06_MNIST-CNN_v1.0-PauloBraga

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Convolutional Neural Networks

[1]:
```
'''
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    11.07.2020
'''
import warnings
warnings.filterwarnings("ignore")
import tensorflow as tf
import numpy as np
import keras
from keras.models import Sequential
from keras.layers import Conv2D, Dense, Dropout, Flatten, MaxPooling2D
print('keras using %s backend'%keras.backend.backend())
import matplotlib.pyplot as graph
import pandas as pd
%matplotlib inline
graph.rcParams['figure.figsize'] = (15,5)
graph.rcParams["font.family"] = 'DejaVu Sans'
graph.rcParams["font.size"] = '12'
graph.rcParams['image.cmap'] = 'rainbow'
```

```
keras using tensorflow backend
```

[2]:
```
train_df = pd.read_csv('Data/train.csv')
# test_df = pd.read_csv('Data/test.csv')
```

[3]:
```
train_df.shape
```

[3]:
```
(42000, 785)
```

[5]:
```
# Linhas_Total = 42000; Linhas_60pct=25200; Linhas_20pct=8400;
# Linhas_20pct=8400
# train: 0~25199
# valid: 25200~33599
# test: 33600~41999
# Dividindo o set de treinamento em 'train', 'validation' e 'test'
train_X = train_df.loc[:25199, train_df.columns != 'label']
```

```python
train_Y = train_df.loc[:25199, train_df.columns == 'label']

valid_X = train_df.loc[25200:33599, train_df.columns != 'label']
valid_Y = train_df.loc[25200:33599, train_df.columns == 'label']

test_X = train_df.loc[33600:41999, train_df.columns != 'label']
test_Y = train_df.loc[33600:41999, train_df.columns == 'label']
```

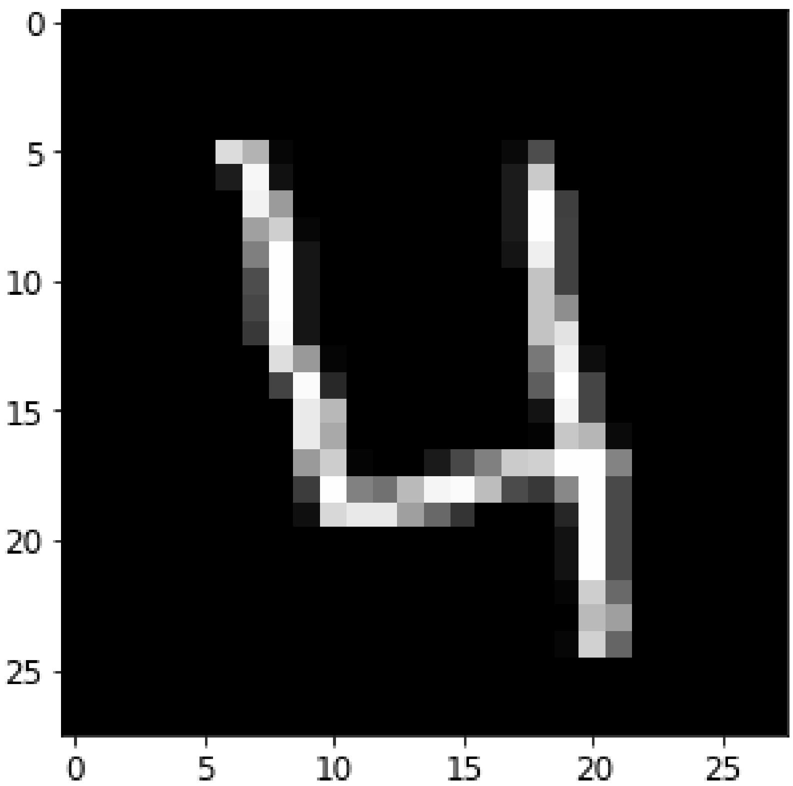
[6]:
```python
print(train_X.shape)
print(train_Y.shape)
print(valid_X.shape)
print(valid_Y.shape)
print(test_X.shape)
print(test_Y.shape)
```

```
(25200, 784)
(25200, 1)
(8400, 784)
(8400, 1)
(8400, 784)
(8400, 1)
```

[7]:
```python
# Redimensiona para 28x28
train_X = train_X.values.reshape(-1, 28, 28, 1)
valid_X = valid_X.values.reshape(-1, 28, 28, 1)
test_X = test_X.values.reshape(-1, 28, 28, 1)
```

[8]:
```python
graph.imshow(train_X[3, :, :, 0]\
             , cmap='gray', interpolation='nearest')
```

[8]:
```
<matplotlib.image.AxesImage at 0x7fc73632b390>
```



[9]:
```
# Normalização
train_X = train_X/255
valid_X = valid_X/255
test_X = test_X/255
```

[10]:
```
# One-hot encoding - Utilizando a função 'to_categorical', para
# converter para binário e assim a rede neural entende como
# categoria
train_Y = keras.utils.to_categorical(train_Y, 10)
valid_Y = keras.utils.to_categorical(valid_Y, 10)
test_Y = keras.utils.to_categorical(test_Y, 10)

print(train_Y[3])
```

```
[0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
```

[11]:
```
# Sets a randomisation seed for replicatability.
np.random.seed(6)

# Declara o objeto
model = Sequential()
```

[12]:
```python
# Pré-processamento feito pela rede neural
model.add(Conv2D(28, kernel_size = (3, 3), activation = 'relu', input_shape =␣
↪(28, 28, 1)))
model.add(Conv2D(56, (3, 3), activation = 'relu'))
```

[13]:
```python
# Pooling - Reduz a amostragem e a complexidade dos dados
model.add(MaxPooling2D(pool_size = (2, 2)))

# Dropout - Remove nodes de maneira aleatória, para evitar
# overfitting
model.add(Dropout(0.125))

# flatten - Transforma os dados em vetor
model.add(Flatten())
```

[14]:
```python
# Dense layers - Fazem a classificação
model.add(Dense(128, activation='relu'))

# Dropout novamente
model.add(Dropout(0.25))

# A função de ativação softmax, no 'output', faz a classificação
# de cada categoria
model.add(Dense(10, activation=tf.nn.softmax))

# Compila o modelo
model.compile(loss='categorical_crossentropy', optimizer='Adamax',\
              metrics=['accuracy'])
```

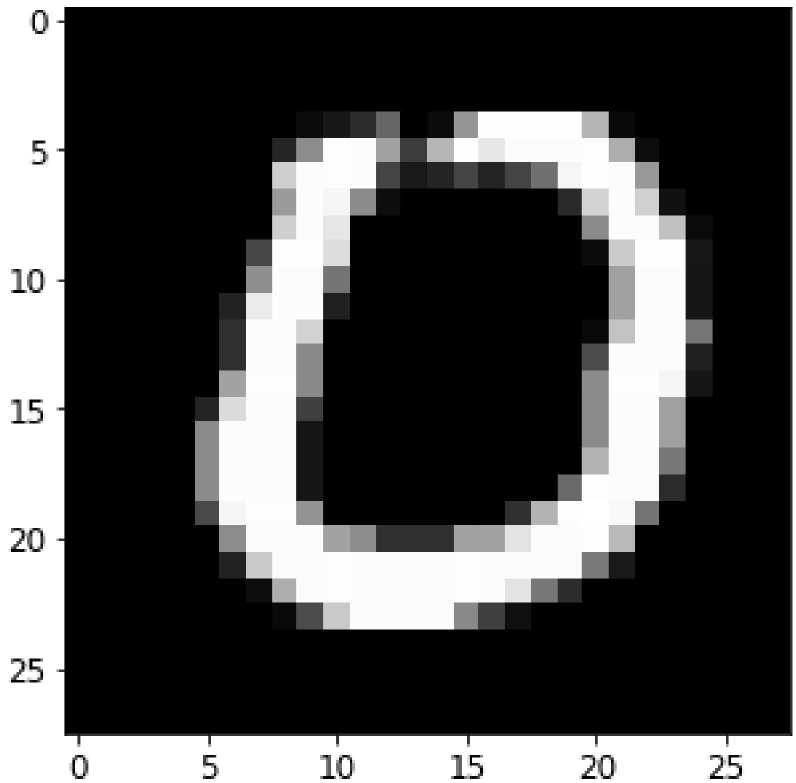
[15]:
```python
# Treina o modelo com os dados de treinamento e validação
training_stats = model.fit(train_X, train_Y, batch_size = 128,\
    epochs = 10, verbose = 1, validation_data = (valid_X, valid_Y))
# Por fim, é feita a avaliação do modelo
evaluation = model.evaluate(test_X, test_Y, verbose=0)
print('Test Set Evaluation: loss = %0.6f, accuracy = %0.2f'\
      %(evaluation[0], 100 * evaluation[1]))
```

```
Epoch 1/10
197/197 [==============================] - 33s 170ms/step - loss: 0.4332 -
accuracy: 0.8672 - val_loss: 0.1706 - val_accuracy: 0.9485
Epoch 2/10
197/197 [==============================] - 34s 174ms/step - loss: 0.1503 -
accuracy: 0.9558 - val_loss: 0.1003 - val_accuracy: 0.9695
Epoch 3/10
197/197 [==============================] - 35s 179ms/step - loss: 0.1040 -
accuracy: 0.9685 - val_loss: 0.0781 - val_accuracy: 0.9769
Epoch 4/10
```

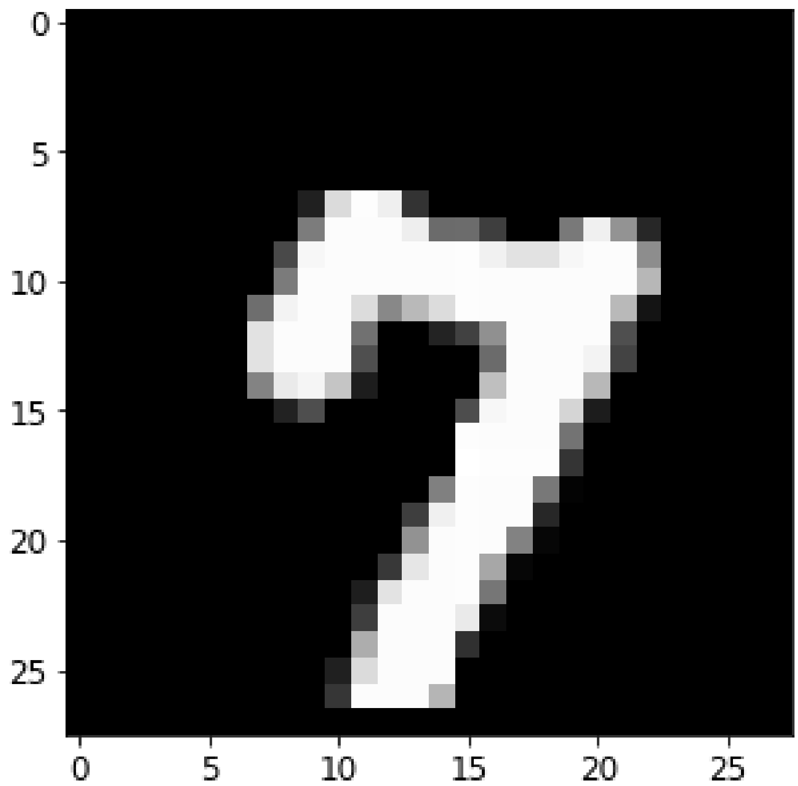
```
197/197 [==============================] - 36s 185ms/step - loss: 0.0787 -
accuracy: 0.9766 - val_loss: 0.0648 - val_accuracy: 0.9812
Epoch 5/10
197/197 [==============================] - 36s 184ms/step - loss: 0.0661 -
accuracy: 0.9803 - val_loss: 0.0608 - val_accuracy: 0.9812
Epoch 6/10
197/197 [==============================] - 37s 188ms/step - loss: 0.0518 -
accuracy: 0.9838 - val_loss: 0.0576 - val_accuracy: 0.9820
Epoch 7/10
197/197 [==============================] - 37s 189ms/step - loss: 0.0450 -
accuracy: 0.9860 - val_loss: 0.0533 - val_accuracy: 0.9844
Epoch 8/10
197/197 [==============================] - 37s 186ms/step - loss: 0.0390 -
accuracy: 0.9884 - val_loss: 0.0521 - val_accuracy: 0.9840
Epoch 9/10
197/197 [==============================] - 37s 187ms/step - loss: 0.0338 -
accuracy: 0.9895 - val_loss: 0.0493 - val_accuracy: 0.9868
Epoch 10/10
197/197 [==============================] - 38s 192ms/step - loss: 0.0293 -
accuracy: 0.9917 - val_loss: 0.0487 - val_accuracy: 0.9858
Test Set Evaluation: loss = 0.041454, accuracy = 98.74
```

[16]:

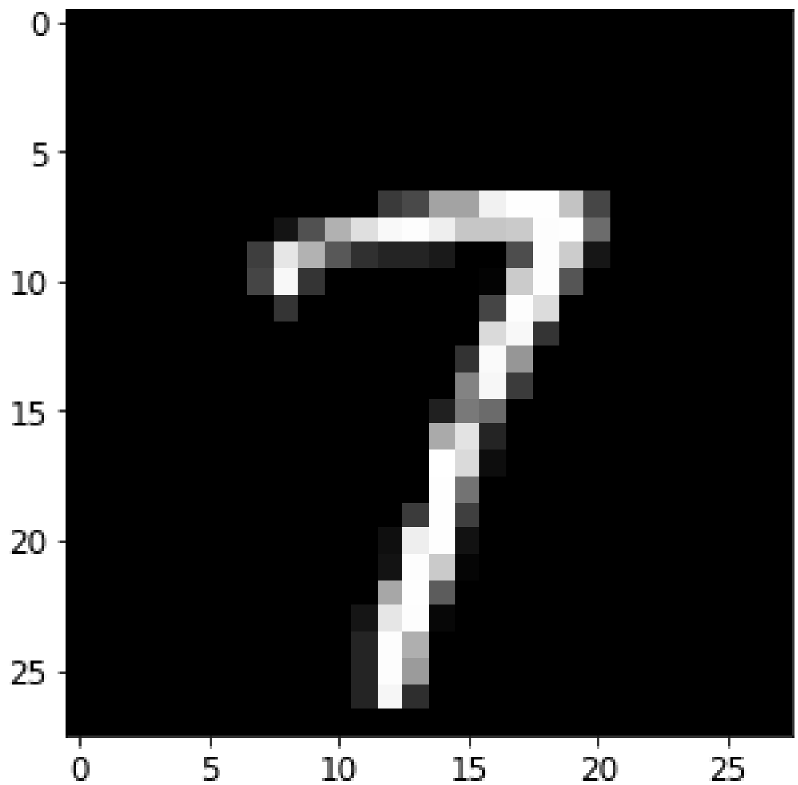
```python
# Aqui são apresentados 5 exemplos para demonstrar a aplicação e
# o resultado satisfatório do modelo
for i in range(5):
    sample = test_X[i].reshape(28, 28)

    graph.imshow(sample, cmap = 'gray', interpolation = 'nearest')
    graph.show()

    prediction = model.predict(sample.reshape(1, 28, 28, 1))
    print('prediction: %i' %(np.argmax(prediction)))
```



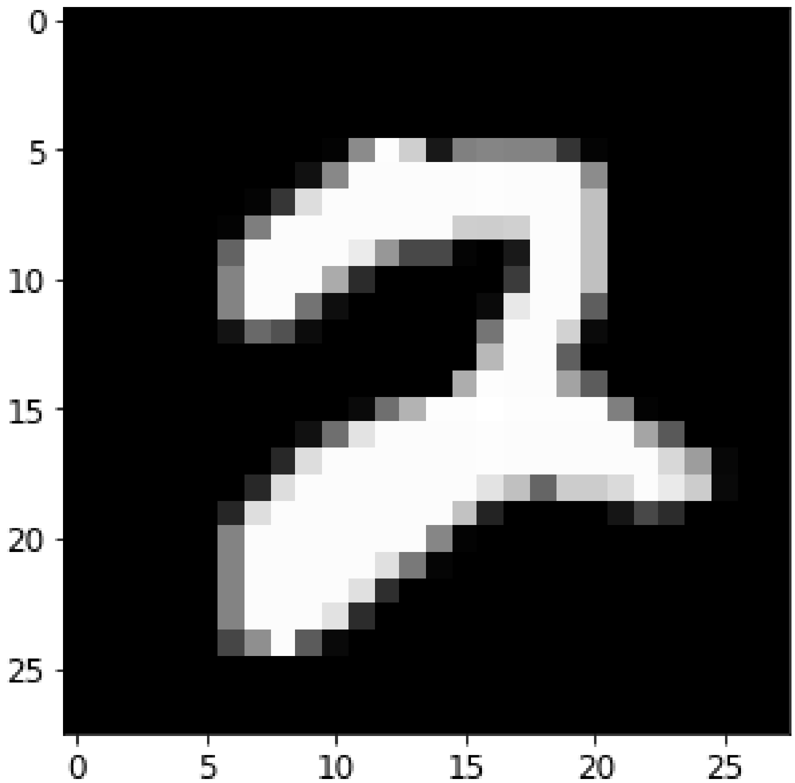

```
prediction: 0
```



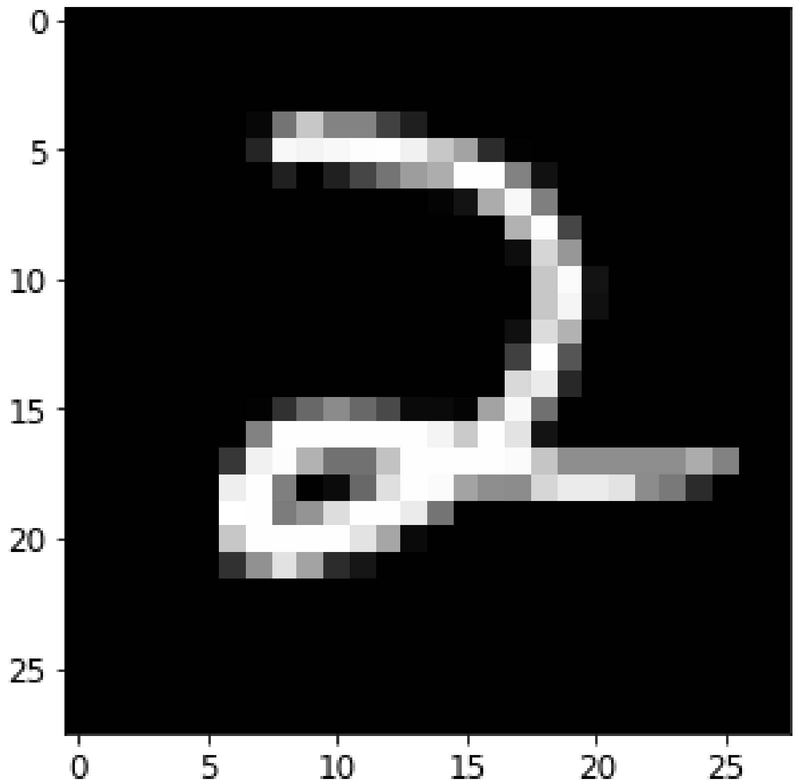
prediction: 7




```
prediction: 7
```




```
prediction: 2
```



```
prediction: 2
```