CIAFR-10 image-classfication project

Implemented by Yiyang Zhang 1800013111

Using ResNet-50 model

About CIAFR-10 Datasets:

Datasets

References

Import modules

```
#import required packages#
import pickle
import numpy as np
import keras
from keras.layers import Dense, Conv2D, BatchNormalization, Activation, Add,
Input, Flatten, ZeroPadding2D, MaxPooling2D, AveragePooling2D
from keras.models import Model
from keras.utils import to_categorical
from keras.preprocessing.image import ImageDataGenerator
```

1 Using TensorFlow backend.

Load Datasets

```
# If you have already downloaded the dataset and unpackaged it, make
    file_local true
    file_local = True
 5
    #load dataset#
    def unpickle(file):
        with open(file, 'rb') as fo:
 8
            dict = pickle.load(fo, encoding='bytes')
 9
        return dict
10
    def load_data():
11
12
        #load train data
13
14
        X_train = []
        Y_train = []
16
        for i in range(1,6):
17
            train_batch = unpickle("data_batch_"+ str(i))
18
            X_orig = train_batch[b"data"]
19
            Y_orig = train_batch[b"labels"]
            X_processed =
    X_{orig.} reshape((10000,3,32,32)).transpose(0,2,3,1).astype('float32')
21
            Y_processed = to_categorical(np.array(Y_orig),10)
22
            X_train.append(X_processed)
            Y_train.append(Y_processed)
```

```
Y_train = np.concatenate(Y_train)
26
27
        #load test data
        test_batch = unpickle("test_batch")
28
        X_orig = test_batch[b"data"]
29
30
        Y_orig = test_batch[b"labels"]
31
        X_test =
    x_{\text{orig.reshape}}((10000,3,32,32)).transpose(0,2,3,1).astype('float32')
32
        Y_test = to_categorical(np.array(Y_orig),10)
33
34
         return X_train, Y_train, X_test, Y_test
35
    if file_local:
36
37
        X_train, Y_train, X_test, Y_test = load_data()
38
39
    else:
40
        (X_train, Y_train), (X_test, Y_test) =
    keras.datasets.cifar10.load_data()
41
        Y_train = to_categorical(np.array(Y_train),10)
42
        Y_test = to_categorical(np.array(Y_test),10)
43
44
45
    (M, n_H, n_W, n_C) = X_{train.shape}
46
    input\_shape = (n_H, n_W, n_C)
47
48
49
    print ("data loading completed")
    print ("number of training examples = " + str(X_train.shape[0]))
50
    print ("number of test examples = " + str(X_test.shape[0]))
51
    print ("X_train shape: " + str(X_train.shape))
52
53
    print ("Y_train shape: " + str(Y_train.shape))
54
    print ("X_test shape: " + str(X_test.shape))
    print ("Y_test shape: " + str(Y_test.shape))
55
56
57
1 data loading completed
  number of training examples = 50000
2
   number of test examples = 10000
```

```
X_train shape: (50000, 32, 32, 3)
4
5
  Y_train shape: (50000, 10)
  X_test shape: (10000, 32, 32, 3)
6
  Y_test shape: (10000, 10)
```

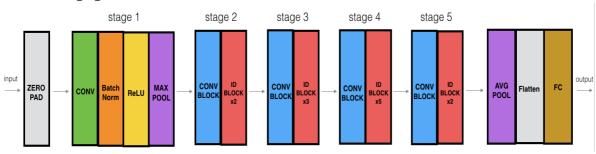
Build ResNet-50 Model

24

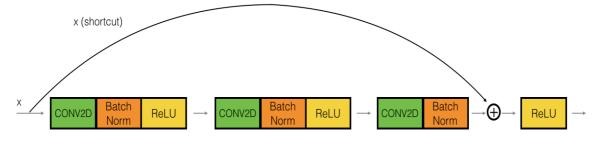
25

X_train = np.concatenate(X_train)

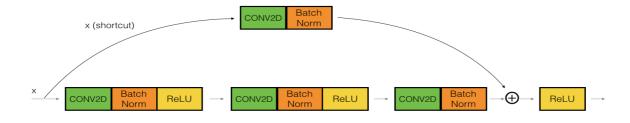
The following figure describes in detail the architecture of this network



And firstly We will impletemt convolutional residual block and identity residual block



Identity block



convolutional block

```
def id_block(X, f, kernel_channels ,activation = 'relu'):
 1
 2
 3
        X_shortcut = X
 4
 5
        F1,F2,F3 = kernel_channels
 6
        X = Conv2D(filters = F1, kernel\_size = (1, 1), strides = (1,1), padding
 7
    = 'valid')(X)
        X = BatchNormalization(axis = 3)(X)
 8
 9
        X = Activation(activation)(X)
10
11
        X = Conv2D(filters = F2, kernel\_size = (f, f), strides = (1,1), padding
    = 'same')(X)
        X = BatchNormalization(axis = 3)(X)
12
13
        X = Activation(activation)(X)
14
15
        X = Conv2D(filters = F3, kernel\_size = (1, 1), strides = (1,1), padding
    = 'valid')(X)
16
        X = BatchNormalization(axis = 3)(X)
17
18
        X = Add()([X,X\_shortcut])
19
        X = Activation(activation)(X)
20
21
        return X
22
23
    def conv_block(X, f, kernel_channels, strides, activation = 'relu'):
24
25
26
        X_shortcut = X
27
28
        F1,F2,F3 = kernel_channels
29
```

```
30
        X = Conv2D(filters = F1, kernel_size = (1, 1), strides =
    (strides, strides), padding = 'valid')(X)
31
        X = BatchNormalization(axis = 3)(X)
32
        X = Activation(activation)(X)
33
        X = Conv2D(filters = F2, kernel\_size = (f, f), strides = (1,1), padding
34
    = 'same')(X)
35
        X = BatchNormalization(axis = 3)(X)
        X = Activation(activation)(X)
36
37
38
        X = Conv2D(filters = F3, kernel\_size = (1, 1), strides = (1,1), padding
    = 'valid')(X)
39
        X = BatchNormalization(axis = 3)(X)
40
41
        X_shortcut = Conv2D(filters = F3, kernel_size = (1, 1), strides =
    (strides, strides), padding = 'valid')(X_shortcut)
        X_shortcut = BatchNormalization(axis = 3)(X_shortcut )
42
43
44
        X = Add()([X,X\_shortcut])
        X = Activation(activation)(X)
45
46
47
        return X
48
49
50
    def ResNet50(Input_shape = (32, 32, 3), classes = 10):
51
52
53
        X_input = Input(Input_shape)
54
        X = ZeroPadding2D((1, 1))(X_input)
55
56
        #stage 1
        X = Conv2D(64, (3, 3), strides = (2, 2), padding = 'valid')(X)
57
58
        X = BatchNormalization(axis = 3)(X)
59
        X = Activation('relu')(X)
        X = MaxPooling2D((3, 3), strides=(2, 2))(X)
60
61
62
        #stage 2
63
64
        X = conv_block(X, 3, kernel_channels = [64, 64, 256], strides = 1)
        X = id\_block(X, 3, kernel\_channels = [64, 64, 256])
65
        X = id\_block(X, 3, kernel\_channels = [64, 64, 256])
66
67
68
        #stage 3
69
70
        X = conv_block(X, 3, kernel_channels = [128, 128, 512], strides = 2)
        X = id_block(X, 3, kernel_channels = [128, 128, 512])
71
        X = id\_block(X, 3, kernel\_channels = [128, 128, 512])
72
        X = id_block(X, 3, kernel_channels = [128, 128, 512])
73
74
75
        #stage 4
76
77
        X = conv_block(X, 3, kernel_channels = [256, 256, 1024], strides = 2)
        X = id\_block(X, 3, kernel\_channels = [256, 256, 1024])
78
        X = id_block(X, 3, kernel_channels = [256, 256, 1024])
79
80
        \#X = id\_block(X, 3, kernel\_channels = [256, 256, 1024])
        \#X = id\_block(X, 3, kernel\_channels = [256, 256, 1024])
81
        \#X = id\_block(X, 3, kernel\_channels = [256, 256, 1024])
82
83
```

```
84
        #stage 5
85
         \#X = conv\_block(X, 3, kernel\_channels = [512, 512, 2048], strides = 2)
 86
         \#X = id\_block(X, 3, kernel\_channels = [512, 512, 2048])
87
         \#X = id\_block(X, 3, kernel\_channels = [512, 512, 2048])
88
89
         X = AveragePooling2D(pool_size = (2, 2))(X)
90
91
         X = Flatten()(X)
92
93
         X = Dense(1024, activation='relu')(X)
94
         X = Dense(classes, activation='softmax')(X)
95
96
97
         model = Model(inputs = X_input, outputs = X, name='ResNet50')
98
99
         return model
100
101
```

Train the model

```
model = ResNet50(input_shape, classes= 10)
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=
   ['accuracy'])

model.fit(X_train, Y_train, epochs = 200, batch_size = 256)

preds = model.evaluate(X_test, Y_test)
print ("Loss = " + str(preds[0]))
print ("Test Accuracy = " + str(preds[1]))
```

```
1 | Epoch 1/200
 1.6875 - accuracy: 0.4302s - 1
3 Epoch 2/200
 1.0912 - accuracy: 0.6119
5
 Epoch 3/200
  0.8783 - accuracy: 0.6904s - loss: 0.8779 - accu
  Epoch 4/200
  50000/50000 [============= ] - 19s 375us/step - loss:
  0.7256 - accuracy: 0.7444
  Epoch 5/200
10 50000/50000 [============= ] - 19s 374us/step - loss:
  0.6015 - accuracy: 0.7894
11 Epoch 6/200
0.5069 - accuracy: 0.8236
13 | Epoch 7/200
 0.4209 - accuracy: 0.8531
15 | Epoch 8/200
0.3496 - accuracy: 0.8776
17
 Epoch 9/200
```

```
18 | 50000/50000 [=======] - 19s 377us/step - loss:
  0.2966 - accuracy: 0.8969
19
  Epoch 10/200
 0.2379 - accuracy: 0.9174
21 Epoch 11/200
 0.2019 - accuracy: 0.9297
23 | Epoch 12/200
 0.1793 - accuracy: 0.9367s
25 Epoch 13/200
0.1479 - accuracy: 0.9485
27
 Epoch 14/200
  50000/50000 [============ ] - 19s 381us/step - loss:
  0.1376 - accuracy: 0.9523
29
 Epoch 15/200
  0.1274 - accuracy: 0.9557
31 Epoch 16/200
 0.1254 - accuracy: 0.9549
33
 Epoch 17/200
0.1010 - accuracy: 0.9651
35
 Epoch 18/200
36 | 50000/50000 [============ ] - 19s 381us/step - loss:
  0.0926 - accuracy: 0.9676
37
 Epoch 19/200
0.0942 - accuracy: 0.9669
39
 Epoch 20/200
  50000/50000 [========== ] - 19s 380us/step - loss:
  0.0794 - accuracy: 0.9731
41 Epoch 21/200
  0.0776 - accuracy: 0.9731
43 | Epoch 22/200
  50000/50000 [============ ] - 19s 382us/step - loss:
  0.0768 - accuracy: 0.9735
45
  Epoch 23/200
 46
  0.0686 - accuracy: 0.9762
47
  Epoch 24/200
 0.0819 - accuracy: 0.9723
49
 Epoch 25/200
 0.0667 - accuracy: 0.9771
51 | Epoch 26/200
 0.0549 - accuracy: 0.9808
53 Epoch 27/200
 0.0639 - accuracy: 0.9782
55 Epoch 28/200
```

```
56 | 50000/50000 [=======] - 19s 381us/step - loss:
  0.0679 - accuracy: 0.9771
  Epoch 29/200
  0.0547 - accuracy: 0.9818
  Epoch 30/200
59
0.0655 - accuracy: 0.9770
61 | Epoch 31/200
  62
  0.0610 - accuracy: 0.9792
63 Epoch 32/200
  0.0516 - accuracy: 0.9830
65
  Epoch 33/200
  50000/50000 [=========== ] - 19s 378us/step - loss:
  0.0570 - accuracy: 0.9802
  Epoch 34/200
67
  50000/50000 [============ ] - 19s 379us/step - loss:
  0.0501 - accuracy: 0.9830s - 1
69
  Epoch 35/200
  0.0523 - accuracy: 0.9824
71
  Epoch 36/200
 0.0494 - accuracy: 0.9828
73
  Epoch 37/200
74
  0.0500 - accuracy: 0.9837
75
  Epoch 38/200
  50000/50000 [======] - 19s 379us/step - loss:
76
  0.0468 - accuracy: 0.9839s - loss: 0.0465
77
  Epoch 39/200
  50000/50000 [=========== ] - 19s 378us/step - loss:
  0.0471 - accuracy: 0.9841
79
  Epoch 40/200
  0.0447 - accuracy: 0.9845
81 | Epoch 41/200
  0.0446 - accuracy: 0.9848
83
  Epoch 42/200
  0.0490 - accuracy: 0.9836
85
  Epoch 43/200
86 | 50000/50000 [============ ] - 19s 380us/step - loss:
  0.0416 - accuracy: 0.9863
87
  Epoch 44/200
 0.0371 - accuracy: 0.9876
89 Epoch 45/200
  50000/50000 [============== ] - 19s 378us/step - loss:
  0.0389 - accuracy: 0.9865
91 Epoch 46/200
  0.0375 - accuracy: 0.9870
93 Epoch 47/200
```

```
0.0513 - accuracy: 0.9826
  Epoch 48/200
  0.0331 - accuracy: 0.9883
  Epoch 49/200
97
  50000/50000 [============== ] - 19s 380us/step - loss:
  0.0362 - accuracy: 0.9875
  Epoch 50/200
99
  50000/50000 [============ ] - 19s 378us/step - loss:
100
  0.0420 - accuracy: 0.9859
101
  Epoch 51/200
102
  0.0332 - accuracy: 0.9890s - loss: 0.0330 - accu
103
  Epoch 52/200
104
  50000/50000 [=========== ] - 19s 387us/step - loss:
  0.0265 - accuracy: 0.9916
105
  Epoch 53/200
106
  0.0311 - accuracy: 0.9894
  Epoch 54/200
107
  108
  0.0374 - accuracy: 0.9876
109
  Epoch 55/200
110 | 50000/50000 [============= ] - 19s 383us/step - loss:
  0.0364 - accuracy: 0.9878
111 | Epoch 56/200
112
  0.0361 - accuracy: 0.9880
113 | Epoch 57/200
  114
  0.0349 - accuracy: 0.9884
115
  Epoch 58/200
116
  0.0307 - accuracy: 0.9896
117 Epoch 59/200
  0.0347 - accuracy: 0.9882
119 Epoch 60/200
120
  0.0260 - accuracy: 0.9911
121
  Epoch 61/200
  50000/50000 [============ ] - 19s 383us/step - loss:
122
  0.0303 - accuracy: 0.9893
123
  Epoch 62/200
  124
  0.0334 - accuracy: 0.9891
125
  Epoch 63/200
126 | 50000/50000 [============= ] - 19s 382us/step - loss:
  0.0309 - accuracy: 0.9900
127
  Epoch 64/200
  128
  0.0252 - accuracy: 0.9916
129
  Epoch 65/200
130
  0.0302 - accuracy: 0.9899
131 Epoch 66/200
```

```
0.0306 - accuracy: 0.9895
133
  Epoch 67/200
  134
  0.0426 - accuracy: 0.9859
  Epoch 68/200
135
0.0229 - accuracy: 0.9921
  Epoch 69/200
137
  138
  0.0277 - accuracy: 0.9905
139 Epoch 70/200
  50000/50000 [============= ] - 19s 385us/step - loss:
140
  0.0207 - accuracy: 0.9927
141
  Epoch 71/200
142
  50000/50000 [=========== ] - 19s 386us/step - loss:
  0.0246 - accuracy: 0.9916
143
  Epoch 72/200
  0.0282 - accuracy: 0.9905
145
  Epoch 73/200
  146
  0.0241 - accuracy: 0.9918s - loss: 0
147
  Epoch 74/200
0.0237 - accuracy: 0.9921
149
  Epoch 75/200
150
  0.0288 - accuracy: 0.9900
151 | Epoch 76/200
152
  0.0199 - accuracy: 0.9931
153
  Epoch 77/200
  0.0246 - accuracy: 0.9919
155 | Epoch 78/200
  0.0276 - accuracy: 0.9906
157
  Epoch 79/200
158
  0.0176 - accuracy: 0.9944
159
  Epoch 80/200
  50000/50000 [============ ] - 23s 456us/step - loss:
160
  0.0246 - accuracy: 0.9914
161
  Epoch 81/200
  162
  0.0213 - accuracy: 0.9925
163
  Epoch 82/200
  164
  0.0184 - accuracy: 0.9937
165 | Epoch 83/200
  166
  0.0209 - accuracy: 0.9936
167
  Epoch 84/200
  0.0244 - accuracy: 0.9917
169 Epoch 85/200
```

```
0.0230 - accuracy: 0.9919
171
  Epoch 86/200
  172
  0.0222 - accuracy: 0.9925
  Epoch 87/200
173
  0.0166 - accuracy: 0.9945
  Epoch 88/200
175
0.0168 - accuracy: 0.9941
177
  Epoch 89/200
  178
  0.0285 - accuracy: 0.9906
179
  Epoch 90/200
180
  50000/50000 [=========== ] - 20s 398us/step - loss:
  0.0230 - accuracy: 0.9922s - loss: 0.0227 - accura
181
  Epoch 91/200
  0.0137 - accuracy: 0.9955
183
  Epoch 92/200
  184
  0.0200 - accuracy: 0.9935
185
  Epoch 93/200
0.0197 - accuracy: 0.9933
187
  Epoch 94/200
188
  0.0189 - accuracy: 0.9935
189
  Epoch 95/200
190
  0.0222 - accuracy: 0.9929
191
  Epoch 96/200
  0.0196 - accuracy: 0.9934s - loss: 0.0195 - accuracy:
193 | Epoch 97/200
  0.0167 - accuracy: 0.9946
195 | Epoch 98/200
196
  0.0205 - accuracy: 0.9933
197
  Epoch 99/200
198
  50000/50000 [============ ] - 21s 422us/step - loss:
  0.0167 - accuracy: 0.9945
199
  Epoch 100/200
200 50000/50000 [============= ] - 21s 426us/step - loss:
  0.0247 - accuracy: 0.9918
201 Epoch 101/200
  202
  0.0184 - accuracy: 0.9941
203 Epoch 102/200
  50000/50000 [============= ] - 21s 418us/step - loss:
204
  0.0146 - accuracy: 0.9954
205
  Epoch 103/200
  0.0150 - accuracy: 0.9951
207 Epoch 104/200
```

```
0.0158 - accuracy: 0.9948
209
  Epoch 105/200
  210
  0.0217 - accuracy: 0.9925
211 Epoch 106/200
  50000/50000 [============= ] - 20s 395us/step - loss:
  0.0140 - accuracy: 0.9952s - loss: 0.014
213 | Epoch 107/200
  214
  0.0132 - accuracy: 0.9955
215
  Epoch 108/200
  50000/50000 [============ ] - 20s 394us/step - loss:
216
  0.0231 - accuracy: 0.9922
217
  Epoch 109/200
218
  50000/50000 [=========== ] - 20s 398us/step - loss:
  0.0130 - accuracy: 0.9958
219
  Epoch 110/200
220
  0.0183 - accuracy: 0.9941
221 Epoch 111/200
  222
  0.0172 - accuracy: 0.9940
223
  Epoch 112/200
224
  0.0169 - accuracy: 0.9945
225
  Epoch 113/200
226
  0.0124 - accuracy: 0.9961
227
  Epoch 114/200
228
  0.0112 - accuracy: 0.9962
229
  Epoch 115/200
  50000/50000 [========= ] - 19s 385us/step - loss:
230
  0.0205 - accuracy: 0.9933
231 Epoch 116/200
  0.0144 - accuracy: 0.9954
233 Epoch 117/200
234
  0.0143 - accuracy: 0.9952
235
  Epoch 118/200
  50000/50000 [============ ] - 19s 390us/step - loss:
236
  0.0128 - accuracy: 0.9954
237
  Epoch 119/200
  238
  0.0228 - accuracy: 0.9925
239
  Epoch 120/200
  0.0107 - accuracy: 0.9962
241 Epoch 121/200
  50000/50000 [============= ] - 20s 394us/step - loss:
242
  0.0145 - accuracy: 0.9955
243
  Epoch 122/200
  0.0178 - accuracy: 0.9940
245 Epoch 123/200
```

```
0.0161 - accuracy: 0.9948
247
  Epoch 124/200
  248
  0.0123 - accuracy: 0.9960
249
  Epoch 125/200
0.0145 - accuracy: 0.9949
251 Epoch 126/200
252
  0.0104 - accuracy: 0.9963
253
  Epoch 127/200
  50000/50000 [============= ] - 20s 396us/step - loss:
254
  0.0170 - accuracy: 0.9943
255
  Epoch 128/200
256
  50000/50000 [=========== ] - 20s 394us/step - loss:
  0.0160 - accuracy: 0.9950
257
  Epoch 129/200
  258
  0.0192 - accuracy: 0.9937
  Epoch 130/200
259
  260
  0.0077 - accuracy: 0.9974
261
  Epoch 131/200
262
  0.0041 - accuracy: 0.9985
263
  Epoch 132/200
264
  0.0206 - accuracy: 0.9934
265
  Epoch 133/200
266
  0.0125 - accuracy: 0.9958
267
  Epoch 134/200
  50000/50000 [========= ] - 19s 385us/step - loss:
268
  0.0093 - accuracy: 0.9970
269 Epoch 135/200
  0.0142 - accuracy: 0.9951
271
  Epoch 136/200
272
  0.0157 - accuracy: 0.9948
273
  Epoch 137/200
  50000/50000 [============ ] - 19s 383us/step - loss:
274
  0.0148 - accuracy: 0.9948
275
  Epoch 138/200
  0.0131 - accuracy: 0.9957
277
  Epoch 139/200
  278
  0.0097 - accuracy: 0.9967
279
  Epoch 140/200
  50000/50000 [============= ] - 20s 394us/step - loss:
280
  0.0150 - accuracy: 0.9949
281 | Epoch 141/200
  0.0172 - accuracy: 0.9941
283 Epoch 142/200
```

```
50000/50000 [============ ] - 19s 388us/step - loss:
  0.0133 - accuracy: 0.9955
285
  Epoch 143/200
  286
  0.0102 - accuracy: 0.9968
  Epoch 144/200
287
  0.0106 - accuracy: 0.9965s - 1
  Epoch 145/200
289
290
  50000/50000 [============ ] - 19s 383us/step - loss:
  0.0110 - accuracy: 0.9964
291
  Epoch 146/200
  50000/50000 [=========== ] - 19s 383us/step - loss:
292
  0.0123 - accuracy: 0.9958
293
  Epoch 147/200
294
  50000/50000 [============ ] - 19s 382us/step - loss:
  0.0100 - accuracy: 0.9968
295
  Epoch 148/200
296
  0.0082 - accuracy: 0.9972
  Epoch 149/200
297
  298
  0.0130 - accuracy: 0.9956
299
  Epoch 150/200
0.0148 - accuracy: 0.9953
301 Epoch 151/200
302
  0.0093 - accuracy: 0.9969
303
  Epoch 152/200
304
  50000/50000 [============ ] - 20s 409us/step - loss:
  0.0110 - accuracy: 0.9965
305
  Epoch 153/200
306
  0.0123 - accuracy: 0.9959
307
  Epoch 154/200
  0.0097 - accuracy: 0.9965
309
  Epoch 155/200
310
  0.0137 - accuracy: 0.9960
311
  Epoch 156/200
  50000/50000 [============ ] - 20s 392us/step - loss:
312
  0.0092 - accuracy: 0.9971
313
  Epoch 157/200
314
  0.0111 - accuracy: 0.9963
315
  Epoch 158/200
  316
  0.0149 - accuracy: 0.9954
317 Epoch 159/200
  318
  0.0102 - accuracy: 0.9967
319 | Epoch 160/200
320
  0.0067 - accuracy: 0.9978
321 Epoch 161/200
```

```
322 50000/50000 [============ ] - 19s 383us/step - loss:
   0.0108 - accuracy: 0.9967
323
   Epoch 162/200
   324
   0.0078 - accuracy: 0.9975
325
   Epoch 163/200
  0.0122 - accuracy: 0.9960
  Epoch 164/200
327
  328
   0.0145 - accuracy: 0.9954s - 1
329
  Epoch 165/200
   50000/50000 [============= ] - 20s 390us/step - loss:
330
   0.0114 - accuracy: 0.9963
331
  Epoch 166/200
332
   50000/50000 [=========== ] - 19s 384us/step - loss:
   0.0120 - accuracy: 0.9959
333
   Epoch 167/200
   0.0081 - accuracy: 0.9973s - loss: 0.0080 -
335
   Epoch 168/200
  50000/50000 [============= ] - 19s 388us/step - loss:
336
   0.0117 - accuracy: 0.9961
337
   Epoch 169/200
338
  0.0091 - accuracy: 0.9971
339
  Epoch 170/200
340
   0.0078 - accuracy: 0.9976s - loss: 0.0075
341
  Epoch 171/200
342
   50000/50000 [============ ] - 19s 389us/step - loss:
   0.0123 - accuracy: 0.9961
343
  Epoch 172/200
   50000/50000 [=======] - 20s 399us/step - loss:
   0.0093 - accuracy: 0.9967
345
  Epoch 173/200
   0.0323 - accuracy: 0.9904
347
  Epoch 174/200
   0.0083 - accuracy: 0.9971
349
   Epoch 175/200
   50000/50000 [============ ] - 20s 407us/step - loss:
350
   0.0059 - accuracy: 0.9983
351
   Epoch 176/200
  352
   0.0100 - accuracy: 0.9968
353
  Epoch 177/200
   0.0165 - accuracy: 0.9949s - los
355
  Epoch 178/200
  50000/50000 [============== ] - 19s 387us/step - loss:
356
   0.0123 - accuracy: 0.9959
357
  Epoch 179/200
   0.0056 - accuracy: 0.9982
359 Epoch 180/200
```

```
0.0093 - accuracy: 0.9970
361
   Epoch 181/200
   362
   0.0050 - accuracy: 0.9980
  Epoch 182/200
363
  0.0053 - accuracy: 0.9982
  Epoch 183/200
365
366 | 50000/50000 [============ ] - 20s 403us/step - loss:
   0.0148 - accuracy: 0.9955
367
  Epoch 184/200
   50000/50000 [============= ] - 21s 412us/step - loss:
368
   0.0134 - accuracy: 0.9959
369
  Epoch 185/200
370
   50000/50000 [=========== ] - 21s 416us/step - loss:
   0.0081 - accuracy: 0.9974s - loss: 0.0081 - accura
371
   Epoch 186/200
   50000/50000 [============= ] - ETA: Os - loss: 0.0050 -
372
   accuracy: 0.9984 ETA: 0s - loss: 0.0051 - accu - 21s 414us/step - loss:
   0.0050 - accuracy: 0.9984
373
  Epoch 187/200
374
   0.0084 - accuracy: 0.9974
375
  Epoch 188/200
  376
   0.0102 - accuracy: 0.9968
377
   Epoch 189/200
   50000/50000 [============ ] - 22s 437us/step - loss:
   0.0077 - accuracy: 0.9976
379
  Epoch 190/200
   0.0083 - accuracy: 0.9972
381
   Epoch 191/200
   0.0118 - accuracy: 0.9959s -
383
   Epoch 192/200
384
   0.0071 - accuracy: 0.9977
385
   Epoch 193/200
  0.0061 - accuracy: 0.9981
387
  Epoch 194/200
388
   0.0063 - accuracy: 0.9980
389
  Epoch 195/200
   50000/50000 [========= ] - 20s 396us/step - loss:
390
   0.0090 - accuracy: 0.9969
391
  Epoch 196/200
   0.0080 - accuracy: 0.9973
393
  Epoch 197/200
394
   50000/50000 [============ ] - 20s 405us/step - loss:
   0.0115 - accuracy: 0.9963s - 1
395
  396
   0.0095 - accuracy: 0.9969
397
  Epoch 199/200
```

```
50000/50000 [========] - 20s 400us/step - loss:
0.0063 - accuracy: 0.9977

Epoch 200/200

50000/50000 [========] - 20s 400us/step - loss:
0.0100 - accuracy: 0.9968

401 10000/10000 [=========] - 5s 523us/step

Loss = 1.8030616061210631

403 Test Accuracy = 0.7542999982833862
```

1