digit-recognizer-cnn

March 6, 2024

[65]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

[66]:
```
train_df = pd.read_csv('/kaggle/input/digitrecognition/train.csv')
test_df = pd.read_csv('/kaggle/input/digitrecognition/test.csv')
```

[67]:
```
train_df.head()
```

[67]:
```
   label  pixel0  pixel1  pixel2  pixel3  pixel4  pixel5  pixel6  pixel7  \
0      1       0       0       0       0       0       0       0       0
1      0       0       0       0       0       0       0       0       0
2      1       0       0       0       0       0       0       0       0
3      4       0       0       0       0       0       0       0       0
4      0       0       0       0       0       0       0       0       0

   pixel8  …  pixel774  pixel775  pixel776  pixel777  pixel778  pixel779  \
0       0  …         0         0         0         0         0         0
1       0  …         0         0         0         0         0         0
2       0  …         0         0         0         0         0         0
3       0  …         0         0         0         0         0         0
4       0  …         0         0         0         0         0         0

   pixel780  pixel781  pixel782  pixel783
0         0         0         0         0
1         0         0         0         0
2         0         0         0         0
3         0         0         0         0
4         0         0         0         0

[5 rows x 785 columns]
```

[68]:
```
train_df.shape
```

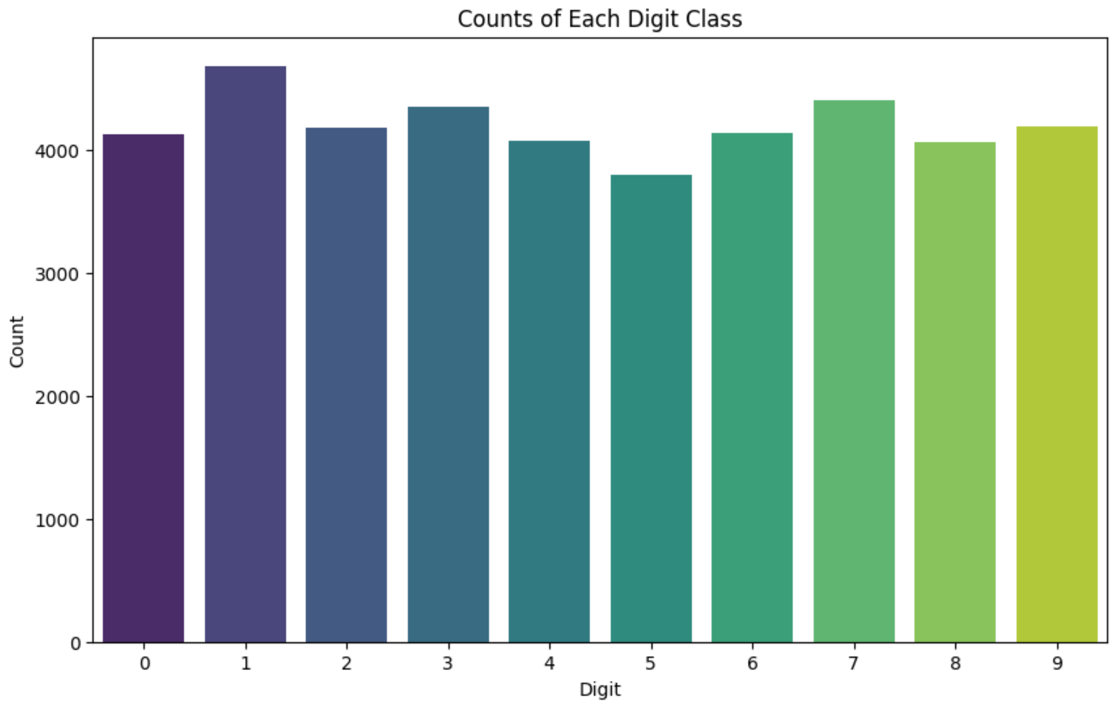
[68]: (42000, 785)

[69]:
```python
y = train_df["label"]
X = train_df.drop(labels=["label"], axis=1)
```

[72]:
```python
digit_counts = y.value_counts()
digit_counts
```

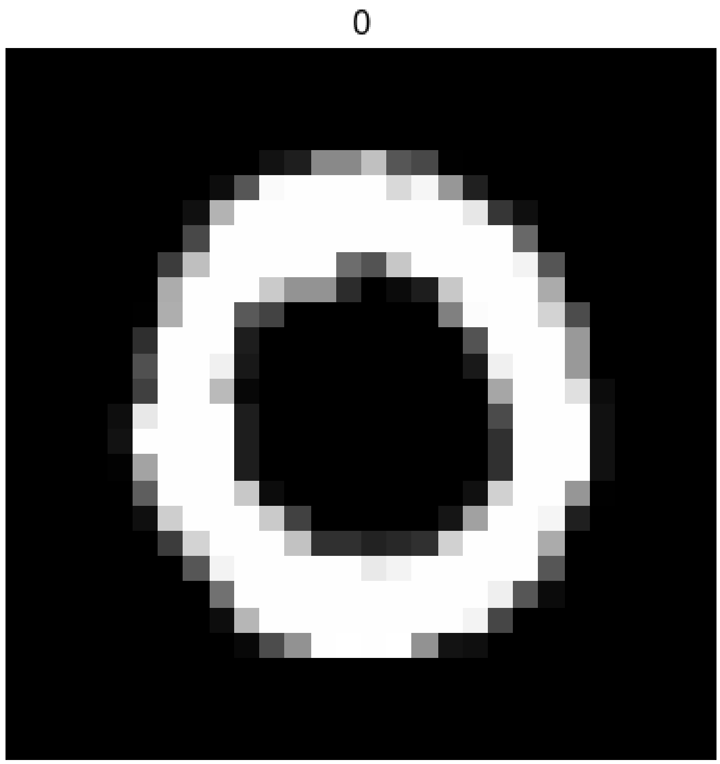
[72]:
```
label
1    4684
7    4401
3    4351
9    4188
2    4177
6    4137
0    4132
4    4072
8    4063
5    3795
Name: count, dtype: int64
```

[74]:
```python
# Plot the count plot with Viridis palette
plt.figure(figsize=(10, 6))
sns.countplot(x=y, palette="viridis")
plt.title("Counts of Each Digit Class")
plt.xlabel("Digit")
plt.ylabel("Count")
plt.xticks(rotation=0)
plt.show()
```



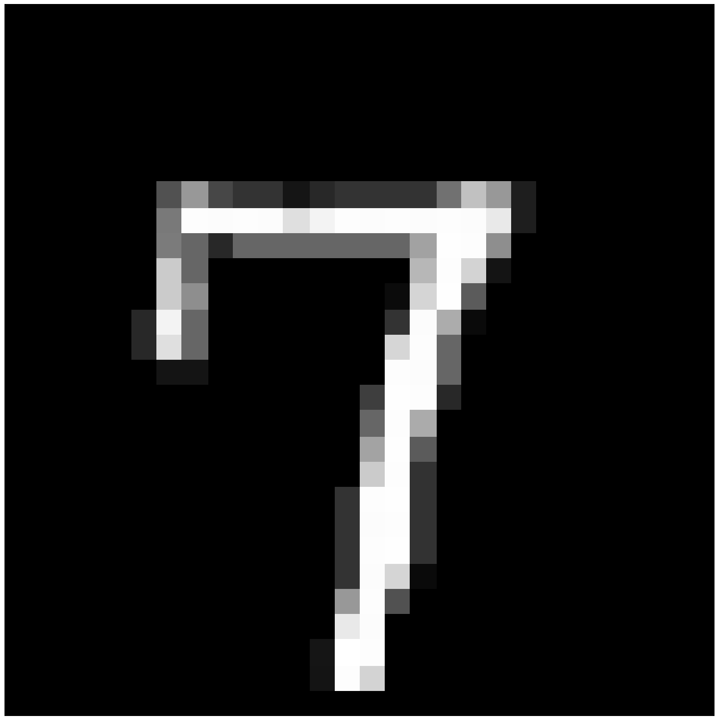
[76]:

```
# Plot the 2nd sample
img = X.iloc[1].values
img = img.reshape((28,28))
plt.imshow(img, cmap='gray')
plt.title(train_df.iloc[1,0])
plt.axis("off")
plt.show()
```



[77]:
```
# Plot the 7th sample
img = X.iloc[6].values
img = img.reshape((28,28))
plt.imshow(img, cmap='gray')
plt.title(train_df.iloc[6,0])
plt.axis("off")
plt.show()
```

7



0.1 Normalization, Reshape and Label Encoding

0.1.1 Normalization

—–We perform a grayscale normalization to reduce the effect of illumination's differences.

—–If we perform normalization, CNN works faster.

0.1.2 Reshape

—–Train and test images (28 x 28)

—–We reshape all data to 28x28x1 3D matrices.

—–Keras needs an extra dimension in the end which correspond to channels. Our images are gray scaled so it use only one channel.

0.1.3 Label Encoding

—-Encode labels to one hot vectors

————–-2 => [0,0,1,0,0,0,0,0,0,0]

————–-4 => [0,0,0,0,1,0,0,0,0,0]

[78]:
```
# Normalize the data
X = X / 255.0
test_df = test_df / 255.0
```

[79]:
```
# Reshape the data
X = X.values.reshape(-1, 28, 28, 1)
test_df = test_df.values.reshape(-1, 28, 28, 1)
```

[80]:
```
from sklearn.preprocessing import LabelEncoder
# Label Encoding
le = LabelEncoder()
y_encoded = le.fit_transform(y)
```

0.2 Train Test Split

We split the data into train and test sets.

test size is 20%.

train size is 80%.

[81]:
```
from sklearn.model_selection import train_test_split
X_train, X_val, y_train, y_val = train_test_split(X, y_encoded, test_size=0.2,␣
↪random_state=2)
```

[83]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D
from keras.optimizers import Adam
from keras.utils import to_categorical

from keras.utils import to_categorical

# Convert labels to one-hot encoding
Y_train = to_categorical(y_train)
Y_val = to_categorical(y_val)

# Define the model architecture
model = Sequential()
model.add(Conv2D(filters=8, kernel_size=(5, 5), padding='Same',␣
↪activation='relu', input_shape=(28, 28, 1)))
model.add(MaxPool2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
```

```
model.add(Conv2D(filters=16, kernel_size=(3, 3), padding='Same',␣
 ↪activation='relu'))
model.add(MaxPool2D(pool_size=(2, 2), strides=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))

# Compile the model
model.compile(optimizer=Adam(), loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

# Train the model
history = model.fit(X_train, Y_train, epochs=10, batch_size=64,␣
 ↪validation_data=(X_val, Y_val), verbose=1)
```

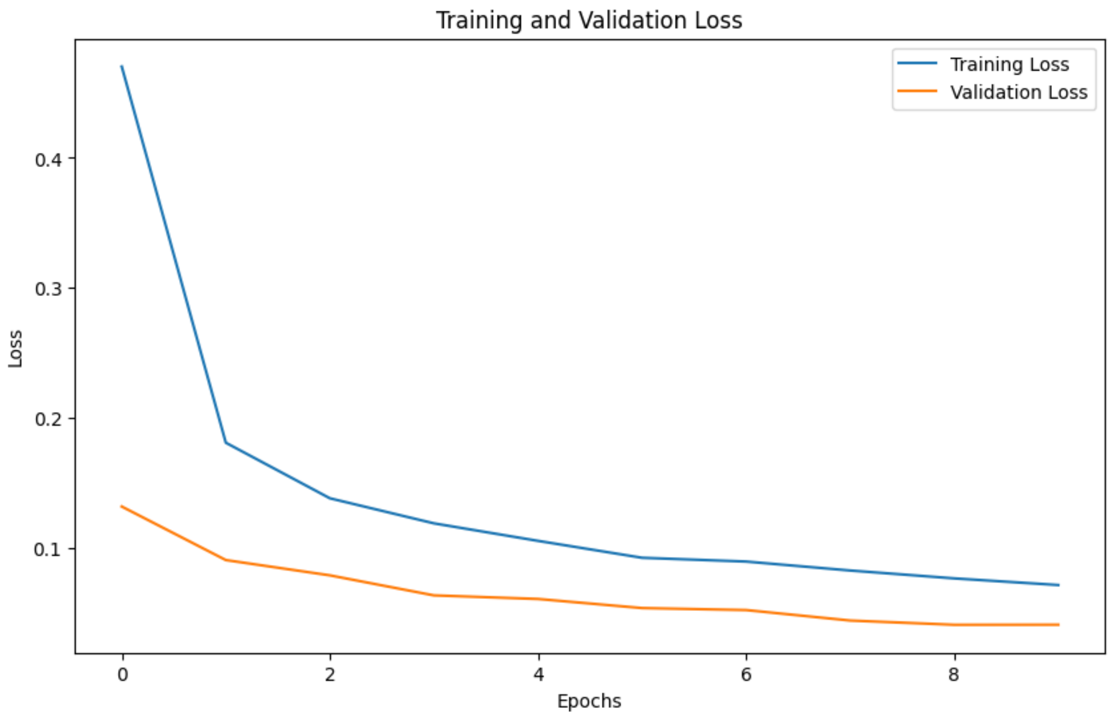
```
Epoch 1/10
525/525              20s 34ms/step -
accuracy: 0.7206 - loss: 0.8540 - val_accuracy: 0.9580 - val_loss: 0.1321
Epoch 2/10
525/525              21s 36ms/step -
accuracy: 0.9381 - loss: 0.1988 - val_accuracy: 0.9708 - val_loss: 0.0909
Epoch 3/10
525/525              20s 35ms/step -
accuracy: 0.9544 - loss: 0.1463 - val_accuracy: 0.9754 - val_loss: 0.0792
Epoch 4/10
525/525              20s 34ms/step -
accuracy: 0.9587 - loss: 0.1266 - val_accuracy: 0.9798 - val_loss: 0.0638
Epoch 5/10
525/525              18s 34ms/step -
accuracy: 0.9648 - loss: 0.1109 - val_accuracy: 0.9801 - val_loss: 0.0611
Epoch 6/10
525/525              18s 34ms/step -
accuracy: 0.9711 - loss: 0.0948 - val_accuracy: 0.9823 - val_loss: 0.0541
Epoch 7/10
525/525              19s 36ms/step -
accuracy: 0.9732 - loss: 0.0850 - val_accuracy: 0.9830 - val_loss: 0.0525
Epoch 8/10
525/525              21s 38ms/step -
accuracy: 0.9744 - loss: 0.0779 - val_accuracy: 0.9856 - val_loss: 0.0445
Epoch 9/10
525/525              19s 36ms/step -
accuracy: 0.9769 - loss: 0.0751 - val_accuracy: 0.9857 - val_loss: 0.0412
Epoch 10/10
525/525              20s 34ms/step -
accuracy: 0.9773 - loss: 0.0712 - val_accuracy: 0.9873 - val_loss: 0.0413
```

0.3 Evaluate the model

Test Loss visualization

Confusion matrix

[84]:
```
# Plot the training and validation loss
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



[86]:
```
# Predict probabilities for each class
y_pred_probs = model.predict(X_val)
y_pred = np.argmax(y_pred_probs, axis=1)
conf_matrix = confusion_matrix(y_val, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(10, 8))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='coolwarm')
plt.title('Confusion Matrix')
```

```
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```

```
263/263                    2s 8ms/step
```