ChessBoardClassificationConvnet

June 19, 2022

1 Chess Piece Classification with CNN

1.1 Preparing the data

[1]:
```
import json
import numpy as np
from typing import List

from tensorflow.keras.preprocessing.image import load_img, img_to_array

N_SQUARES = 8  # Chessboard is 8x8 squares

def load_square_images(board_image_file: str) -> List[np.ndarray]:

    board_image = img_to_array(load_img(board_image_file,␣
 ↪color_mode='grayscale'))
    assert board_image.shape[0] == board_image.shape[1]  # Square image

    sq_size = int(board_image.shape[0] / N_SQUARES) # pixel size

    # obtain individual images of all sqaures on a chess board
    images = []
    for row in range(N_SQUARES):
        for col in range(N_SQUARES):
            images.append(
                board_image[
                    row*sq_size : (row+1)*sq_size,
                    col*sq_size : (col+1)*sq_size
                ]
            )

    return images # of shape (64, 50, 50, 1) (NUM_SQUARES_ON_CHESSBOARD,␣
 ↪HEIGHT, WIDTH, DEPTH)

def load_board_images(image_dir: str, board_data: list) -> np.ndarray:

    # load squares for each board
    images = []
```

```
    for board_dict in board_data:
        board_image_file = f'./data/{image_dir}/{board_dict["image"]}'
        images.append(load_square_images(board_image_file))

    return np.array(images)

def load_board_labels(board_data: list) -> np.ndarray:

    labels = []
    for board in board_data:
        for s in board["board"]:
            labels += list(s)

    return np.array(labels)
```

1.2 Loading and preprocessing the data

[2]:
```
def load_data():

    # training data
    with open('./data/boards.train.json') as training_file:
        data = json.load(training_file)

    train_data = load_board_images('clean', data)
    train_labels = load_board_labels(data)

    # test data
    with open('./data/boards.dev.json') as test_file:
        data = json.load(test_file)

    test_data = load_board_images('clean', data)
    test_labels = load_board_labels(data)

    train_data = train_data.reshape(100*64, 50, 50, 1) # 100 boards, 6400␣
↪squares
    test_data = test_data.reshape(25*64, 50, 50, 1) # 25 boards, 1600 squares

    return (train_data, train_labels), (test_data, test_labels)
```

[3]:
```
(train_data, train_labels), (test_data, test_labels) = load_data()

validation_data = train_data[4800:]
validation_labels = train_labels[4800:]
train_data = train_data[:4800]
train_labels = train_labels[:4800]

# normalise data
```

```python
# scale pixels values in range [0,1]
# makes learning process easier for neural networks
train_data = train_data.astype('float32') / 255
test_data = test_data.astype('float32') / 255
```

[4]:
```python
PIECES = ['.', 'K', 'Q', 'B', 'N', 'R', 'P', 'k', 'q', 'b', 'n', 'r', 'p']

for p in PIECES:
    print(f"{p} {train_labels.tolist().count(p)}")
```

```
. 3659
K 74
Q 37
B 49
N 51
R 71
P 294
k 74
q 34
b 51
n 39
r 70
p 297
```

[5]:
```python
from sklearn.preprocessing import LabelBinarizer
encoder = LabelBinarizer()

one_hot_train_labels = encoder.fit_transform(train_labels)
one_hot_validation_labels = encoder.fit_transform(validation_labels)
one_hot_test_labels = encoder.fit_transform(test_labels)
```

1.3 Developing and training model

[6]:
```python
from tensorflow.keras import models
from tensorflow.keras import layers

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(50, 50, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
# softmax typically used for output layer for single-label multi-class␣
↪classification problems
```

```python
model.add(layers.Dense(13, activation='softmax'))

model.compile(optimizer='rmsprop', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])
history = model.fit(train_data, one_hot_train_labels, epochs=20, batch_size=48,
                    validation_data=(validation_data, one_hot_validation_labels)
)

test_loss, test_acc = model.evaluate(test_data, one_hot_test_labels)
test_acc
```

```
Epoch 1/20
100/100 [==============================] - 10s 95ms/step - loss: 0.7237 -
accuracy: 0.8388 - val_loss: 137.6523 - val_accuracy: 0.8050
Epoch 2/20
100/100 [==============================] - 9s 94ms/step - loss: 0.1256 -
accuracy: 0.9646 - val_loss: 28.3410 - val_accuracy: 0.9419
Epoch 3/20
100/100 [==============================] - 10s 97ms/step - loss: 0.0422 -
accuracy: 0.9867 - val_loss: 139.7565 - val_accuracy: 0.8550
Epoch 4/20
100/100 [==============================] - 10s 102ms/step - loss: 0.0507 -
accuracy: 0.9873 - val_loss: 89.4626 - val_accuracy: 0.8931
Epoch 5/20
100/100 [==============================] - 10s 102ms/step - loss: 0.0148 -
accuracy: 0.9960 - val_loss: 6.5770 - val_accuracy: 0.9894
Epoch 6/20
100/100 [==============================] - 10s 105ms/step - loss: 0.0098 -
accuracy: 0.9967 - val_loss: 450.6511 - val_accuracy: 0.8019
Epoch 7/20
100/100 [==============================] - 11s 107ms/step - loss: 0.0110 -
accuracy: 0.9977 - val_loss: 18.8489 - val_accuracy: 0.9756
Epoch 8/20
100/100 [==============================] - 11s 110ms/step - loss: 0.0120 -
accuracy: 0.9977 - val_loss: 103.8638 - val_accuracy: 0.9131
Epoch 9/20
100/100 [==============================] - 12s 123ms/step - loss: 0.0153 -
accuracy: 0.9954 - val_loss: 20.7110 - val_accuracy: 0.9706
Epoch 10/20
100/100 [==============================] - 12s 124ms/step - loss: 0.0039 -
accuracy: 0.9992 - val_loss: 41.4200 - val_accuracy: 0.9581
Epoch 11/20
100/100 [==============================] - 13s 133ms/step - loss: 0.0034 -
accuracy: 0.9987 - val_loss: 73.1232 - val_accuracy: 0.9306
Epoch 12/20
100/100 [==============================] - 13s 134ms/step - loss: 0.0041 -
accuracy: 0.9990 - val_loss: 192.8120 - val_accuracy: 0.8869
Epoch 13/20
```

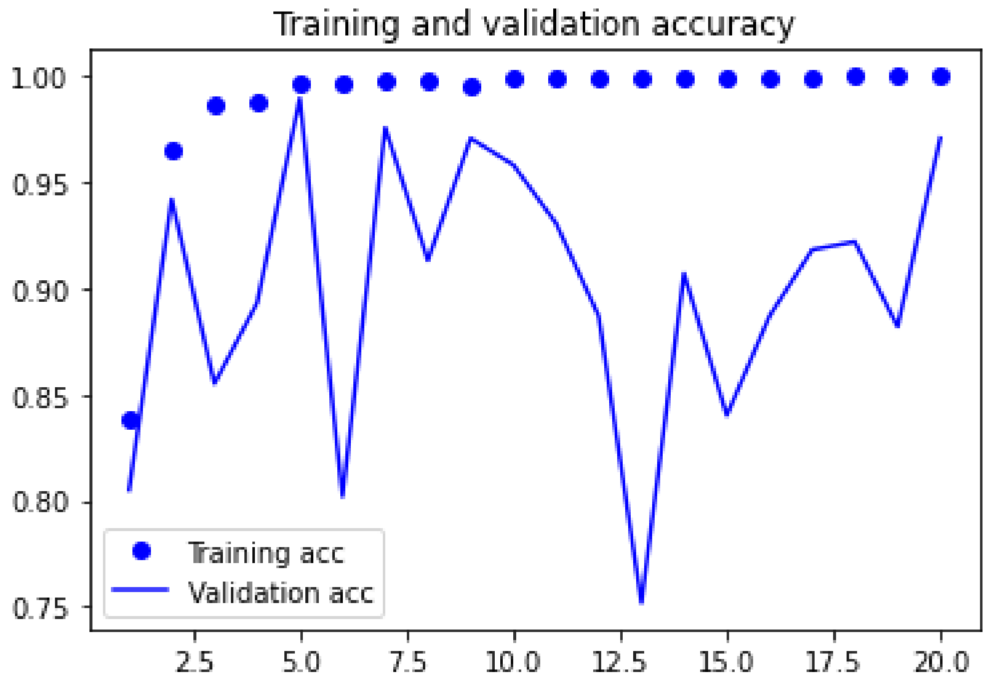
```
100/100 [==============================] - 13s 132ms/step - loss: 0.0040 -
accuracy: 0.9996 - val_loss: 720.9739 - val_accuracy: 0.7519
Epoch 14/20
100/100 [==============================] - 13s 134ms/step - loss: 0.0035 -
accuracy: 0.9987 - val_loss: 146.2093 - val_accuracy: 0.9069
Epoch 15/20
100/100 [==============================] - 13s 131ms/step - loss: 0.0030 -
accuracy: 0.9992 - val_loss: 445.0411 - val_accuracy: 0.8400
Epoch 16/20
100/100 [==============================] - 13s 131ms/step - loss: 0.0031 -
accuracy: 0.9996 - val_loss: 216.3239 - val_accuracy: 0.8869
Epoch 17/20
100/100 [==============================] - 13s 133ms/step - loss: 0.0042 -
accuracy: 0.9992 - val_loss: 132.2050 - val_accuracy: 0.9181
Epoch 18/20
100/100 [==============================] - 14s 143ms/step - loss: 4.0323e-05 -
accuracy: 1.0000 - val_loss: 188.1476 - val_accuracy: 0.9219
Epoch 19/20
100/100 [==============================] - 13s 135ms/step - loss: 0.0017 -
accuracy: 0.9998 - val_loss: 312.9486 - val_accuracy: 0.8819
Epoch 20/20
100/100 [==============================] - 13s 132ms/step - loss: 0.0013 -
accuracy: 0.9998 - val_loss: 25.9343 - val_accuracy: 0.9706
50/50 [==============================] - 1s 29ms/step - loss: 0.0367 - accuracy:
0.9962
```

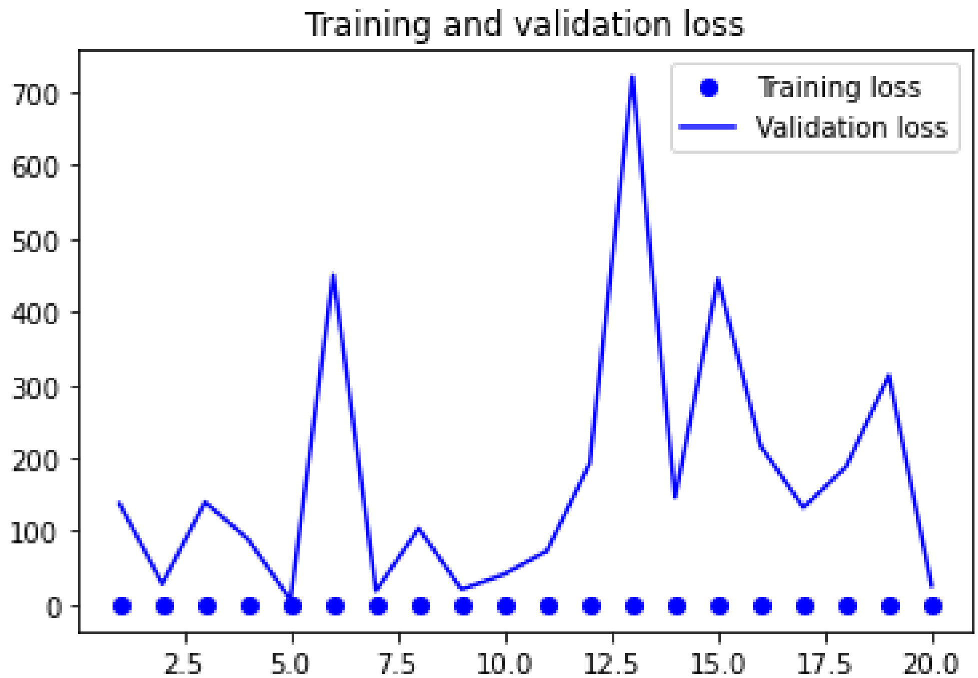
[6]:
```
0.9962499737739563
```

1.4 Evaluating model and tuning hyperparameters

[7]:
```python
import matplotlib.pyplot as plt

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
loss = history.history['loss']
val_loss = history.history['val_loss']

epochs = range(1, len(acc) + 1)

plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()

plt.figure()

plt.plot(epochs, loss, 'bo', label='Training loss')
```

```
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()

plt.show()
```





[9]:
```
model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(50, 50, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))

model.add(layers.Flatten())
model.add(layers.Dense(64, activation='relu'))
model.add(layers.Dense(13, activation='softmax'))

model.compile(optimizer='rmsprop',
                loss='categorical_crossentropy',
                metrics=['accuracy'])
history = model.fit(train_data, one_hot_train_labels, epochs=5, batch_size=48,
                    validation_data=(validation_data, one_hot_validation_labels)
)

test_loss, test_acc = model.evaluate(test_data, one_hot_test_labels)
test_acc
```

```
Epoch 1/5
100/100 [==============================] - 13s 126ms/step - loss: 0.7574 -
accuracy: 0.8240 - val_loss: 42.0924 - val_accuracy: 0.8806
Epoch 2/5
```

```
100/100 [==============================] - 13s 134ms/step - loss: 0.1246 -
accuracy: 0.9663 - val_loss: 18.8519 - val_accuracy: 0.9444
Epoch 3/5
100/100 [==============================] - 13s 135ms/step - loss: 0.0391 -
accuracy: 0.9908 - val_loss: 90.0314 - val_accuracy: 0.8938
Epoch 4/5
100/100 [==============================] - 13s 132ms/step - loss: 0.0288 -
accuracy: 0.9906 - val_loss: 23.2716 - val_accuracy: 0.9556
Epoch 5/5
100/100 [==============================] - 14s 136ms/step - loss: 0.0127 -
accuracy: 0.9967 - val_loss: 21.2030 - val_accuracy: 0.9719
50/50 [==============================] - 1s 28ms/step - loss: 0.0109 - accuracy:
0.9969
```

```
[9]: 0.996874988079071
```