```
'''

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'''
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```
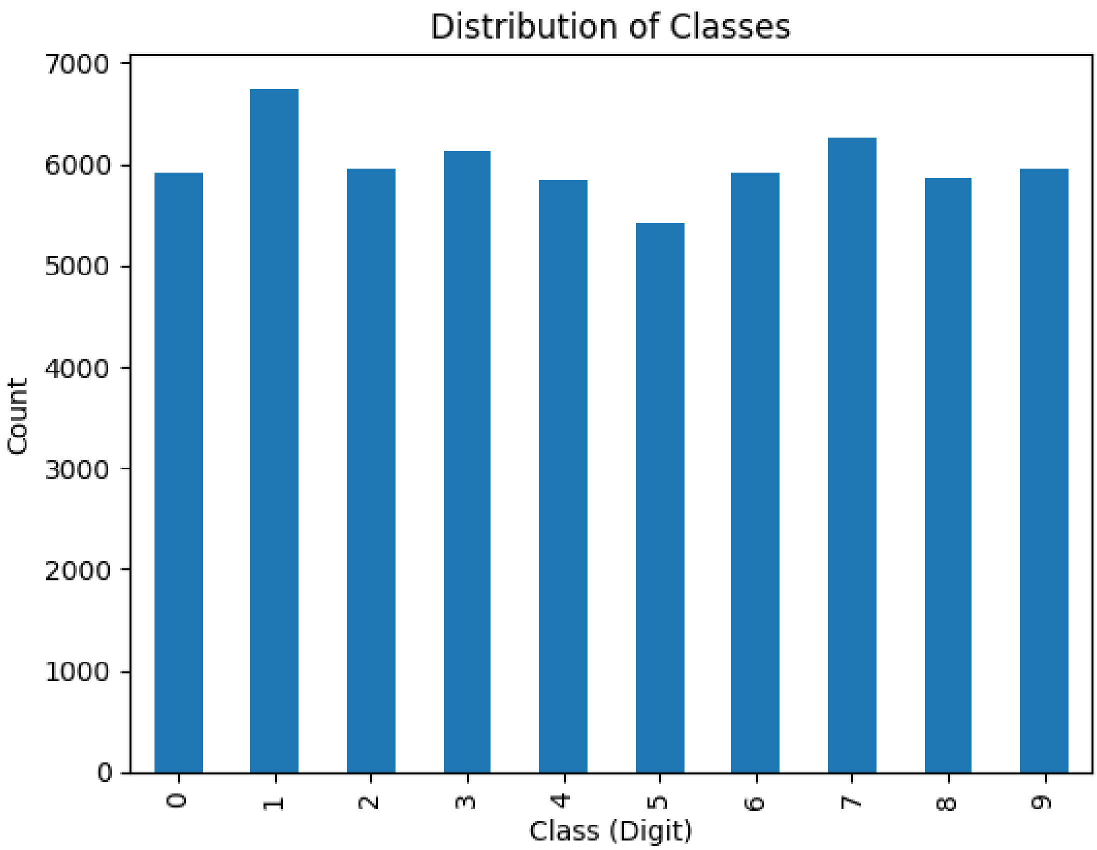

```
# import libraries.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from skimage.transform import resize
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

## (a) Data Exploration and preparation:
# Load the dataset and perform initial data exploration.
data_train = pd.read_csv('/kaggle/input/mnist-in-csv/mnist_train.csv')
data_test = pd.read_csv('/kaggle/input/mnist-in-csv/mnist_test.csv')

# Visualize the distribution of classes (labels)
data_train['label'].value_counts().sort_index().plot(kind='bar')
plt.title('Distribution of Classes')
plt.xlabel('Class (Digit)')
plt.ylabel('Count')
plt.show()


# Begin by familiarizing yourself with the dataset.
print("First five rows of the training data:")
print(data_train.head())


#  Identify the number of unique classes.
num_classes = data_train['label'].nunique()
print("Number of unique classes:",num_classes)


# Identify the number of features.
```

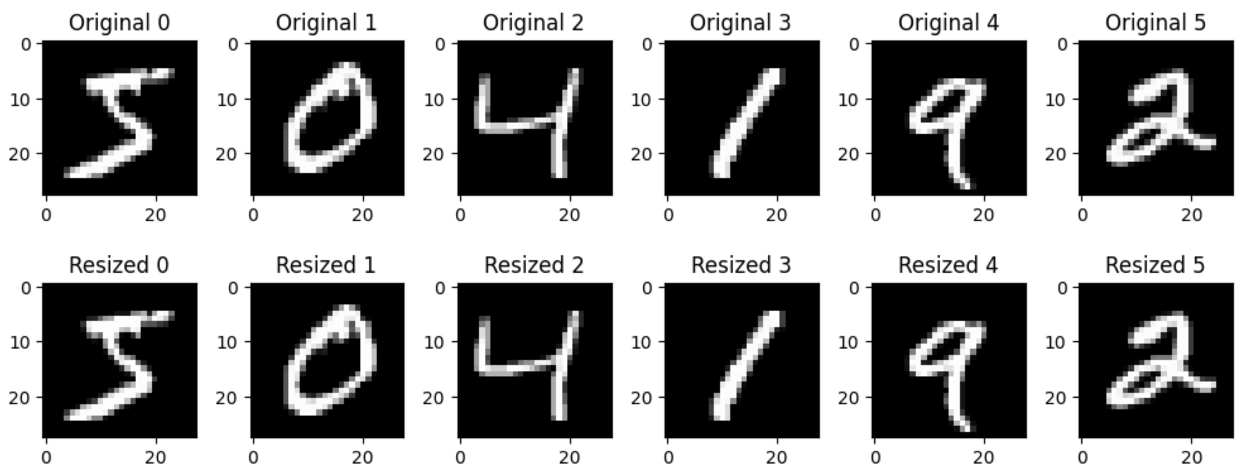
```
num_features = len(data_train.columns) - 1  # Subtract 1 for the label
column
print("Number of features:",num_features)


# Check for missing values.
missing_values = data_train.isnull().sum()
print("\nMissing values in the train data:")
print(missing_values)
missing_values1 = data_test.isnull().sum()
print("\nMissing values in the test data:")
print(missing_values1)


# Extract labels and pixel (target and features) values from the
training data.
train_labels = data_train['label'].values # Target
train_pixels = data_train.drop('label', axis=1).values # Feauters

test_labels = data_test['label'].values # Target
test_pixels = data_test.drop('label', axis=1).values # Feauters

# Normalize each image by dividing each pixel by 255.
train_pixels_normalized = train_pixels / 255.0
test_pixels_normalized = test_pixels / 255.0

# Resize images to dimensions of 28 by 28.
train_images_resized = np.array([resize(img.reshape(28, 28), (28, 28))
for img in train_pixels_normalized])
test_images_resized = np.array([resize(img.reshape(28, 28), (28, 28))
for img in test_pixels_normalized])

# After resizing, visualize some images to verify the correctness of
the reshaping process.
num_images = 6
plt.figure(figsize=(10, 4))

for i in range(num_images):
    plt.subplot(2, num_images, i + 1)
    plt.imshow(train_pixels_normalized[i].reshape(28, 28),
cmap='gray')
    plt.title(f"Original {i}")

    plt.subplot(2, num_images, i + 1 + num_images)
    plt.imshow(train_images_resized[i], cmap='gray')
    plt.title(f"Resized {i}")

plt.tight_layout()
plt.show()
```

```python
# Split the training data (mnist_train) into training and validation sets.
X_train, X_test, y_train, y_test =
train_test_split(train_images_resized, train_labels, test_size=0.25,
random_state=42)

# reshape data test
test_features =
test_images_resized.reshape(test_images_resized.shape[0], -1)
```




```
First five rows of the training data:
   label  1x1  1x2  1x3  1x4  1x5  1x6  1x7  1x8  1x9  ...  28x19
28x20  \
0      5    0    0    0    0    0    0    0    0    0  ...      0
0
1      0    0    0    0    0    0    0    0    0    0  ...      0
0
2      4    0    0    0    0    0    0    0    0    0  ...      0
0
3      1    0    0    0    0    0    0    0    0    0  ...      0
0
4      9    0    0    0    0    0    0    0    0    0  ...      0
```

```
0

   28x21  28x22  28x23  28x24  28x25  28x26  28x27  28x28
0      0      0      0      0      0      0      0      0
1      0      0      0      0      0      0      0      0
2      0      0      0      0      0      0      0      0
3      0      0      0      0      0      0      0      0
4      0      0      0      0      0      0      0      0

[5 rows x 785 columns]
Number of unique classes: 10
Number of features: 784

Missing values in the train data:
label    0
1x1      0
1x2      0
1x3      0
1x4      0
        ..
28x24    0
28x25    0
28x26    0
28x27    0
28x28    0
Length: 785, dtype: int64

Missing values in the test data:
label    0
1x1      0
1x2      0
1x3      0
1x4      0
        ..
28x24    0
28x25    0
28x26    0
28x27    0
28x28    0
Length: 785, dtype: int64
```




```
import keras
import seaborn as sns
from keras.layers import Dense
from keras.optimizers import SGD
from keras.models import Sequential
from sklearn.metrics import confusion_matrix

# Handling the shape of the data.
X_train = X_train.reshape(X_train.shape[0],784)
X_test = X_test.reshape(X_test.shape[0],784)
y_train = keras.utils.to_categorical(y_train, 10)
y_test = keras.utils.to_categorical(y_test, 10)

# Experiment 1

# Architecture 1
first_model = Sequential()
first_model.add(Dense(units = 512, activation ='relu', input_shape =
(784,)))
first_model.add(Dense(units = 256, activation = 'relu'))
first_model.add(Dense(units = 128, activation = 'relu'))
first_model.add(Dense(units = 64, activation = 'relu'))
first_model.add(Dense(units = 10, activation = 'softmax'))
first_model.compile(optimizer = SGD(0.001), loss =
'categorical_crossentropy', metrics = ['accuracy'])
first_model.fit(X_train, y_train,  batch_size = 32, epochs =
10,verbose = 1)
accuracy1 = first_model.evaluate(x = X_test,y = y_test,batch_size =
32)
print("Score for model 1 =",accuracy1[1])

# Architecture 2
second_model = Sequential()
second_model.add(Dense(units = 256, activation = 'relu', input_shape =
(784,)))
```

```
second_model.add(Dense(units = 64, activation = 'sigmoid'))
second_model.add(Dense(units = 10, activation = 'softmax'))
second_model.compile(optimizer = SGD(0.0001), loss =
'categorical_crossentropy', metrics = ['accuracy'])
second_model.fit(X_train, y_train,  batch_size = 64, epochs =
10,verbose = 1)
accuracy2 = second_model.evaluate(x = X_test,y = y_test,batch_size =
64)
print("Score for model 2 =",accuracy2[1])

# Get the confusion matrix of the best model.
def conf_matrix_ann(model):
    print("ANN Confusion Matrix.")
    # Get predictions from the models
    y_pred = np.argmax(model.predict(X_test), axis=1)
    # Calculate the confusion matrices
    conf_matrix = confusion_matrix(np.argmax(y_test, axis=1), y_pred)
    # Display the confusion matrix using seaborn
    plt.figure(figsize = (8, 6))
    sns.heatmap(conf_matrix, annot = True, fmt = 'd', cmap = 'Blues',
xticklabels = range(10), yticklabels = range(10))
    plt.title('Confusion Matrix for the best architecture')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.show()

ann_best_model = Sequential()

if(accuracy1[1] >= accuracy2[1]):
    # Save the best architecture.
    ann_best_model = first_model
else:
    # Save the best architecture.
    ann_best_model = second_model

Ann_accuracy = ann_best_model.evaluate(x = X_test,y =
y_test,batch_size = 64)
print("Score for best architecture =",Ann_accuracy[1])
```

```
Epoch 1/10
1407/1407 [==============================] - 6s 3ms/step - loss:
1.9513 - accuracy: 0.5033
Epoch 2/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.9950 - accuracy: 0.7875
Epoch 3/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.5651 - accuracy: 0.8585
Epoch 4/10
1407/1407 [==============================] - 5s 3ms/step - loss:
```

```
0.4400 - accuracy: 0.8813
Epoch 5/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.3825 - accuracy: 0.8939
Epoch 6/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.3477 - accuracy: 0.9026
Epoch 7/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.3226 - accuracy: 0.9096
Epoch 8/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.3031 - accuracy: 0.9142
Epoch 9/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.2871 - accuracy: 0.9189
Epoch 10/10
1407/1407 [==============================] - 5s 3ms/step - loss:
0.2734 - accuracy: 0.9232
469/469 [==============================] - 1s 2ms/step - loss: 0.2770
- accuracy: 0.9206
Score for model 1 = 0.9205999970436096
Epoch 1/10
704/704 [==============================] - 3s 3ms/step - loss: 2.6129
- accuracy: 0.1040
Epoch 2/10
704/704 [==============================] - 2s 3ms/step - loss: 2.5413
- accuracy: 0.1135
Epoch 3/10
704/704 [==============================] - 2s 3ms/step - loss: 2.4831
- accuracy: 0.1243
Epoch 4/10
704/704 [==============================] - 2s 3ms/step - loss: 2.4356
- accuracy: 0.1371
Epoch 5/10
704/704 [==============================] - 2s 3ms/step - loss: 2.3965
- accuracy: 0.1502
Epoch 6/10
704/704 [==============================] - 2s 3ms/step - loss: 2.3640
- accuracy: 0.1638
Epoch 7/10
704/704 [==============================] - 2s 3ms/step - loss: 2.3367
- accuracy: 0.1767
Epoch 8/10
704/704 [==============================] - 2s 3ms/step - loss: 2.3135
- accuracy: 0.1892
Epoch 9/10
704/704 [==============================] - 2s 3ms/step - loss: 2.2936
- accuracy: 0.2006
```

```
Epoch 10/10
704/704 [==============================] - 2s 3ms/step - loss: 2.2763
- accuracy: 0.2107
235/235 [==============================] - 1s 2ms/step - loss: 2.2721
- accuracy: 0.2187
Score for model 2 = 0.21873334050178528
235/235 [==============================] - 1s 3ms/step - loss: 0.2770
- accuracy: 0.9206
Score for best architecture = 0.9205999970436096
```

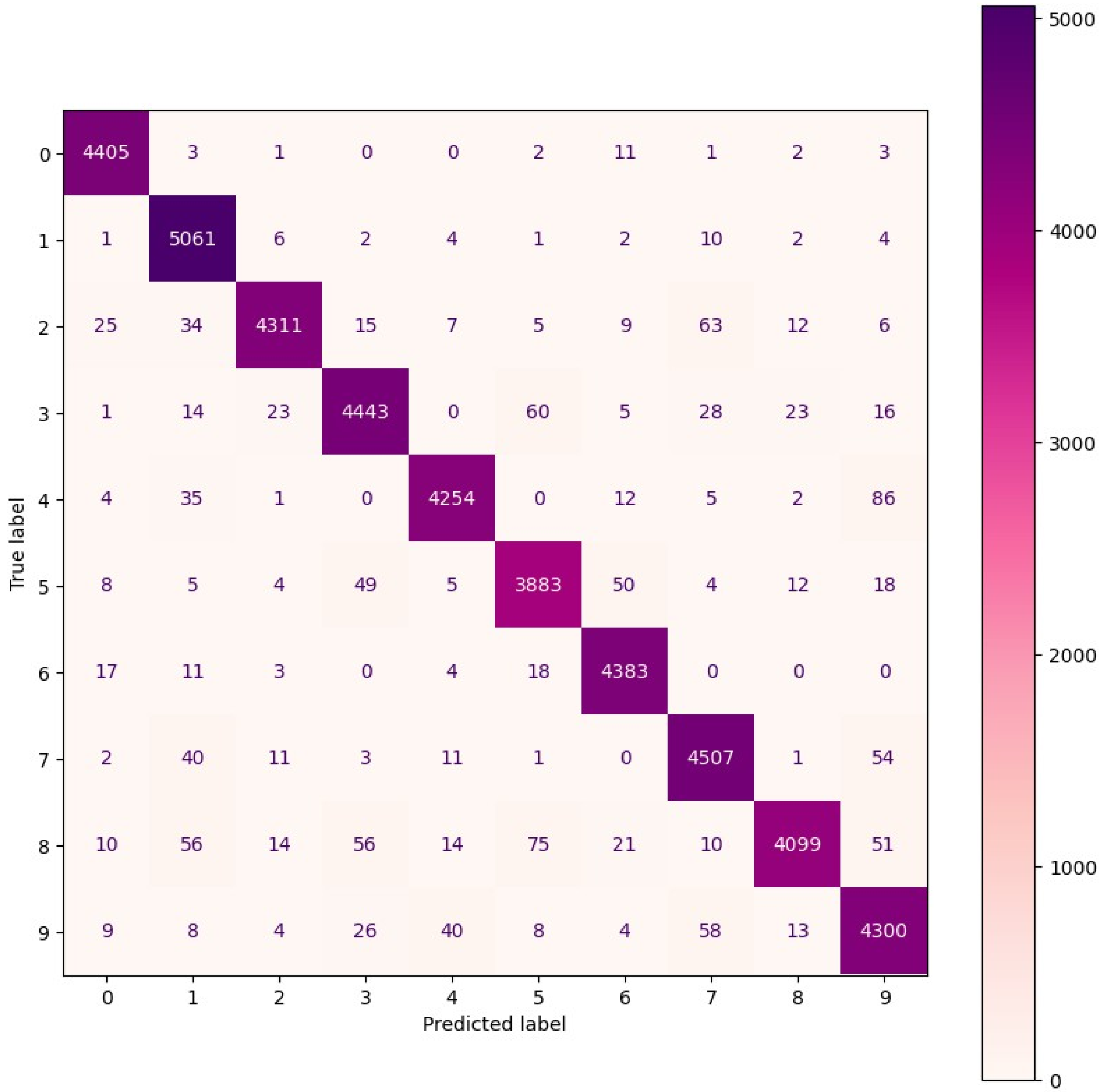
```
from sklearn.model_selection import GridSearchCV,cross_val_predict
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, ConfusionMatrixDisplay


# Split the training data (mnist_train) into training and validation
sets.
X_train_flat =
train_images_resized.reshape(train_images_resized.shape[0], -1)
X_train, X_test, y_train, y_test = train_test_split(X_train_flat,
train_labels, test_size=0.25, random_state=42)

# Trying three different values for neighbors.
trials_of_grid={
  'n_neighbors': [3,5,7],
  'weights': ['uniform', 'distance']
}


KNN_Model=KNeighborsClassifier()

# KNN Model using Grid Search
KNN_Grid_Search=GridSearchCV(KNN_Model,trials_of_grid,cv=5)
KNN_Grid_Search.fit(X_train,y_train)

#finding best parameters for nearst neighbors and weight too
Best_K=KNN_Grid_Search.best_params_
Best_KNN_Model=KNeighborsClassifier(n_neighbors=Best_K['n_neighbors'],
weights=Best_K['weights'])

Best_KNN_Model.fit(X_train,y_train)
y_predict=Best_KNN_Model.predict(X_test)

#calculating accuracy
Knn_accuracy=accuracy_score(y_predict,y_test)
print("KNN-Accuracy =", Knn_accuracy)

# Confusion_Matrix
def conf_matrix_knn():
    print("KNN Confusion Matrix.")
```

```
predications_KNN=cross_val_predict(Best_KNN_Model,X_train,y_train,cv=5
)
    Confusion_Matrix=confusion_matrix(y_train,predications_KNN)
    # Display_Confusion_Matrix
    cm_fig, cm_ax = plt.subplots(figsize=(10, 10))
    Confusion_Matrix_display=ConfusionMatrixDisplay(Confusion_Matrix)
    Confusion_Matrix_display.plot(ax=cm_ax, cmap=plt.cm.RdPu)
    plt.show()
```

```
KNN-Accuracy = 0.9716
```

```
import joblib

# Save the best model, then reload it in a separate file.
if(Ann_accuracy[1] > Knn_accuracy):
    print("ANN is better.")
    # Get the confusion matrix.
    conf_matrix_ann(ann_best_model)
    ann_best_model.save('best_model.h5')
    best_model_loaded = keras.models.load_model('best_model.h5')

else:
    print("KNN is better.")
    # Get the confusion matrix.
    conf_matrix_knn()
    joblib.dump(Best_KNN_Model, 'best_knn_model.joblib')
    best_model_loaded = joblib.load('best_knn_model.joblib')


y_pred = best_model_loaded.predict(test_features)
accuracy=accuracy_score(y_pred, test_labels)
print("The accuracy for the best model loaded =", accuracy)
```

```
KNN is better.
KNN Confusion Matrix.
```




```
The accuracy for the best model loaded = 0.9692
```