Module 7 Assignment 1: Digit Recognizer Using the MNIST Dataset

Background and Motivation

This analysis was performed on the MNIST dataset, made available via the "Digit Recognizer - Learn Computer Vision Fundamentals with the Famous MNIST Data" Kaggle competition. The dataset contains 60,000 handwritten numbers, represented as a 28x28 pixel image with each pixel's level of shading captured. The "training" dataset is enriched with the number captured in the image. Successful work with this dataset allows for the application of computer vision to automate scanning of handwritten numbers for, e.g., postal mail or bank check details.

Approaches to Pre-Processing the Data

The original dataset contained 784 pixels, scored from 0-255 representing the depth of shading. Since all metrics were scaled identically, no further processing was performed. A 20% holdout was used for validation, and the 80% training set was enriched through image manipulation. Each image in the training set was permuted three times in three ways, for a 10x multiplier of training images:

- **Permutation 1**: random translation and rotation of the image
- **Permutation 2**: random translation and zoom in/out on the image
- **Permutation 3**: random translation, zooming, and rotation.

Modeling Approach

The focus this week was on developing artificial neural networks, comparing the impact of varying the number of hidden layers and nodes per layer. Six network structures were tested: 2 hidden layers with 100 nodes each, 2 hidden layers with 200 nodes each, 3 hidden layers with 100 nodes each, 3 hidden layers with 200 nodes each, 5 hidden layers with 100 nodes each, and 5 hidden layers with 200 nodes each. All networks used a ReLU activation function, a default learning rate, and a dropout rate of 0.2 to mitigate overfitting.

Training Results and Kaggle Submission Scores (Trained on Google Collab T4 GPU)

Layer	Node	Epoch	Training Time	Training Accuracy	Validation Accuracy	Kaggle Score
2	100	10	0:02:51.095087	0.8887	0.9698	0.96982
2	200	10	0:03:33.783321	0.9209	0.9745	0.97542
3	100	10	0:03:17.633334	0.8971	0.9732	0.96946
3	200	10	0:03:08.757135	0.9287	0.9783	0.97610
5	100	10	0:03:25.177272	0.8944	0.9732	0.96971
5	200	10	0:03:23.110893	0.9311	0.9785	0.97700

Evaluation and Discussion

The models were evaluated based on their training accuracy, validation accuracy, and Kaggle submission scores. As seen in the results, models with more layers and nodes generally performed better, achieving higher validation accuracy and Kaggle scores. Specifically, the model with 5 layers and 200 nodes per layer showed the highest validation accuracy and a Kaggle score of 0.9785. The increase in layers and nodes provided better learning capacity for the models, which translated into better performance on unseen data.

The use of data augmentation significantly enhanced the training process by providing more diverse training samples, thus reducing overfitting and improving model generalization. The data augmentation techniques included random translations, rotations, and zooms, which helped in creating varied versions of the original images, making the model more robust to variations in handwritten digits.

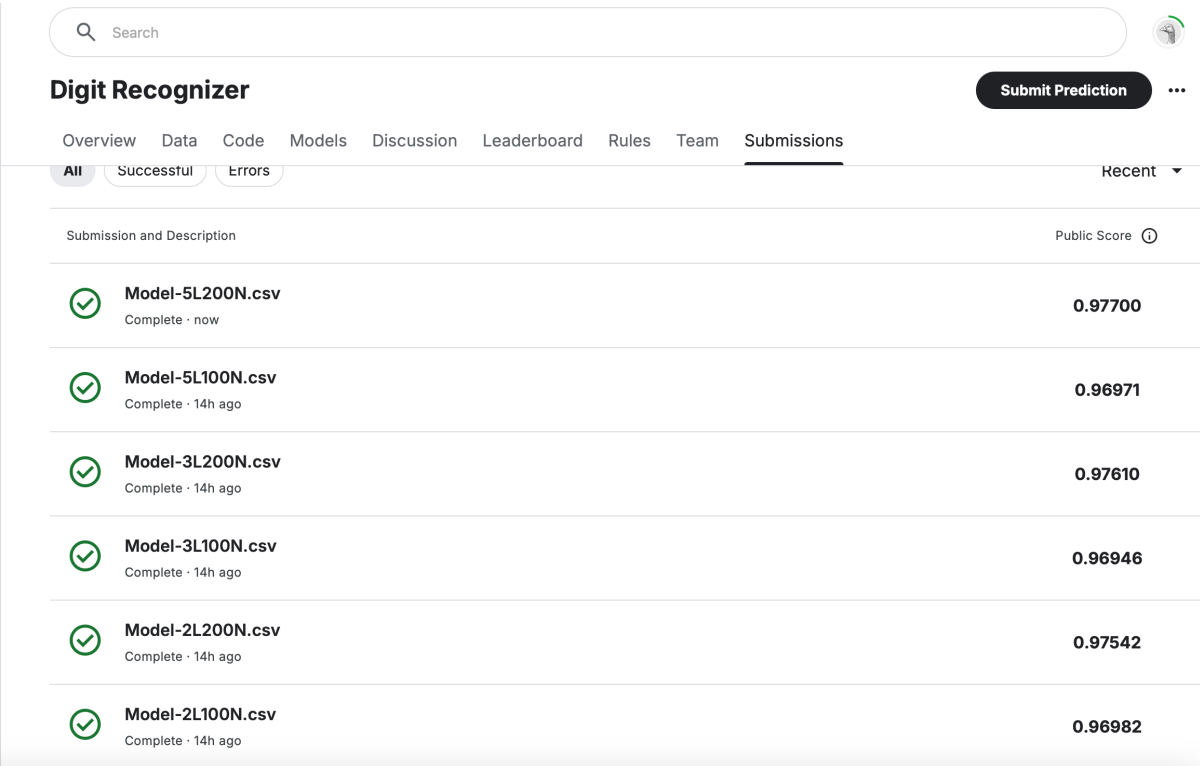
The time taken for training each model varied, with the models having 200 nodes per layer generally taking longer than those with 100 nodes. This increase in training time is expected due to the larger number of parameters being optimized during training.

Appendix:

Kaggle Details

Username: sachinsharma03

Submission Screenshot



Python Code

Module 7 Assignment 1: Digit Recognizer

Sachin Sharma

MSDS-422

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Management/Research Question

In layman's terms, what is the management/research question of interest, and why would anyone care?

Requirements

1. Conduct your analysis using a cross-validation design.
2. Conduct / refine EDA.
3. Conduct Design of Experiments to evaluate the performance of various neural networks by changing the layers and nodes. Tested neural network structures should be explored within a benchmark experiment, a 2x2 completely crossed design. An example of a completely crossed designed with {2, 5} layers and {10,20} nodes follows.

Layers	Nodes	Time	Training Accuracy	Testing Accuracy
2	10	63.61	0.935	0.927
2	20	115.25	0.967	0.952
5	10	74.28	0.944	0.933
5	20	75.1	0.964	0.952

1. Due to the time required to fit each neural network, we will observe only one trial for each cell in the design.
2. You will build your models on csv and submit your forecasts for test.csv to Kaggle.com, providing your name and user ID for each experimental trial.
3. Evaluate goodness of fit metrics on the training and validation sets.
4. Provide a multi-class confusion matrix.
5. Discuss how your models performed.

Libraries to be loaded

```
import matplotlib as mpl
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from datetime import datetime
from scipy import stats
from sklearn.model_selection import train_test_split, StratifiedKFold
```

```
from sklearn.metrics import confusion_matrix
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
import tensorflow.keras.layers as preprocessing
import warnings
import os
# Ignore all FutureWarnings
warnings.filterwarnings('ignore')

from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly
remount, call drive.mount("/content/drive", force_remount=True).
```

```
%cd drive/MyDrive
```

```
/content/drive/MyDrive
```

```
def set_seed(seed=422):
    np.random.seed(seed)
    tf.random.set_seed(seed)
    os.environ['PYTHONHASHSEED'] = str(seed)
    os.environ['TF_DETERMINISTIC_OPS'] = '1'
set_seed()
```

Ingest

```
df_train = pd.read_csv("MNIST/train.csv")
df_train.name = 'Training Set'
df_train.shape
```

```
(42000, 785)
```

```
df_train.describe()
```


```
{"type":"dataframe"}
```


```
df_test = pd.read_csv("MNIST/test.csv")
df_test.name = 'Test Set'
df_test.shape
```

```
(28000, 784)
```

EDA

```
print("Null values in Train DF: ",df_train.isna().sum().sum())
print("Null values in Test DF: ",df_test.isna().sum().sum())
```

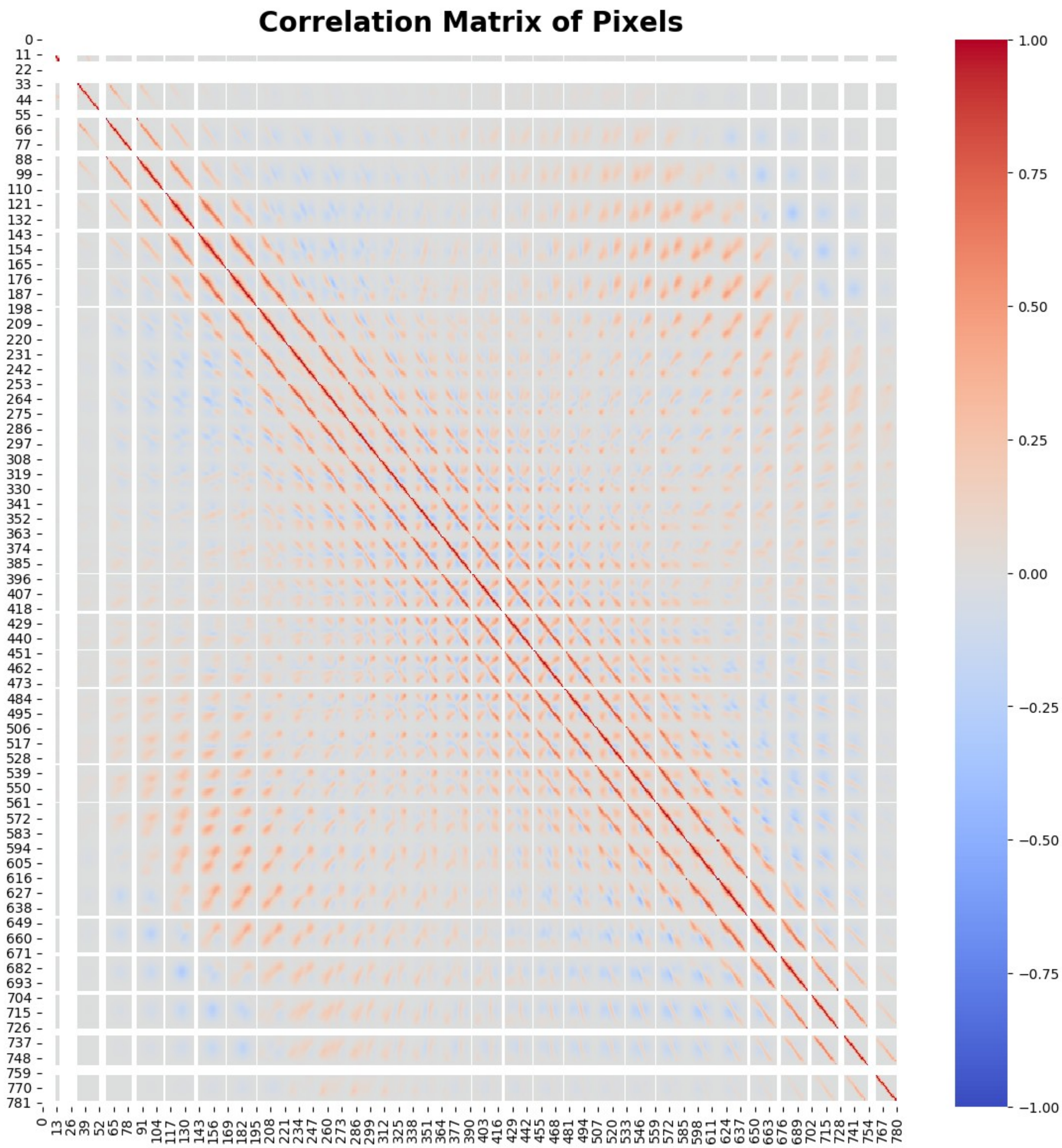
```
Null values in Train DF:  0
Null values in Test DF:  0
```

```
dfs = [df_train, df_test]

for df in dfs:
  obs = df.shape[0]
  tot = df.shape[1]
  numeric = df.select_dtypes(include=np.number).shape[1]
  categorical = df.select_dtypes(exclude=np.number).shape[1]
  print('In {} we have {} observations, {} variables: {} numeric and
{} categorical'.format(df.name, obs, tot, numeric, categorical))
```

```
In Training Set we have 42000 observations, 785 variables: 785 numeric
and 0 categorical
In Test Set we have 28000 observations, 784 variables: 784 numeric and
0 categorical
```

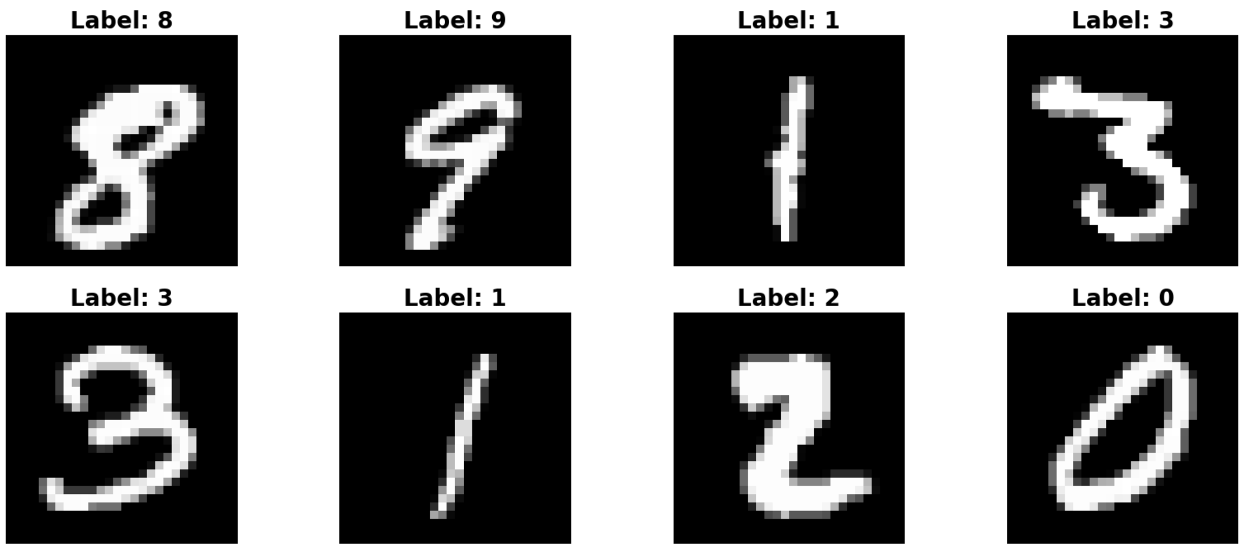
Let's output some sample digits as a 28x28 pixel image.

```
# Compute the correlation matrix
images = df_train.drop(columns=['label']).values
labels = df_train['label'].values

flat_images = images.reshape(-1, 28*28)
correlation_matrix = np.corrcoef(flat_images.T)

# Plot the correlation matrix
plt.figure(figsize=(14, 14))
sns.heatmap(correlation_matrix, cmap='coolwarm', vmin=-1, vmax=1)
plt.title("Correlation Matrix of Pixels", size=20, fontweight='bold')
plt.show();
```




```python
labels = df_train['label'].values
images = df_train.drop(columns=['label']).values

# Reshape the images
images = images.reshape(-1, 28, 28)

# Combine images and labels into a single dataset
dataset = list(zip(images, labels))

# Plot images from the dataset with their corresponding labels
```

```
plt.figure(figsize=(20, 8))
for i in range(10, 18):
    image, label = dataset[i]
    plt.subplot(2, 4, i-9)  # Adjust subplot indexing to match the
desired layout (2 rows, 4 columns)
    plt.imshow(image, cmap='gray')
    plt.title('Label: ' + str(label), fontweight='bold', size=20)
    plt.axis('off')  # Turn off axis

plt.show()
```



Let's look at the distribution of digits in the training set.

```
# Set the style and color palette
sns.set(style="whitegrid", palette="pastel")

# Create the figure and axis objects
fig, ax = plt.subplots(figsize=(18, 6))

# Plot the countplot
sns.countplot(x='label', data=df_train, ax=ax)

# Customize the plot
ax.set_title("Class Distribution", size=24, fontweight='bold')
ax.set_ylabel("No. of Observations", size=20)
ax.set_xlabel("Class Name", size=20)
ax.tick_params(axis='both', which='major', labelsize=14)
ax.tick_params(axis='x', rotation=45)  # Rotate x-axis labels for
better readability

# Remove the top and right spines
sns.despine()
```

```python
# Show the plot
plt.show()
```


```python
df_train['label'].value_counts().sort_values()
```

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

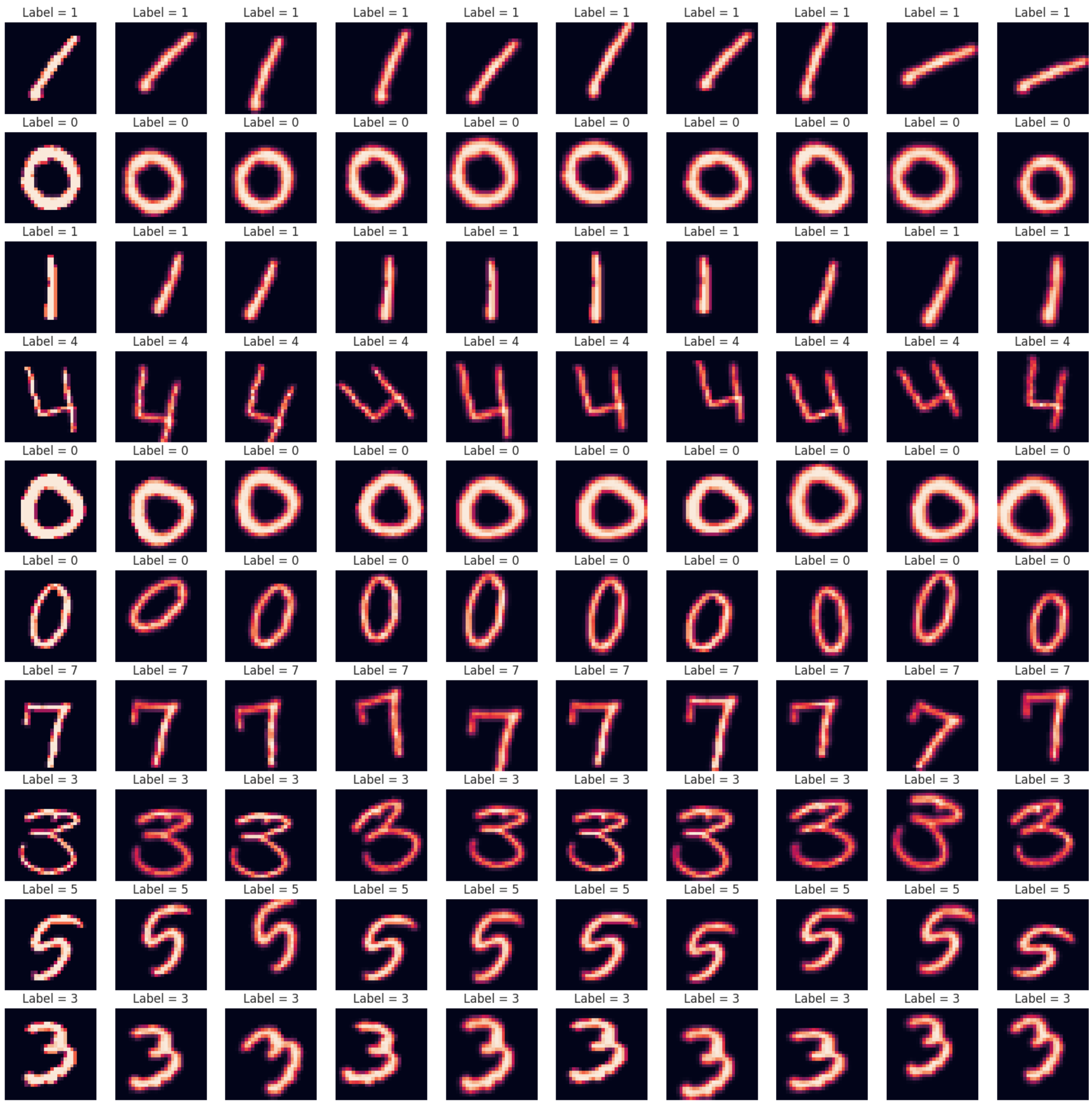
```python
df_train_original = df_train.copy()
df_test_original = df_test.copy()

# ntrain allows us to keep track of the length of the training set for
later segmentation of train/test
ntrain = df_train.shape[0]

y_var = 'label'
y_train_original = df_train[y_var]
y_train = y_train_original.copy()

df_train.drop([y_var], axis=1, inplace=True)
df_train = df_train.astype(float) / 255 # This converts all of the
shadings from 0-255 --> 0-1
df_test = df_test.astype(float) / 255 # Same as above

df_train = df_train.to_numpy().reshape(df_train.shape[0],28,28,1)  #
```

```
This reorients the data into the shape Keras expects
df_test = df_test.to_numpy().reshape(df_test.shape[0],28,28,1) # Same
as above
```

Augmentation Function

```
def data_augmentation(X, y):

    # Defining the data augmentations using Keras preprocessing layers
    data_augmentation1 = keras.Sequential([
        preprocessing.RandomTranslation(height_factor=0.1,
width_factor=0.1, fill_mode='constant'),
        preprocessing.RandomRotation(factor=0.1, fill_mode='constant')
    ])

    data_augmentation2 = keras.Sequential([
        preprocessing.RandomTranslation(height_factor=0.1,
width_factor=0.1, fill_mode='constant'),
        preprocessing.RandomZoom(height_factor=0.15,
width_factor=0.15, fill_mode='constant')
    ])

    data_augmentation3 = keras.Sequential([
        preprocessing.RandomTranslation(height_factor=0.1,
width_factor=0.1, fill_mode='constant'),
        preprocessing.RandomZoom(height_factor=0.15,
width_factor=0.15, fill_mode='constant'),
        preprocessing.RandomRotation(factor=0.1, fill_mode='constant')
    ])

    # Generating the augmented samples
    X_new1_1 = data_augmentation1(X)
    X_new1_2 = data_augmentation1(X)
    X_new1_3 = data_augmentation1(X)
    X_new2_1 = data_augmentation2(X)
    X_new2_2 = data_augmentation2(X)
    X_new2_3 = data_augmentation2(X)
    X_new3_1 = data_augmentation3(X)
    X_new3_2 = data_augmentation3(X)
    X_new3_3 = data_augmentation3(X)

    # Concatenating X with the augmented samples
    X = np.concatenate((X, X_new1_1, X_new1_2, X_new1_3, X_new2_1,
X_new2_2, X_new2_3, X_new3_1, X_new3_2, X_new3_3))
    y = pd.concat([y, y.copy(), y.copy(), y.copy(), y.copy(),
y.copy(), y.copy(), y.copy(), y.copy(), y.copy()], ignore_index=True)

    return X, y
```

```python
X10 = df_train[0:10]
y10 = y_train[0:10]
X100, y100 = data_augmentation(X10, y10)

fig=plt.figure(figsize=(20,20))
pos = 1
for i in range(0, 10):
    for j in range(i+0, i+100, 10):
        fig.add_subplot(10, 10, pos)
        plt.imshow(tf.squeeze(X100[j]))
        plt.title('Label = ' + str(y100[j]))
        plt.axis('off')
        pos = pos + 1
plt.show()
```



Build Neural Networks (6 Models)

1. 2 Layers 100 Nodes
2. 2 Layers 200 Nodes
3. 3 Layers 100 Nodes
4. 3 Layers 200 Nodes
5. 5 Layers 100 Nodes
6. 5 Layers 200 Nodes

```
def build_model(hidden_layers, hidden_nodes, dropout):

  model = tf.keras.models.Sequential()
```

```
  model.add(tf.keras.layers.Flatten(input_shape=[28, 28]))

  for i in range(1,hidden_layers+1):
    model.add(tf.keras.layers.Dense(hidden_nodes, activation='relu'))
    model.add(tf.keras.layers.Dropout(dropout))
  model.add(tf.keras.layers.Dense(10, activation="softmax"))

  model.compile(loss="sparse_categorical_crossentropy",
optimizer="sgd", metrics=["accuracy"])

  return model

model = build_model(hidden_layers = 2, hidden_nodes = 300, dropout =
0.2)
model.summary()
```

```
Model: "sequential_3"
```

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 300)	235,500
dropout (Dropout)	(None, 300)	0
dense_1 (Dense)	(None, 300)	90,300
dropout_1 (Dropout)	(None, 300)	0
dense_2 (Dense)	(None, 10)	3,010

```
 Total params: 328,810 (1.25 MB)
```

```
 Trainable params: 328,810 (1.25 MB)

 Non-trainable params: 0 (0.00 B)

N_EPOCHS = 10
# Cross Validation with N_SPLITS.
N_SPLITS = 5
N_ITERATION = 1
```

Model 1 (2 layers, 100 node) Training with Cross-Validation

```
start_time = datetime.now()
# Creating hist_df to store history objects for each training / split
hist_df = pd.DataFrame(columns=['iteration', 'history'])
iteration = 1
index = 0

hidden_layers = 2
hidden_nodes = 100
dropout = 0.2

saved_model = False
X_train = df_train.reshape(42000, 784)

skf = StratifiedKFold(n_splits = N_SPLITS, shuffle = True,
random_state = 422)
for train_index, val_index in skf.split(X_train, y_train):

    # Getting the training set and validation set before data
augmentation
    X_train_, X_val_ = X_train[train_index], X_train[val_index]
    X_train_ = X_train_.reshape(33600,28,28,1) # Reshaping X_train to
Keras input format
    X_val_ = X_val_.reshape(8400,28,28,1) # Reshaping X_val to Keras
input format
    y_train_, y_val_ = y_train[train_index], y_train[val_index]

    # Generating augmented samples
    X_train_, y_train_ = data_augmentation(X_train_, y_train_)

    # Building the model
    model = build_model(hidden_layers, hidden_nodes, dropout)

    # EDIT THE NEXT ROW FOR EACH MODEL
    checkpoint_cb =
tf.keras.callbacks.ModelCheckpoint("MNIST/checkpoint/Model-
2L100N.keras", save_best_only=True)
    early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=10,
restore_best_weights=True)

    # Training and evaluating each model for this split
```

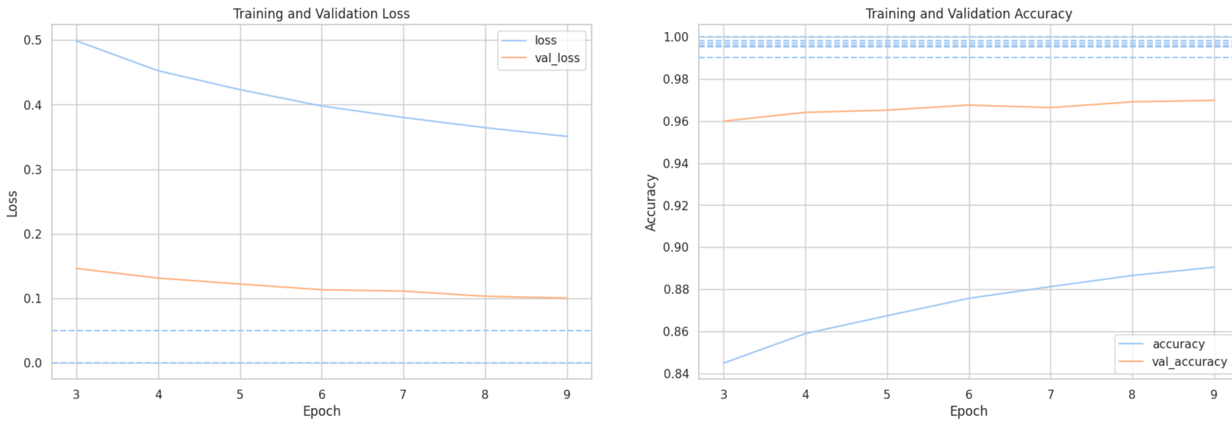
```
    history = model.fit(x = X_train_, y = y_train_, 
validation_data=(X_val_, y_val_),
                        epochs=N_EPOCHS, batch_size=64, 
callbacks=[checkpoint_cb, early_stopping_cb])

    # Saving the trained model as a saved model file -- only one model 
is saved
    if(saved_model == False):
        model.save('MNIST/trained_models/Model-2L100N.keras')
        saved_model = True

    # Storing the history objects into a dataframe
    hist_df.loc[index, 'iteration'] = iteration
    hist_df.loc[index, 'history'] = history

    if(iteration == N_ITERATION):
        break

    index = index + 1
    iteration = iteration + 1

end_time = datetime.now()
print('\nTime taken to Train Model with 2 Layers and 100 nodes: 
{}'.format(end_time - start_time))
```

```
Epoch 1/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 18s 3ms/step - accuracy: 0.4601 - loss: 
1.5978 - val_accuracy: 0.9223 - val_loss: 0.3316
Epoch 2/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 18s 3ms/step - accuracy: 0.7573 - loss: 
0.7710 - val_accuracy: 0.9454 - val_loss: 0.2102
Epoch 3/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - accuracy: 0.8136 - loss: 
0.5940 - val_accuracy: 0.9561 - val_loss: 0.1687
Epoch 4/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.8399 - loss: 
0.5136 - val_accuracy: 0.9599 - val_loss: 0.1465
Epoch 5/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.8557 - loss: 
0.4626 - val_accuracy: 0.9640 - val_loss: 0.1315
Epoch 6/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.8646 - loss: 
0.4320 - val_accuracy: 0.9651 - val_loss: 0.1223
Epoch 7/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.8737 - loss: 
0.4040 - val_accuracy: 0.9675 - val_loss: 0.1135
Epoch 8/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - accuracy: 0.8793 - loss: 
0.3854 - val_accuracy: 0.9663 - val_loss: 0.1114
Epoch 9/10
```

```
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8852 - loss: 
0.3689 - val_accuracy: 0.9690 - val_loss: 0.1034
Epoch 10/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.8887 - loss: 
0.3551 - val_accuracy: 0.9698 - val_loss: 0.1006

Time taken to Train Model with 2 Layers and 100 nodes: 0:02:51.095087
```

Model Performance Evaluation

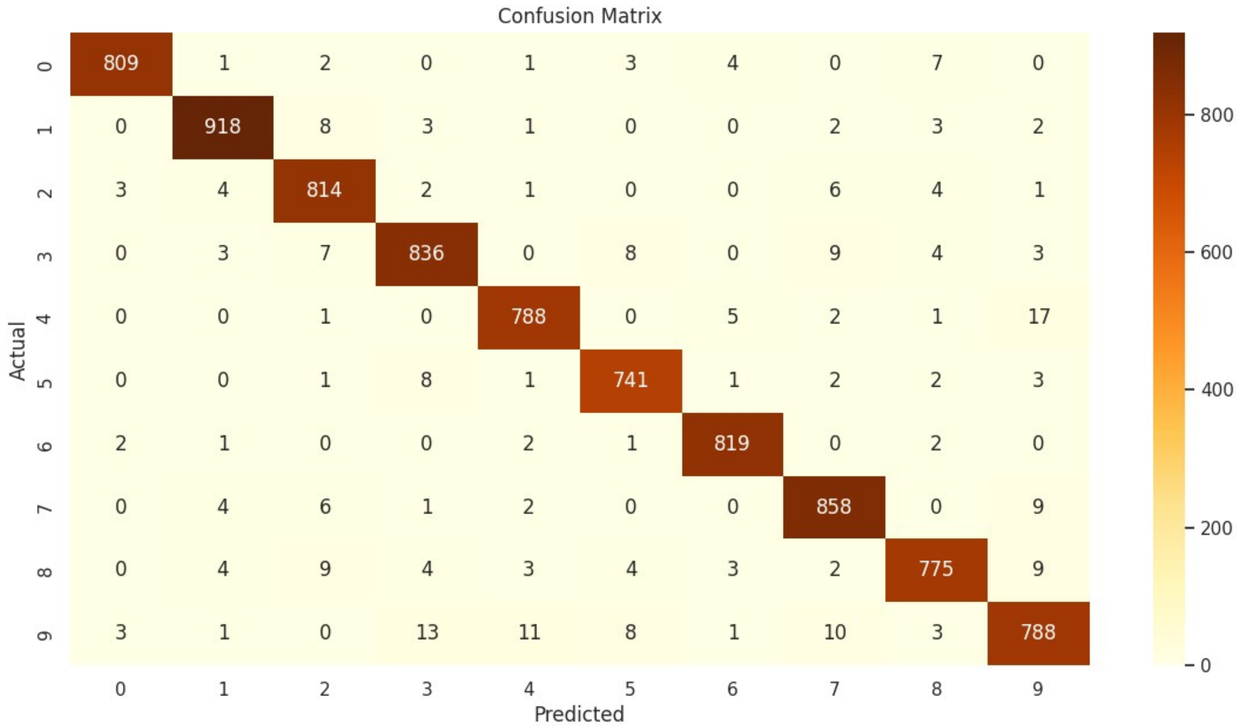
```
hist = []
for i in range(N_ITERATION):
    hist.append(pd.DataFrame(hist_df[hist_df['iteration']==(i+1)]
['history'][i].history))
    if i==0:
        hist_full = hist[0]
    else:
        hist_full = pd.concat([hist_full, hist[i]])

# Dropping the 1st EPOCHS of each iteration because their losses are 
high and their accuracies are low
hist_full.drop([0,1,2], inplace=True)  # 3 EPOCHS dropped / iteration

# Displaying CV metrics
fig,axes=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(data=hist_full[['loss','val_loss']], dashes=False, 
ax=axes[0])
axes[0].axhline(0.05, ls='--')
axes[0].axhline(0, ls='--')
axes[0].set_title('Training and Validation Loss')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
sns.lineplot(data=hist_full[['accuracy', 'val_accuracy']], 
dashes=False, ax=axes[1])
axes[1].axhline(0.99, ls='--')
axes[1].axhline(0.995, ls='--')
axes[1].axhline(0.996, ls='--')
axes[1].axhline(0.997, ls='--')
axes[1].axhline(0.998, ls='--')
axes[1].axhline(1, ls='--')
axes[1].set_title('Training and Validation Accuracy')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Accuracy')
plt.show()
```



Model Confusion Matrix

```
# Load the saved model
try:
    model = keras.models.load_model('MNIST/trained_models/Model-
2L100N.keras')
except Exception as e:
    print(f"Error loading model: {e}")

# Reshape X_train
X_train = df_train.reshape(-1, 784)

# Initialize StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=422)

# Retrieve the validation set from the first fold
for _, val_index in skf.split(X_train, y_train):
    X_val = X_train[val_index]
    y_val = y_train[val_index]
    break

# Reshape validation set for Keras
X_val = X_val.reshape(-1, 28, 28, 1)

# Make predictions
scores = model.predict(X_val)
y_pred = np.argmax(scores, axis=1)

# Display the confusion matrix
plt.figure(figsize=(14, 7))
cm = confusion_matrix(y_val, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
263/263 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



Submission

```
X_test = df_test.copy()
X_test = X_test.reshape(28000,28,28,1)

model = keras.models.load_model('MNIST/trained_models/Model-
2L100N.keras')
predictions = model.predict(X_test)

output = pd.DataFrame({'ImageId': list(range(1, 28001)), 'Label':
np.argmax(predictions, axis=1)})
output.to_csv('MNIST/submission/Model-2L100N.csv', index=False)
```

```
875/875 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step
```

Model 2 (2 layers, 200 node) Training with Cross-Validation

```
start_time = datetime.now()
# Creating hist_df to store history objects for each training / split
hist_df = pd.DataFrame(columns=['iteration', 'history'])
iteration = 1
index = 0

hidden_layers = 2
hidden_nodes = 200
dropout = 0.2
```

```
saved_model = False
X_train = df_train.reshape(42000, 784)

skf = StratifiedKFold(n_splits = N_SPLITS, shuffle = True,
random_state = 422)
for train_index, val_index in skf.split(X_train, y_train):

    # Getting the training set and validation set before data
augmentation
    X_train_, X_val_ = X_train[train_index], X_train[val_index]
    X_train_ = X_train_.reshape(33600,28,28,1) # Reshaping X_train to
Keras input format
    X_val_ = X_val_.reshape(8400,28,28,1) # Reshaping X_val to Keras
input format
    y_train_, y_val_ = y_train[train_index], y_train[val_index]

    # Generating augmented samples
    X_train_, y_train_ = data_augmentation(X_train_, y_train_)

    # Building the model
    model = build_model(hidden_layers, hidden_nodes, dropout)

    # EDIT THE NEXT ROW FOR EACH MODEL
    checkpoint_cb =
tf.keras.callbacks.ModelCheckpoint("MNIST/checkpoint/Model-
2L200N.keras", save_best_only=True)
    early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=10,
restore_best_weights=True)

    # Training and evaluating each model for this split
    history = model.fit(x = X_train_, y = y_train_,
validation_data=(X_val_, y_val_),
                        epochs=N_EPOCHS, batch_size=64,
callbacks=[checkpoint_cb, early_stopping_cb])

    # Saving the trained model as a saved model file -- only one model
is saved
    if(saved_model == False):
        model.save('MNIST/trained_models/Model-2L200N.keras')
        saved_model = True

    # Storing the history objects into a dataframe
    hist_df.loc[index, 'iteration'] = iteration
    hist_df.loc[index, 'history'] = history

    if(iteration == N_ITERATION):
        break

    index = index + 1
    iteration = iteration + 1
```

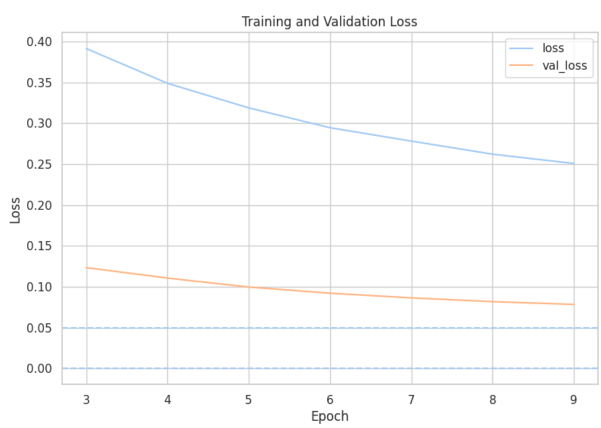
```
end_time = datetime.now()
print('\nTime taken to Train Model with 2 Layers and 200 nodes:
{}'.format(end_time - start_time))
```

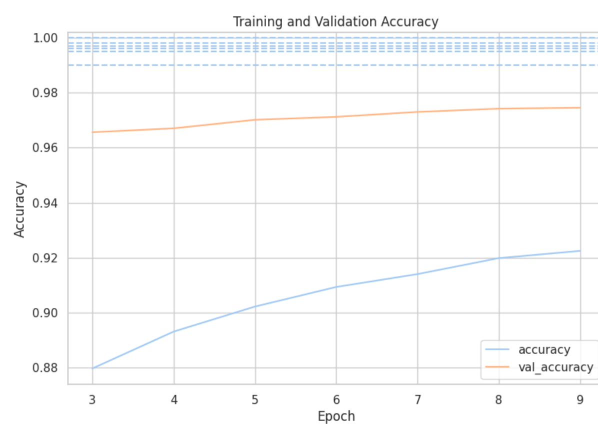
```
Epoch 1/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 18s 3ms/step - accuracy: 0.5056 - loss:
1.4934 - val_accuracy: 0.9279 - val_loss: 0.2975
Epoch 2/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.7958 - loss:
0.6611 - val_accuracy: 0.9489 - val_loss: 0.1836
Epoch 3/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8506 - loss:
0.4837 - val_accuracy: 0.9601 - val_loss: 0.1448
Epoch 4/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8749 - loss:
0.4072 - val_accuracy: 0.9656 - val_loss: 0.1234
Epoch 5/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.8902 - loss:
0.3613 - val_accuracy: 0.9670 - val_loss: 0.1106
Epoch 6/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - accuracy: 0.8999 - loss:
0.3279 - val_accuracy: 0.9701 - val_loss: 0.0996
Epoch 7/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - accuracy: 0.9071 - loss:
0.3029 - val_accuracy: 0.9712 - val_loss: 0.0921
Epoch 8/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.9129 - loss:
0.2838 - val_accuracy: 0.9730 - val_loss: 0.0864
Epoch 9/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 27s 4ms/step - accuracy: 0.9181 - loss:
0.2677 - val_accuracy: 0.9742 - val_loss: 0.0818
Epoch 10/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 33s 3ms/step - accuracy: 0.9209 - loss:
0.2554 - val_accuracy: 0.9745 - val_loss: 0.0784

Time taken to Train Model with 2 Layers and 200 nodes: 0:03:33.783321
```

Model Performance Evaluation

```
hist = []
for i in range(N_ITERATION):
    hist.append(pd.DataFrame(hist_df[hist_df['iteration']==(i+1)]
['history'][i].history))
    if i==0:
        hist_full = hist[0]
    else:
        hist_full = pd.concat([hist_full, hist[i]])

# Dropping the 1st EPOCHS of each iteration because their losses are
```

```
high and their accuracies are low
hist_full.drop([0,1,2], inplace=True)  # 3 EPOCHS dropped / iteration

# Displaying CV metrics
fig,axes=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(data=hist_full[['loss','val_loss']], dashes=False,
ax=axes[0])
axes[0].axhline(0.05, ls='--')
axes[0].axhline(0, ls='--')
axes[0].set_title('Training and Validation Loss')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
sns.lineplot(data=hist_full[['accuracy', 'val_accuracy']],
dashes=False, ax=axes[1])
axes[1].axhline(0.99, ls='--')
axes[1].axhline(0.995, ls='--')
axes[1].axhline(0.996, ls='--')
axes[1].axhline(0.997, ls='--')
axes[1].axhline(0.998, ls='--')
axes[1].axhline(1, ls='--')
axes[1].set_title('Training and Validation Accuracy')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Accuracy')
plt.show()
```



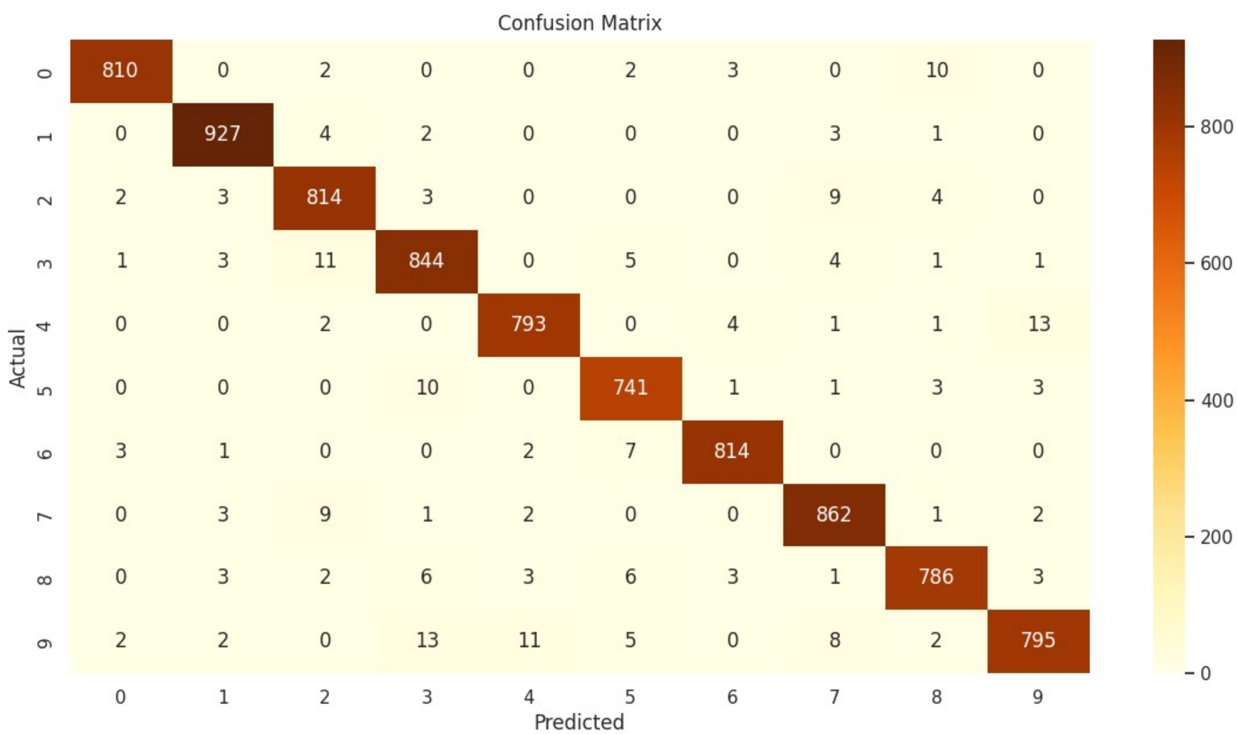


Model Confusion Matrix

```
# Load the saved model
try:
    model = keras.models.load_model('MNIST/trained_models/Model-
2L200N.keras')
except Exception as e:
    print(f"Error loading model: {e}")

# Reshape X_train
X_train = df_train.reshape(-1, 784)
```

```python
# Initialize StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=422)

# Retrieve the validation set from the first fold
for _, val_index in skf.split(X_train, y_train):
    X_val = X_train[val_index]
    y_val = y_train[val_index]
    break

# Reshape validation set for Keras
X_val = X_val.reshape(-1, 28, 28, 1)

# Make predictions
scores = model.predict(X_val)
y_pred = np.argmax(scores, axis=1)

# Display the confusion matrix
plt.figure(figsize=(14, 7))
cm = confusion_matrix(y_val, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
263/263 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



Submission

```
X_test = df_test.copy()
X_test = X_test.reshape(28000,28,28,1)

model = keras.models.load_model('MNIST/trained_models/Model-
2L200N.keras')
predictions = model.predict(X_test)

output = pd.DataFrame({'ImageId': list(range(1, 28001)), 'Label':
np.argmax(predictions, axis=1)})
output.to_csv('MNIST/submission/Model-2L200N.csv', index=False)
```

```
875/875 ━━━━━━━━━━━━━━━━━━━━ 1s 1ms/step
```

Model 3 (3 layers, 100 node) Training with Cross-Validation

```
start_time = datetime.now()
# Creating hist_df to store history objects for each training / split
hist_df = pd.DataFrame(columns=['iteration', 'history'])
iteration = 1
index = 0

hidden_layers = 3
hidden_nodes = 100
dropout = 0.2

saved_model = False
X_train = df_train.reshape(42000, 784)

skf = StratifiedKFold(n_splits = N_SPLITS, shuffle = True,
random_state = 422)
for train_index, val_index in skf.split(X_train, y_train):

    # Getting the training set and validation set before data
augmentation
    X_train_, X_val_ = X_train[train_index], X_train[val_index]
    X_train_ = X_train_.reshape(33600,28,28,1) # Reshaping X_train to
Keras input format
    X_val_ = X_val_.reshape(8400,28,28,1) # Reshaping X_val to Keras
input format
    y_train_, y_val_ = y_train[train_index], y_train[val_index]

    # Generating augmented samples
    X_train_, y_train_ = data_augmentation(X_train_, y_train_)

    # Building the model
    model = build_model(hidden_layers, hidden_nodes, dropout)

    # EDIT THE NEXT ROW FOR EACH MODEL
```

```
    checkpoint_cb =
tf.keras.callbacks.ModelCheckpoint("MNIST/checkpoint/Model-
3L100N.keras", save_best_only=True)
    early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=10,
restore_best_weights=True)

    # Training and evaluating each model for this split
    history = model.fit(x = X_train_, y = y_train_,
validation_data=(X_val_, y_val_),
                        epochs=N_EPOCHS, batch_size=64,
callbacks=[checkpoint_cb, early_stopping_cb])

    # Saving the trained model as a saved model file -- only one model
is saved
    if(saved_model == False):
        model.save('MNIST/trained_models/Model-3L100N.keras')
        saved_model = True

    # Storing the history objects into a dataframe
    hist_df.loc[index, 'iteration'] = iteration
    hist_df.loc[index, 'history'] = history

    if(iteration == N_ITERATION):
        break

    index = index + 1
    iteration = iteration + 1

end_time = datetime.now()
print('\nTime taken to Train Model with 3 Layers and 100 nodes:
{}'.format(end_time - start_time))
```

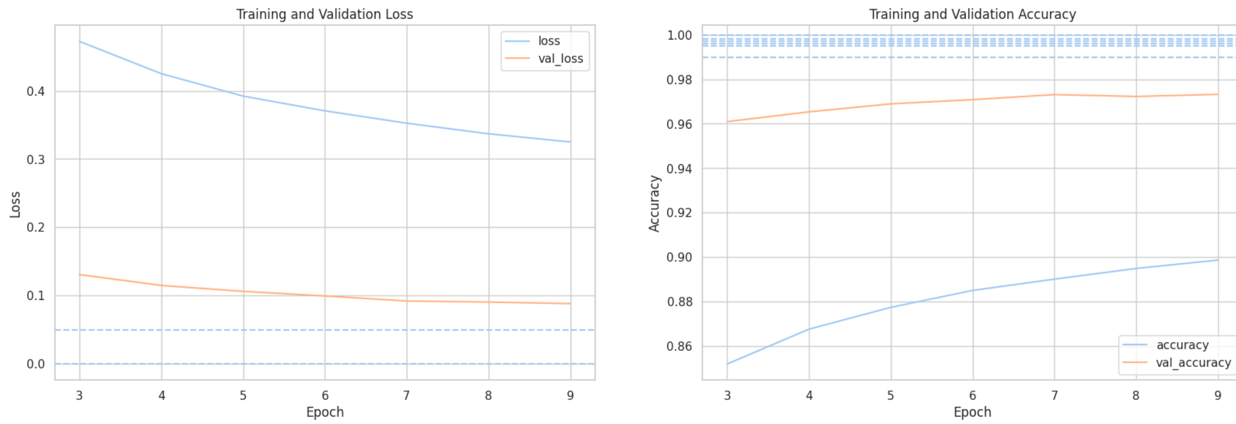
```
Epoch 1/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - accuracy: 0.4330 - loss:
1.6312 - val_accuracy: 0.9192 - val_loss: 0.3044
Epoch 2/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 14s 3ms/step - accuracy: 0.7569 - loss:
0.7581 - val_accuracy: 0.9474 - val_loss: 0.1879
Epoch 3/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - accuracy: 0.8190 - loss:
0.5730 - val_accuracy: 0.9554 - val_loss: 0.1482
Epoch 4/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.8469 - loss:
0.4865 - val_accuracy: 0.9610 - val_loss: 0.1309
Epoch 5/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8639 - loss:
0.4369 - val_accuracy: 0.9654 - val_loss: 0.1150
Epoch 6/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8749 - loss:
0.3999 - val_accuracy: 0.9689 - val_loss: 0.1063
```

```
Epoch 7/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.8832 - loss:
0.3774 - val_accuracy: 0.9708 - val_loss: 0.0995
Epoch 8/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - accuracy: 0.8882 - loss:
0.3582 - val_accuracy: 0.9731 - val_loss: 0.0922
Epoch 9/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8938 - loss:
0.3417 - val_accuracy: 0.9723 - val_loss: 0.0906
Epoch 10/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 22s 3ms/step - accuracy: 0.8971 - loss:
0.3304 - val_accuracy: 0.9732 - val_loss: 0.0884

Time taken to Train Model with 3 Layers and 100 nodes: 0:03:17.633334
```

Model Performance Evaluation

```
hist = []
for i in range(N_ITERATION):
    hist.append(pd.DataFrame(hist_df[hist_df['iteration']==(i+1)]
['history'][i].history))
    if i==0:
        hist_full = hist[0]
    else:
        hist_full = pd.concat([hist_full, hist[i]])

# Dropping the 1st EPOCHS of each iteration because their losses are
high and their accuracies are low
hist_full.drop([0,1,2], inplace=True)  # 3 EPOCHS dropped / iteration

# Displaying CV metrics
fig,axes=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(data=hist_full[['loss','val_loss']], dashes=False,
ax=axes[0])
axes[0].axhline(0.05, ls='--')
axes[0].axhline(0, ls='--')
axes[0].set_title('Training and Validation Loss')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
sns.lineplot(data=hist_full[['accuracy', 'val_accuracy']],
dashes=False, ax=axes[1])
axes[1].axhline(0.99, ls='--')
axes[1].axhline(0.995, ls='--')
axes[1].axhline(0.996, ls='--')
axes[1].axhline(0.997, ls='--')
axes[1].axhline(0.998, ls='--')
axes[1].axhline(1, ls='--')
axes[1].set_title('Training and Validation Accuracy')
axes[1].set_xlabel('Epoch')
```

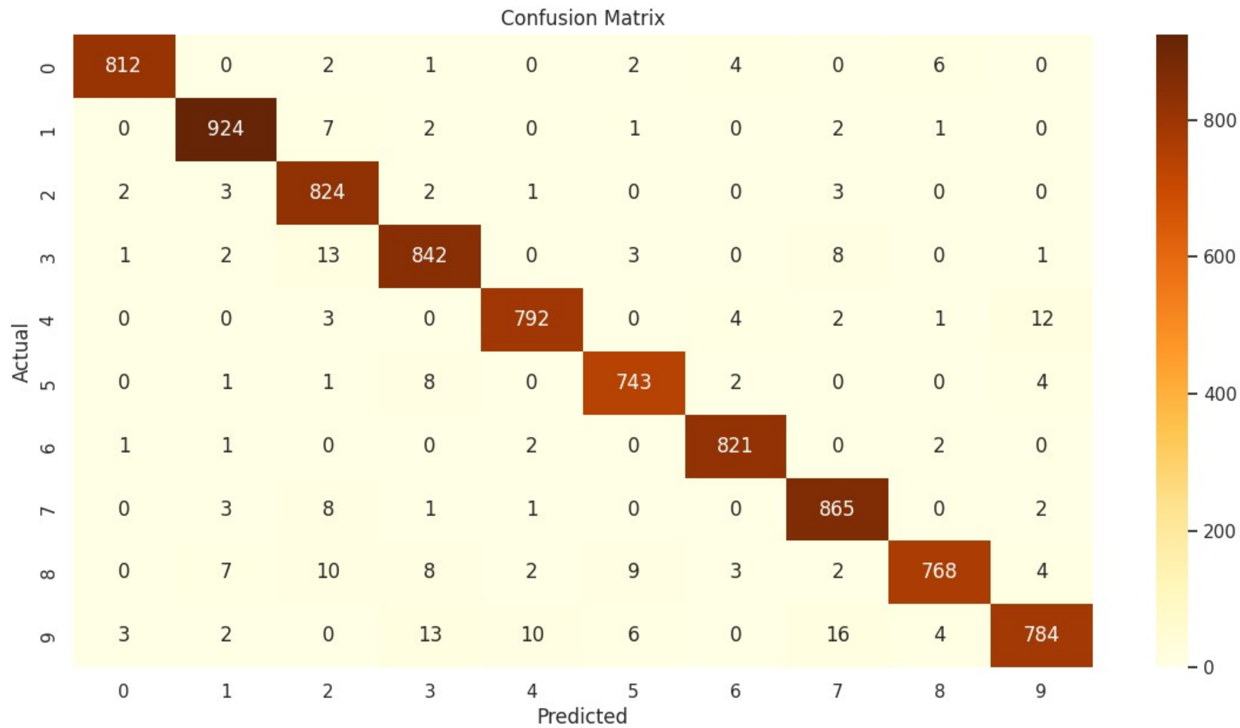
```
axes[1].set_ylabel('Accuracy')
plt.show()
```



Model Confusion Matrix

```
# Load the saved model
try:
    model = keras.models.load_model('MNIST/trained_models/Model-
3L100N.keras')
except Exception as e:
    print(f"Error loading model: {e}")

# Reshape X_train
X_train = df_train.reshape(-1, 784)

# Initialize StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=422)

# Retrieve the validation set from the first fold
for _, val_index in skf.split(X_train, y_train):
    X_val = X_train[val_index]
    y_val = y_train[val_index]
    break

# Reshape validation set for Keras
X_val = X_val.reshape(-1, 28, 28, 1)

# Make predictions
scores = model.predict(X_val)
y_pred = np.argmax(scores, axis=1)

# Display the confusion matrix
plt.figure(figsize=(14, 7))
cm = confusion_matrix(y_val, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.show()

263/263 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



Submission

```
X_test = df_test.copy()
X_test = X_test.reshape(28000,28,28,1)

model = keras.models.load_model('MNIST/trained_models/Model-3L100N.keras')
predictions = model.predict(X_test)

output = pd.DataFrame({'ImageId': list(range(1, 28001)), 'Label': np.argmax(predictions, axis=1)})
output.to_csv('MNIST/submission/Model-3L100N.csv', index=False)

875/875 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

Model 4 (3 layers, 200 node) Training with Cross-Validation

```
start_time = datetime.now()
# Creating hist_df to store history objects for each training / split
hist_df = pd.DataFrame(columns=['iteration', 'history'])
iteration = 1
```

```python
index = 0

hidden_layers = 3
hidden_nodes = 200
dropout = 0.2

saved_model = False
X_train = df_train.reshape(42000, 784)

skf = StratifiedKFold(n_splits = N_SPLITS, shuffle = True,
random_state = 422)
for train_index, val_index in skf.split(X_train, y_train):

    # Getting the training set and validation set before data
augmentation
    X_train_, X_val_ = X_train[train_index], X_train[val_index]
    X_train_ = X_train_.reshape(33600,28,28,1) # Reshaping X_train to
Keras input format
    X_val_ = X_val_.reshape(8400,28,28,1) # Reshaping X_val to Keras
input format
    y_train_, y_val_ = y_train[train_index], y_train[val_index]

    # Generating augmented samples
    X_train_, y_train_ = data_augmentation(X_train_, y_train_)

    # Building the model
    model = build_model(hidden_layers, hidden_nodes, dropout)

    # EDIT THE NEXT ROW FOR EACH MODEL
    checkpoint_cb =
tf.keras.callbacks.ModelCheckpoint("MNIST/checkpoint/Model-
3L200N.keras", save_best_only=True)
    early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=10,
restore_best_weights=True)

    # Training and evaluating each model for this split
    history = model.fit(x = X_train_, y = y_train_,
validation_data=(X_val_, y_val_),
                        epochs=N_EPOCHS, batch_size=64,
callbacks=[checkpoint_cb, early_stopping_cb])

    # Saving the trained model as a saved model file -- only one model
is saved
    if(saved_model == False):
        model.save('MNIST/trained_models/Model-3L200N.keras')
        saved_model = True

    # Storing the history objects into a dataframe
    hist_df.loc[index, 'iteration'] = iteration
    hist_df.loc[index, 'history'] = history
```

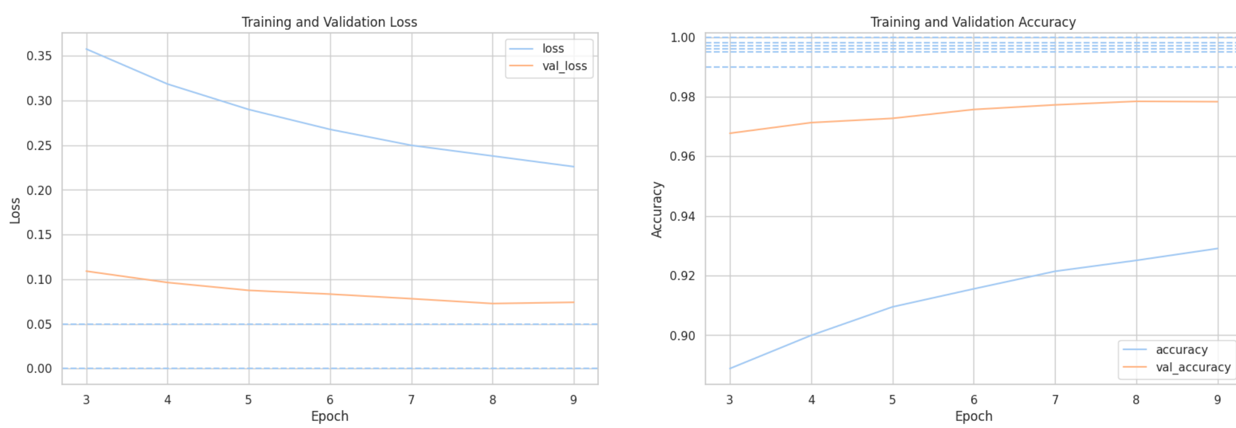
```
    if(iteration == N_ITERATION):
        break

    index = index + 1
    iteration = iteration + 1

end_time = datetime.now()
print('\nTime taken to Train Model with 3 Layers and 200 nodes:
{}'.format(end_time - start_time))
```

```
Epoch 1/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 19s 3ms/step - accuracy: 0.4707 - loss:
1.5589 - val_accuracy: 0.9324 - val_loss: 0.2513
Epoch 2/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.8082 - loss:
0.6075 - val_accuracy: 0.9570 - val_loss: 0.1560
Epoch 3/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8617 - loss:
0.4443 - val_accuracy: 0.9637 - val_loss: 0.1218
Epoch 4/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8861 - loss:
0.3694 - val_accuracy: 0.9677 - val_loss: 0.1091
Epoch 5/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8977 - loss:
0.3254 - val_accuracy: 0.9713 - val_loss: 0.0963
Epoch 6/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - accuracy: 0.9080 - loss:
0.2952 - val_accuracy: 0.9727 - val_loss: 0.0875
Epoch 7/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.9142 - loss:
0.2722 - val_accuracy: 0.9757 - val_loss: 0.0833
Epoch 8/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.9205 - loss:
0.2544 - val_accuracy: 0.9773 - val_loss: 0.0782
Epoch 9/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.9242 - loss:
0.2411 - val_accuracy: 0.9785 - val_loss: 0.0728
Epoch 10/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.9287 - loss:
0.2285 - val_accuracy: 0.9783 - val_loss: 0.0742

Time taken to Train Model with 3 Layers and 200 nodes: 0:03:08.757135
```

Model Performance Evaluation

```
hist = []
for i in range(N_ITERATION):
    hist.append(pd.DataFrame(hist_df[hist_df['iteration']==(i+1)]
['history'][i].history))
```

```python
    if i==0:
        hist_full = hist[0]
    else:
        hist_full = pd.concat([hist_full, hist[i]])

# Dropping the 1st EPOCHS of each iteration because their losses are
high and their accuracies are low
hist_full.drop([0,1,2], inplace=True)  # 3 EPOCHS dropped / iteration

# Displaying CV metrics
fig,axes=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(data=hist_full[['loss','val_loss']], dashes=False,
ax=axes[0])
axes[0].axhline(0.05, ls='--')
axes[0].axhline(0, ls='--')
axes[0].set_title('Training and Validation Loss')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
sns.lineplot(data=hist_full[['accuracy', 'val_accuracy']],
dashes=False, ax=axes[1])
axes[1].axhline(0.99, ls='--')
axes[1].axhline(0.995, ls='--')
axes[1].axhline(0.996, ls='--')
axes[1].axhline(0.997, ls='--')
axes[1].axhline(0.998, ls='--')
axes[1].axhline(1, ls='--')
axes[1].set_title('Training and Validation Accuracy')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Accuracy')
plt.show()
```

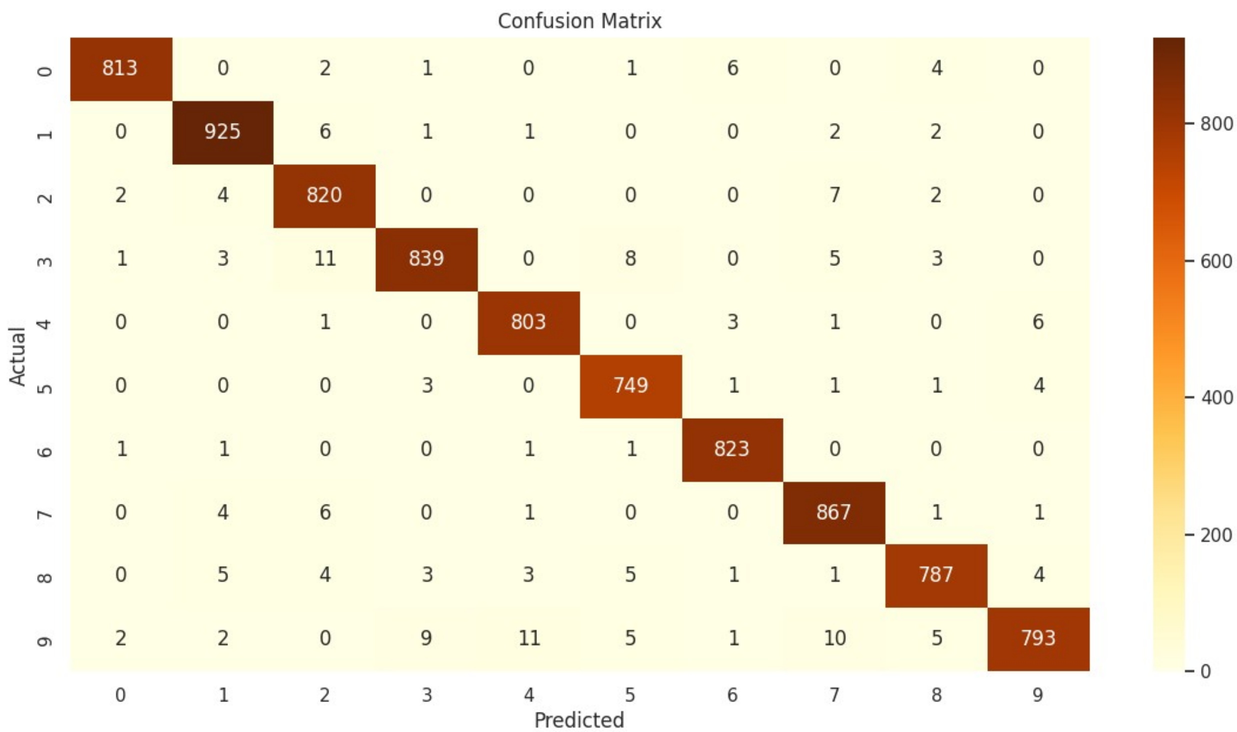


Model Confusion Matrix

```python
# Load the saved model
try:
    model = keras.models.load_model('MNIST/trained_models/Model-
3L200N.keras')
```

```python
except Exception as e:
    print(f"Error loading model: {e}")

# Reshape X_train
X_train = df_train.reshape(-1, 784)

# Initialize StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=422)

# Retrieve the validation set from the first fold
for _, val_index in skf.split(X_train, y_train):
    X_val = X_train[val_index]
    y_val = y_train[val_index]
    break

# Reshape validation set for Keras
X_val = X_val.reshape(-1, 28, 28, 1)

# Make predictions
scores = model.predict(X_val)
y_pred = np.argmax(scores, axis=1)

# Display the confusion matrix
plt.figure(figsize=(14, 7))
cm = confusion_matrix(y_val, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
263/263 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



Submission

```
X_test = df_test.copy()
X_test = X_test.reshape(28000,28,28,1)

model = keras.models.load_model('MNIST/trained_models/Model-
3L200N.keras')
predictions = model.predict(X_test)

output = pd.DataFrame({'ImageId': list(range(1, 28001)), 'Label':
np.argmax(predictions, axis=1)})
output.to_csv('MNIST/submission/Model-3L200N.csv', index=False)

875/875 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

Model 5 (5 layers, 100 node) Training with Cross-Validation

```
start_time = datetime.now()
# Creating hist_df to store history objects for each training / split
hist_df = pd.DataFrame(columns=['iteration', 'history'])
iteration = 1
index = 0

hidden_layers = 5
hidden_nodes = 100
dropout = 0.2
```

```
saved_model = False
X_train = df_train.reshape(42000, 784)

skf = StratifiedKFold(n_splits = N_SPLITS, shuffle = True,
random_state = 422)
for train_index, val_index in skf.split(X_train, y_train):

    # Getting the training set and validation set before data
augmentation
    X_train_, X_val_ = X_train[train_index], X_train[val_index]
    X_train_ = X_train_.reshape(33600,28,28,1) # Reshaping X_train to
Keras input format
    X_val_ = X_val_.reshape(8400,28,28,1) # Reshaping X_val to Keras
input format
    y_train_, y_val_ = y_train[train_index], y_train[val_index]

    # Generating augmented samples
    X_train_, y_train_ = data_augmentation(X_train_, y_train_)

    # Building the model
    model = build_model(hidden_layers, hidden_nodes, dropout)

    # EDIT THE NEXT ROW FOR EACH MODEL
    checkpoint_cb =
tf.keras.callbacks.ModelCheckpoint("MNIST/checkpoint/Model-
5L100N.keras", save_best_only=True)
    early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=10,
restore_best_weights=True)

    # Training and evaluating each model for this split
    history = model.fit(x = X_train_, y = y_train_,
validation_data=(X_val_, y_val_),
                        epochs=N_EPOCHS, batch_size=64,
callbacks=[checkpoint_cb, early_stopping_cb])

    # Saving the trained model as a saved model file -- only one model
is saved
    if(saved_model == False):
        model.save('MNIST/trained_models/Model-5L100N.keras')
        saved_model = True

    # Storing the history objects into a dataframe
    hist_df.loc[index, 'iteration'] = iteration
    hist_df.loc[index, 'history'] = history

    if(iteration == N_ITERATION):
        break

    index = index + 1
    iteration = iteration + 1
```

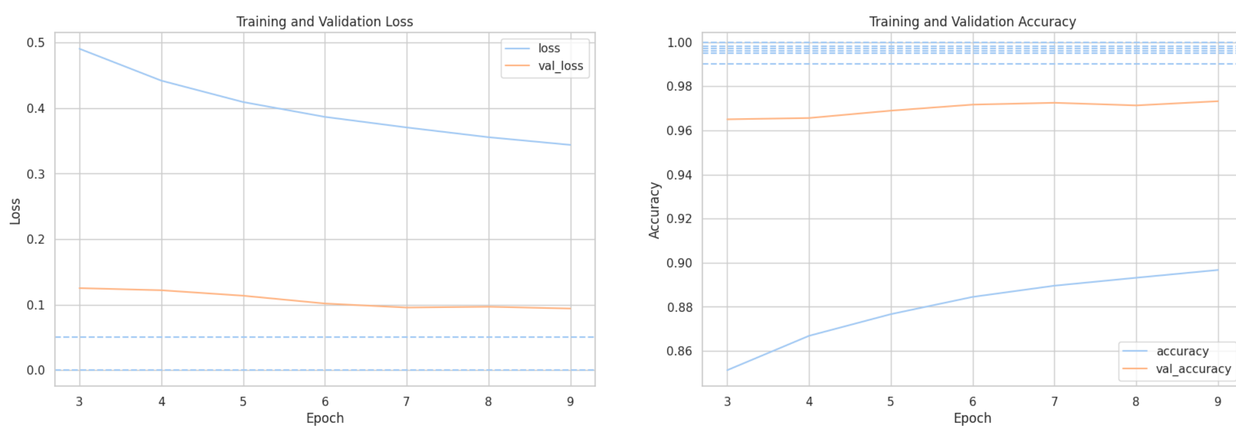
```
end_time = datetime.now()
print('\nTime taken to Train Model with 5 Layers and 100 nodes:
{}'.format(end_time - start_time))
```

```
Epoch 1/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 22s 3ms/step - accuracy: 0.3001 - loss:
1.9434 - val_accuracy: 0.8989 - val_loss: 0.3805
Epoch 2/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 37s 3ms/step - accuracy: 0.7230 - loss:
0.8545 - val_accuracy: 0.9455 - val_loss: 0.1943
Epoch 3/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 19s 3ms/step - accuracy: 0.8120 - loss:
0.6083 - val_accuracy: 0.9580 - val_loss: 0.1438
Epoch 4/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - accuracy: 0.8454 - loss:
0.5101 - val_accuracy: 0.9650 - val_loss: 0.1253
Epoch 5/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.8630 - loss:
0.4539 - val_accuracy: 0.9656 - val_loss: 0.1220
Epoch 6/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - accuracy: 0.8742 - loss:
0.4183 - val_accuracy: 0.9689 - val_loss: 0.1137
Epoch 7/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 17s 3ms/step - accuracy: 0.8826 - loss:
0.3941 - val_accuracy: 0.9717 - val_loss: 0.1018
Epoch 8/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 19s 3ms/step - accuracy: 0.8878 - loss:
0.3748 - val_accuracy: 0.9725 - val_loss: 0.0956
Epoch 9/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 17s 3ms/step - accuracy: 0.8912 - loss:
0.3601 - val_accuracy: 0.9713 - val_loss: 0.0968
Epoch 10/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.8944 - loss:
0.3511 - val_accuracy: 0.9732 - val_loss: 0.0941

Time taken to Train Model with 5 Layers and 100 nodes: 0:03:25.177272
```

Model Performance Evaluation

```
hist = []
for i in range(N_ITERATION):
    hist.append(pd.DataFrame(hist_df[hist_df['iteration']==(i+1)]
['history'][i].history))
    if i==0:
        hist_full = hist[0]
    else:
        hist_full = pd.concat([hist_full, hist[i]])

# Dropping the 1st EPOCHS of each iteration because their losses are
```

```
high and their accuracies are low
hist_full.drop([0,1,2], inplace=True)  # 3 EPOCHS dropped / iteration

# Displaying CV metrics
fig,axes=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(data=hist_full[['loss','val_loss']], dashes=False,
ax=axes[0])
axes[0].axhline(0.05, ls='--')
axes[0].axhline(0, ls='--')
axes[0].set_title('Training and Validation Loss')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
sns.lineplot(data=hist_full[['accuracy', 'val_accuracy']],
dashes=False, ax=axes[1])
axes[1].axhline(0.99, ls='--')
axes[1].axhline(0.995, ls='--')
axes[1].axhline(0.996, ls='--')
axes[1].axhline(0.997, ls='--')
axes[1].axhline(0.998, ls='--')
axes[1].axhline(1, ls='--')
axes[1].set_title('Training and Validation Accuracy')
axes[1].set_xlabel('Epoch')
axes[1].set_ylabel('Accuracy')
plt.show()
```

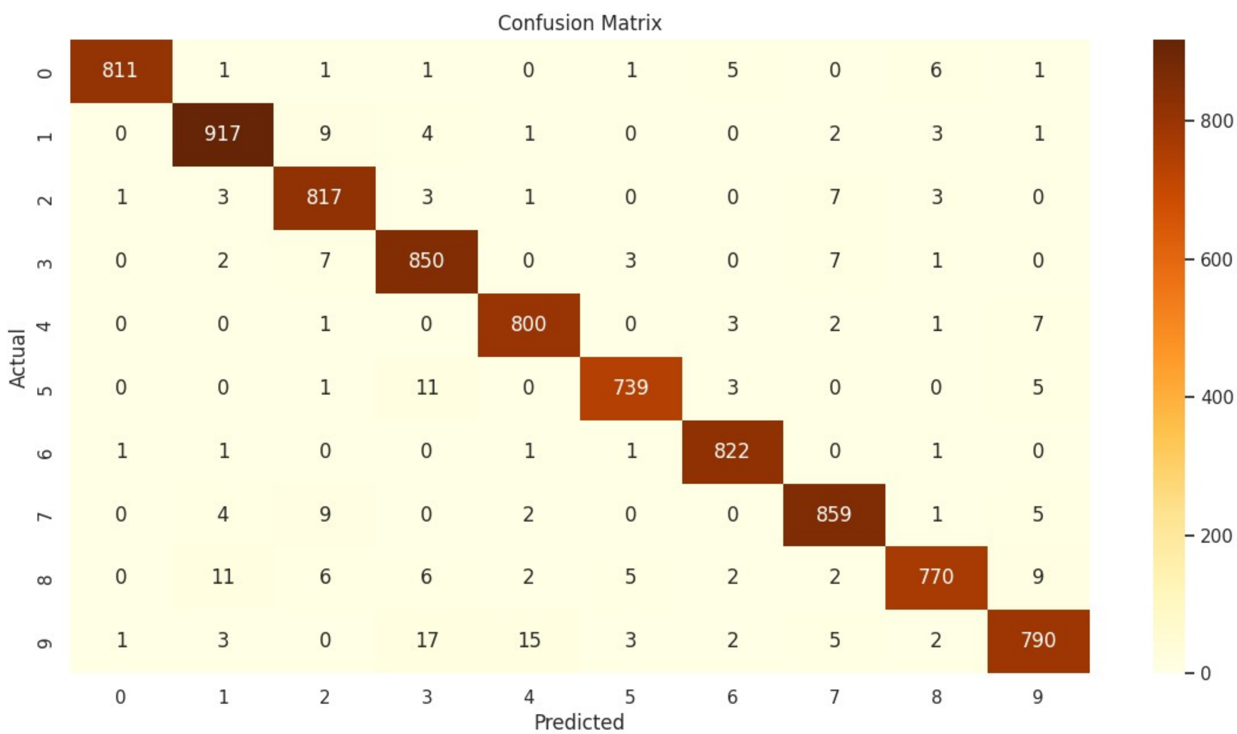


Model Confusion Matrix

```
# Load the saved model
try:
    model = keras.models.load_model('MNIST/trained_models/Model-
5L100N.keras')
except Exception as e:
    print(f"Error loading model: {e}")

# Reshape X_train
X_train = df_train.reshape(-1, 784)
```

```python
# Initialize StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=422)

# Retrieve the validation set from the first fold
for _, val_index in skf.split(X_train, y_train):
    X_val = X_train[val_index]
    y_val = y_train[val_index]
    break

# Reshape validation set for Keras
X_val = X_val.reshape(-1, 28, 28, 1)

# Make predictions
scores = model.predict(X_val)
y_pred = np.argmax(scores, axis=1)

# Display the confusion matrix
plt.figure(figsize=(14, 7))
cm = confusion_matrix(y_val, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
263/263 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
```



Submission

```
X_test = df_test.copy()
X_test = X_test.reshape(28000,28,28,1)

model = keras.models.load_model('MNIST/trained_models/Model-
5L100N.keras')
predictions = model.predict(X_test)

output = pd.DataFrame({'ImageId': list(range(1, 28001)), 'Label':
np.argmax(predictions, axis=1)})
output.to_csv('MNIST/submission/Model-5L100N.csv', index=False)
```

```
875/875 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

Model 6 (5 layers, 200 node) Training with Cross-Validation

```
start_time = datetime.now()
# Creating hist_df to store history objects for each training / split
hist_df = pd.DataFrame(columns=['iteration', 'history'])
iteration = 1
index = 0

hidden_layers = 5
hidden_nodes = 200
dropout = 0.2

saved_model = False
X_train = df_train.reshape(42000, 784)

skf = StratifiedKFold(n_splits = N_SPLITS, shuffle = True,
random_state = 422)
for train_index, val_index in skf.split(X_train, y_train):

    # Getting the training set and validation set before data
augmentation
    X_train_, X_val_ = X_train[train_index], X_train[val_index]
    X_train_ = X_train_.reshape(33600,28,28,1) # Reshaping X_train to
Keras input format
    X_val_ = X_val_.reshape(8400,28,28,1) # Reshaping X_val to Keras
input format
    y_train_, y_val_ = y_train[train_index], y_train[val_index]

    # Generating augmented samples
    X_train_, y_train_ = data_augmentation(X_train_, y_train_)

    # Building the model
    model = build_model(hidden_layers, hidden_nodes, dropout)

    # EDIT THE NEXT ROW FOR EACH MODEL
```

```
    checkpoint_cb =
tf.keras.callbacks.ModelCheckpoint("MNIST/checkpoint/Model-
5L200N.keras", save_best_only=True)
    early_stopping_cb = tf.keras.callbacks.EarlyStopping(patience=10,
restore_best_weights=True)

    # Training and evaluating each model for this split
    history = model.fit(x = X_train_, y = y_train_,
validation_data=(X_val_, y_val_),
                        epochs=N_EPOCHS, batch_size=64,
callbacks=[checkpoint_cb, early_stopping_cb])

    # Saving the trained model as a saved model file -- only one model
is saved
    if(saved_model == False):
        model.save('MNIST/trained_models/Model-5L200N.keras')
        saved_model = True

    # Storing the history objects into a dataframe
    hist_df.loc[index, 'iteration'] = iteration
    hist_df.loc[index, 'history'] = history

    if(iteration == N_ITERATION):
        break

    index = index + 1
    iteration = iteration + 1

end_time = datetime.now()
print('\nTime taken to Train Model with 5 Layers and 200 nodes:
{}'.format(end_time - start_time))
```

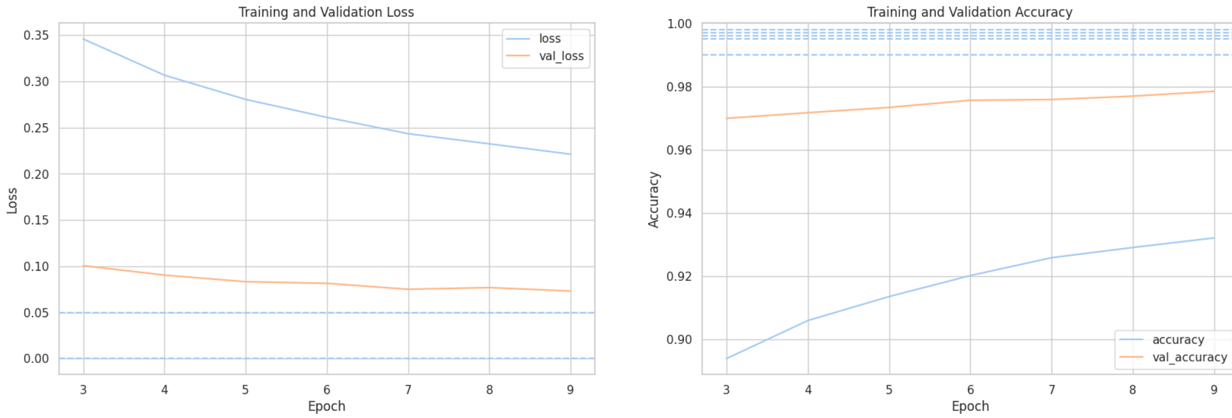
```
Epoch 1/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 22s 3ms/step - accuracy: 0.3637 - loss:
1.7848 - val_accuracy: 0.9287 - val_loss: 0.2437
Epoch 2/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 4ms/step - accuracy: 0.8013 - loss:
0.6271 - val_accuracy: 0.9554 - val_loss: 0.1438
Epoch 3/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.8629 - loss:
0.4401 - val_accuracy: 0.9665 - val_loss: 0.1115
Epoch 4/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.8896 - loss:
0.3598 - val_accuracy: 0.9699 - val_loss: 0.1006
Epoch 5/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 23s 3ms/step - accuracy: 0.9032 - loss:
0.3169 - val_accuracy: 0.9717 - val_loss: 0.0903
Epoch 6/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - accuracy: 0.9109 - loss:
0.2881 - val_accuracy: 0.9733 - val_loss: 0.0832
```

```
Epoch 7/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - accuracy: 0.9184 - loss:
0.2674 - val_accuracy: 0.9756 - val_loss: 0.0815
Epoch 8/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 22s 3ms/step - accuracy: 0.9245 - loss:
0.2480 - val_accuracy: 0.9758 - val_loss: 0.0750
Epoch 9/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 19s 3ms/step - accuracy: 0.9279 - loss:
0.2363 - val_accuracy: 0.9769 - val_loss: 0.0768
Epoch 10/10
5250/5250 ━━━━━━━━━━━━━━━━━━━━ 15s 3ms/step - accuracy: 0.9311 - loss:
0.2244 - val_accuracy: 0.9785 - val_loss: 0.0731

Time taken to Train Model with 5 Layers and 200 nodes: 0:03:23.110893
```

Model Performance Evaluation

```
hist = []
for i in range(N_ITERATION):
    hist.append(pd.DataFrame(hist_df[hist_df['iteration']==(i+1)]
['history'][i].history))
    if i==0:
        hist_full = hist[0]
    else:
        hist_full = pd.concat([hist_full, hist[i]])

# Dropping the 1st EPOCHS of each iteration because their losses are
high and their accuracies are low
hist_full.drop([0,1,2], inplace=True)  # 3 EPOCHS dropped / iteration

# Displaying CV metrics
fig,axes=plt.subplots(1,2,figsize=(20,6))
sns.lineplot(data=hist_full[['loss','val_loss']], dashes=False,
ax=axes[0])
axes[0].axhline(0.05, ls='--')
axes[0].axhline(0, ls='--')
axes[0].set_title('Training and Validation Loss')
axes[0].set_xlabel('Epoch')
axes[0].set_ylabel('Loss')
sns.lineplot(data=hist_full[['accuracy', 'val_accuracy']],
dashes=False, ax=axes[1])
axes[1].axhline(0.99, ls='--')
axes[1].axhline(0.995, ls='--')
axes[1].axhline(0.996, ls='--')
axes[1].axhline(0.997, ls='--')
axes[1].axhline(0.998, ls='--')
axes[1].axhline(1, ls='--')
axes[1].set_title('Training and Validation Accuracy')
axes[1].set_xlabel('Epoch')
```

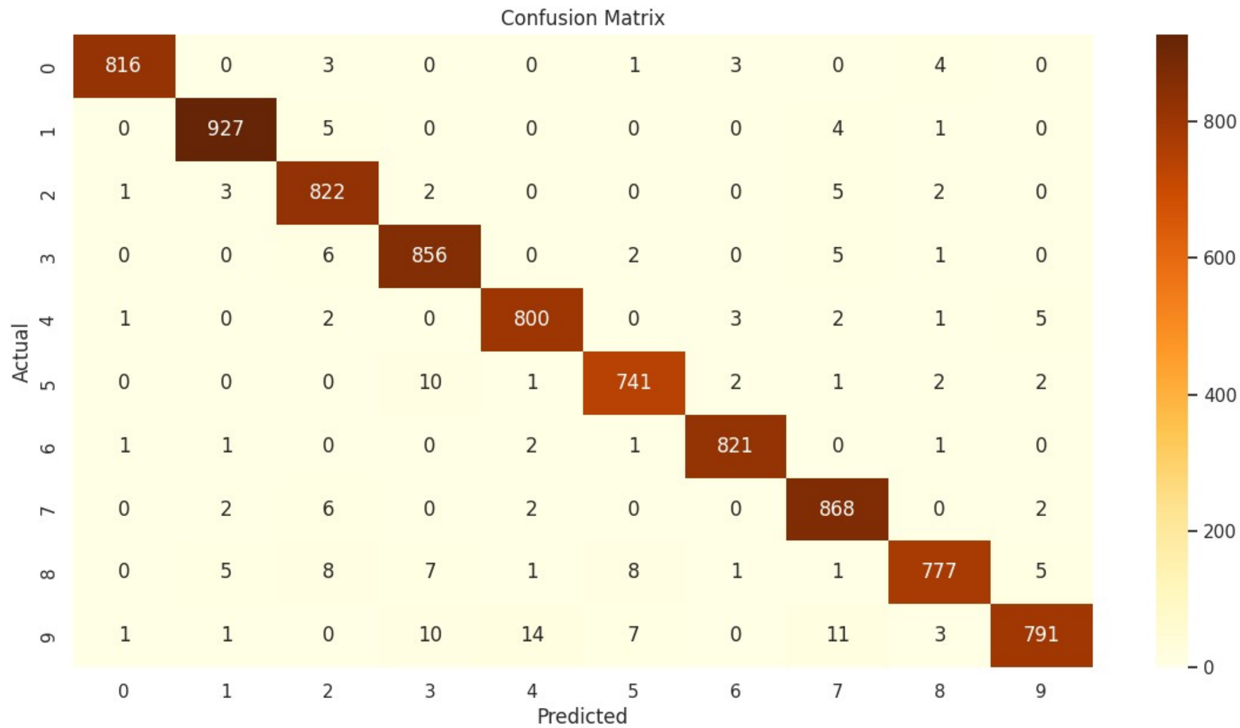
```
axes[1].set_ylabel('Accuracy')
plt.show()
```



Model Confusion Matrix

```
# Load the saved model
try:
    model = keras.models.load_model('MNIST/trained_models/Model-
5L200N.keras')
except Exception as e:
    print(f"Error loading model: {e}")

# Reshape X_train
X_train = df_train.reshape(-1, 784)

# Initialize StratifiedKFold
skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=422)

# Retrieve the validation set from the first fold
for _, val_index in skf.split(X_train, y_train):
    X_val = X_train[val_index]
    y_val = y_train[val_index]
    break

# Reshape validation set for Keras
X_val = X_val.reshape(-1, 28, 28, 1)

# Make predictions
scores = model.predict(X_val)
y_pred = np.argmax(scores, axis=1)

# Display the confusion matrix
plt.figure(figsize=(14, 7))
cm = confusion_matrix(y_val, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='YlOrBr')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.show()

263/263 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
```



Submission

```
X_test = df_test.copy()
X_test = X_test.reshape(28000,28,28,1)

model = keras.models.load_model('MNIST/trained_models/Model-
5L200N.keras')
predictions = model.predict(X_test)

output = pd.DataFrame({'ImageId': list(range(1, 28001)), 'Label':
np.argmax(predictions, axis=1)})
output.to_csv('MNIST/submission/Model-5L200N.csv', index=False)

875/875 ━━━━━━━━━━━━━━━━━━━━ 2s 2ms/step
```

Management/Research Question

In layman's terms, what is the management/research question of interest, and why would anyone care?

Research Question: How can we design the most effective neural network for accurately recognizing handwritten digits?

Why It Matters: In today's digital world, the ability to automatically and accurately recognize handwritten digits has a wide range of applications. From automating the sorting of postal mail to enabling quick and secure check deposits through mobile apps, the potential benefits are significant. Effective digit recognition can streamline processes, reduce errors, and save time.

Understanding which neural network configurations (e.g., number of layers and nodes) yield the best performance is crucial for improving the accuracy and efficiency of these systems. By systematically experimenting with different network structures, we can identify the optimal design that balances accuracy and computational efficiency. This knowledge can then be applied to develop better AI systems for various practical applications, ultimately enhancing productivity and user experience.