1563 [=====] - 402s 257ms/step - loss: 0.5086 - accuracy: 0.8212 - val_loss: 0.6294 - val_accuracy

Epoch 65/100

1563/1563 [=====] - 403s 258ms/step - loss: 0.4994 - accuracy: 0.8255 - val_loss: 0.6351 - val_accuracy

Epoch 66/100

1563/1563 [=====] - 302s 193ms/step - loss: 0.5050 - accuracy: 0.8211 - val_loss: 0.6051 - val_accuracy

Epoch 67/100

1563/1563 [=====] - 181s 116ms/step - loss: 0.4986 - accuracy: 0.8245 - val_loss: 0.6308 - val_accuracy

Epoch 68/100

1563/1563 [=====] - 183s 117ms/step - loss: 0.5000 - accuracy: 0.8257 - val_loss: 0.6475 - val_accuracy

Epoch 69/100

1563/1563 [=====] - 182s 116ms/step - loss: 0.4959 - accuracy: 0.8256 - val_loss: 0.6816 - val_accuracy

Epoch 70/100

1563/1563 [=====] - 185s 118ms/step - loss: 0.4971 - accuracy: 0.8276 - val_loss: 0.6702 - val_accuracy

Epoch 71/100

1563/1563 [=====] - 183s 117ms/step - loss: 0.4913 - accuracy: 0.8269 - val_loss: 0.6446 - val_accuracy

Epoch 72/100

1563/1563 [=====] - 182s 117ms/step - loss: 0.4920 - accuracy: 0.8274 - val_loss: 0.6236 - val_accuracy

Epoch 73/100

1563/1563 [=====] - 184s 117ms/step - loss: 0.4892 - accuracy: 0.8306 - val_loss: 0.6561 - val_accuracy

Epoch 74/100

1563/1563 [=====] - 181s 116ms/step - loss: 0.4998 - accuracy: 0.8255 - val_loss: 0.6279 - val_accuracy

Epoch 75/100

1563/1563 [=====] - 181s 116ms/step - loss: 0.4895 - accuracy: 0.8287 - val_loss: 0.6106 - val_accuracy

Epoch 76/100

1563/1563 [=====] - 181s 116ms/step - loss: 0.4898 - accuracy: 0.8288 - val_loss: 0.6356 - val_accuracy

Epoch 77/100

1563/1563 [=====] - 181s 116ms/step - loss: 0.4818 - accuracy: 0.8290 - val_loss: 0.6200 - val_accuracy

Epoch 78/100

1563/1563 [=====] - 185s 118ms/step - loss: 0.4925 - accuracy: 0.8265 - val_loss: 0.6159 - val_accuracy

Epoch 79/100

1563/1563 [=====] - 196s 126ms/step - loss: 0.4926 - accuracy: 0.8279 - val_loss: 0.6166 - val_accuracy

Epoch 80/100

1563/1563 [=====] - 193s 123ms/step - loss: 0.4970 - accuracy: 0.8260 - val_loss: 0.6562 - val_accuracy

Epoch 81/100

1563/1563 [=====] - 352s 225ms/step - loss: 0.4964 - accuracy: 0.8247 - val_loss: 0.6082 - val_accuracy

Epoch 82/100

1563/1563 [=====] - 391s 250ms/step - loss: 0.4897 - accuracy: 0.8286 - val_loss: 0.6374 - val_accuracy

Epoch 83/100

1563/1563 [=====] - 388s 248ms/step - loss: 0.4902 - accuracy: 0.8278 - val_loss: 0.6541 - val_accuracy

Epoch 84/100

1563/1563 [=====] - 383s 245ms/step - loss: 0.4856 - accuracy: 0.8304 - val_loss: 0.6904 - val_accuracy

Epoch 85/100

1563/1563 [=====] - 380s 243ms/step - loss: 0.4849 - accuracy: 0.8297 - val_loss: 0.6553 - val_accuracy

Epoch 86/100

1563/1563 [=====] - 366s 2s/step - loss: 0.4913 - accuracy: 0.8285 - val_loss: 0.6322 - val_accuracy:

Epoch 87/100

1563/1563 [=====] - 223s 143ms/step - loss: 0.4899 - accuracy: 0.8276 - val_loss: 0.6401 - val_accuracy

Epoch 88/100

1563/1563 [=====] - 229s 147ms/step - loss: 0.4931 - accuracy: 0.8275 - val_loss: 0.6260 - val_accuracy

Epoch 89/100

1563/1563 [=====] - 193s 123ms/step - loss: 0.4916 - accuracy: 0.8285 - val_loss: 0.6360 - val_accuracy

```
Epoch 90/100
1563/1563 [=====] - 193s 123ms/step - loss: 0.4857 - accuracy: 0.8278 - val_loss: 0.6294 - val_accuracy
Epoch 91/100
1563/1563 [=====] - 196s 125ms/step - loss: 0.4906 - accuracy: 0.8277 - val_loss: 0.6158 - val_accuracy: 0.8277 - val_loss:
0.6158 - val_accuracy: 0.7954
Epoch 92/100
uracy: 0.8295 - val_loss: 0.6274 - val_accuracy
1563/1563 [=====] - 200s 128ms/step - loss: 0.4814 - accuracy: 0.8295 - val_loss: 0.6274 - val_accuracy: 0.7942
uracy: 0.8275 - val_loss: 0.6125 - val_accuracy
Epoch 93/100
1563/1563 [=====] - 198s 127ms/step - loss: 0.4908 - accuracy: 0.8286 - val_loss: 0.6132 - val_accuracy: 0.8275 - val_loss:
0.6125 - val_accuracy: 0.7939
Epoch 94/100
uracy: 0.8287 - val_loss: 0.6318 - val_accuracy
1563/1563 [=====] - 192s 123ms/step - loss: 0.4873 - accuracy: 0.8286 - val_loss: 0.6132 - val_accuracy: 0.7980
uracy: 0.8280 - val_loss: 0.6299 - val_accuracy
Epoch 95/100
1563/1563 [=====] - 183s 117ms/step - loss: 0.4882 - accuracy: 0.8287 - val_loss: 0.6318 - val_accuracy: 0.8287 - val_loss:
0.6318 - val_accuracy: 0.7918
Epoch 96/100
uracy: 0.8280 - val_loss: 0.6299 - val_accuracy
1563/1563 [=====] - 182s 116ms/step - loss: 0.4891 - accuracy: 0.8280 - val_loss: 0.6299 - val_accuracy: 0.7945
uracy: 0.8297 - val_loss: 0.6467 - val_accuracy
Epoch 97/100
1563/1563 [=====] - 185s 118ms/step - loss: 0.4847 - accuracy: 0.8297 - val_loss: 0.6467 - val_accuracy
Epoch 98/100
1563/1563 [=====] - 184s 118ms/step - loss: 0.4911 - accuracy: 0.8273 - val_loss: 0.6538 - val_accuracy
Epoch 99/100
1563/1563 [=====] - 183s 117ms/step - loss: 0.4901 - accuracy: 0.8290 - val_loss: 0.6140 - val_accuracy
Epoch 100/100
1563/1563 [=====] - 181s 116ms/step - loss: 0.4949 - accuracy: 0.8253 - val_loss: 0.6279 - val_accuracy
Saved trained model at D:\Master_Degree\DeepLearning\Documents\A3\saved_models\keras_cifar10_trained_model-final.h5
10000/10000 [=====] - 7s 689us/step
```

Tasks 5: Evaluate the results.

Code:

```
# Score trained model.
scores = model.evaluate(x_test, y_test, verbose=1)
print('Test loss:', scores[0])
print('Test accuracy:', scores[1])
```

Testing Results:

Test loss: 0.6278955207347869

Test accuracy: 0.7918999791145325

Comparing the results between Keras document example and Keras document example.

- 100 Epochs

	Keras Document Example	My Design Model
Test Loss	0.7624230746269226	0.6278955207347869
Test Accuracy	0.7490000128746033	0.7918999791145325

Capture output figure when finished:

```
Epoch 98/100
1563/1563 [=====] - 226s 145ms/step - loss: 0.8037 - accuracy: 0.7354 - val_loss: 0.7239 - val_accuracy: 0.7567
Epoch 99/100
1563/1563 [=====] - 211s 135ms/step - loss: 0.8020 - accuracy: 0.7348 - val_loss: 0.6842 - val_accuracy: 0.7777
Epoch 100/100
1563/1563 [=====] - 209s 134ms/step - loss: 0.8072 - accuracy: 0.7340 - val_loss: 0.7624 - val_accuracy: 0.7490
Saved trained model at D:\Master_Degree\DeepLearning\Documents\A3\saved_models\keras_cifar10_trained_model.h5
10000/10000 [=====] - 7s 688us/step
Test loss: 0.7624230746269226
Test accuracy: 0.7490000128746033
```