Name:- Vaibhav Parikh Student ID:- 1217458

Assignment 1

Simple 3 layer MLP:-

It is modern feed forward artificial neural network. Which has neurons with activation function which is not linear.

Algorithm:-

```
import tensorflow as tf
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import confusion_matrix
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import random
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, confusion_matrix
```

Importing important libraries which will be required in the furture.

```
class Simple_MLP_Handwriting_Classifier:
    # this function initailize the basic variables and loadint of
the MNIST handwritten digits dataset
    def __init__(self):
        # this line will get the data for the training and testing
of the MNIST dataset
        (self.mlp_train_digits_data, self.mlp_train_digits_labels),
(self.mlp_test_digits_data, self.mlp_test_digits_labels) =
mnist.load_data()

        # changing the shape of the data to make it faster
```

```
        self.mlp_train_digits_data =
self.mlp_train_digits_data.reshape((60000, 28 *
28)).astype('float32') / 255
        self.mlp_test_digits_data =
self.mlp_test_digits_data.reshape((10000, 28 *
28)).astype('float32') / 255
        self.mlp_train_digits_labels =
to_categorical(self.mlp_train_digits_labels)
        self.mlp_test_digits_labels =
to_categorical(self.mlp_test_digits_labels)
        self.simple_mlp_model = self.Simple_MLP_build_model()

    def Simple_MLP_build_model(self):
        simple_mlp_model = Sequential()
        simple_mlp_model.add(Dense(256, activation='relu',
input_shape=(28 * 28,)))
        simple_mlp_model.add(Dense(128, activation='relu'))
        simple_mlp_model.add(Dense(10, activation='softmax'))
        simple_mlp_model.compile(optimizer='rmsprop',
loss='categorical_crossentropy', metrics=['accuracy'])
        return simple_mlp_model

    def MLP_train_simple_model(self, epochs=5, batch_size=128):
        previous_data =
self.simple_mlp_model.fit(self.mlp_train_digits_data,
self.mlp_train_digits_labels,
                                 epochs=epochs,
batch_size=batch_size,
                                 validation_data=(self.mlp_test_digi
ts_data, self.mlp_test_digits_labels))
        return previous_data

    def MLP_training_history(self, previous_data):
        plt.figure(figsize=(12, 4))
        plt.subplot(1, 2, 1)
        plt.plot(previous_data.history['accuracy'], label='Training
Accuracy')
        plt.plot(previous_data.history['val_accuracy'],
label='Validation Accuracy')
        plt.xlabel('Epoch')
        plt.ylabel('Accuracy')
        plt.title('Training and Validation Accuracy')
```

```
        plt.legend()

        plt.subplot(1, 2, 2)
        plt.plot(previous_data.history['loss'], label='Training
Loss')
        plt.plot(previous_data.history['val_loss'],
label='Validation Loss')
        plt.xlabel('Epoch')
        plt.ylabel('Loss')
        plt.title('Training and Validation Loss')
        plt.legend()

        plt.show()

    def evaluate_simple_mlp_model(self):
        # Evaluate the simple_mlp_model on the test data
        simple_mlp_test_loss, simple_mlp_test_acc =
self.simple_mlp_model.evaluate(self.mlp_test_digits_data,
self.mlp_test_digits_labels)
        print('Test accuracy:', simple_mlp_test_acc)
        return simple_mlp_test_acc

    def visualize_simple_mlp_predictions(self):
        simple_mlp_prediction =
self.simple_mlp_model.predict(self.mlp_test_digits_data)
        simple_mlp_prediction_labels =
np.argmax(simple_mlp_prediction, axis=1)
        mnist_true_labels = np.argmax(self.mlp_test_digits_labels,
axis=1)

        s_mlp_cm = confusion_matrix(mnist_true_labels,
simple_mlp_prediction_labels)
        plt.figure(figsize=(8, 6))
        sns.heatmap(s_mlp_cm, annot=True, fmt='d', cmap='Blues',
xticklabels=range(10), yticklabels=range(10))
        plt.xlabel('Predicted')
        plt.ylabel('True')
        plt.title('Confusion Matrix')
        plt.show()
        return mnist_true_labels, simple_mlp_prediction_labels

    def visualize_random_samples_numbers(self, num_samples=5):
```

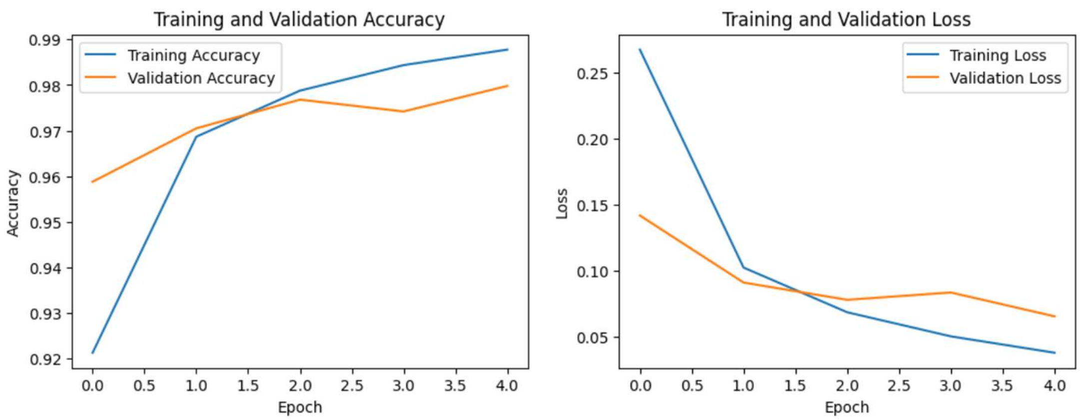
```
        indices =
random.sample(range(len(self.mlp_test_digits_data)), num_samples)
        sample_images = self.mlp_test_digits_data[indices]
        mnist_true_labels =
np.argmax(self.mlp_test_digits_labels[indices], axis=1)
        simple_mlp_prediction =
self.simple_mlp_model.predict(sample_images)
        simple_mlp_prediction_labels =
np.argmax(simple_mlp_prediction, axis=1)
        plt.figure(figsize=(12, 3))
        for i in range(num_samples):
            plt.subplot(1, num_samples, i + 1)
            plt.imshow(sample_images[i].reshape(28, 28),
cmap='gray')
            plt.title(f'True: {mnist_true_labels[i]}\nPred:
{simple_mlp_prediction_labels[i]}')
            plt.axis('off')

        plt.show()

simple_mlp_mnist_digit_classifier =
Simple_MLP_Handwriting_Classifier()

training_history =
simple_mlp_mnist_digit_classifier.MLP_train_simple_model()

simple_mlp_mnist_digit_classifier.MLP_training_history(training_hist
ory)

mlp_simple_accuracy =
simple_mlp_mnist_digit_classifier.evaluate_simple_mlp_model()

mlp_labels, mlp_predictions =
simple_mlp_mnist_digit_classifier.visualize_simple_mlp_predictions()

simple_mlp_mnist_digit_classifier.visualize_random_samples_numbers()
```

Working of the algorithm:-

1) Importing the MNIST handwriting data
2) Splitting the into the training and testing.
3) Making the simple MLP model

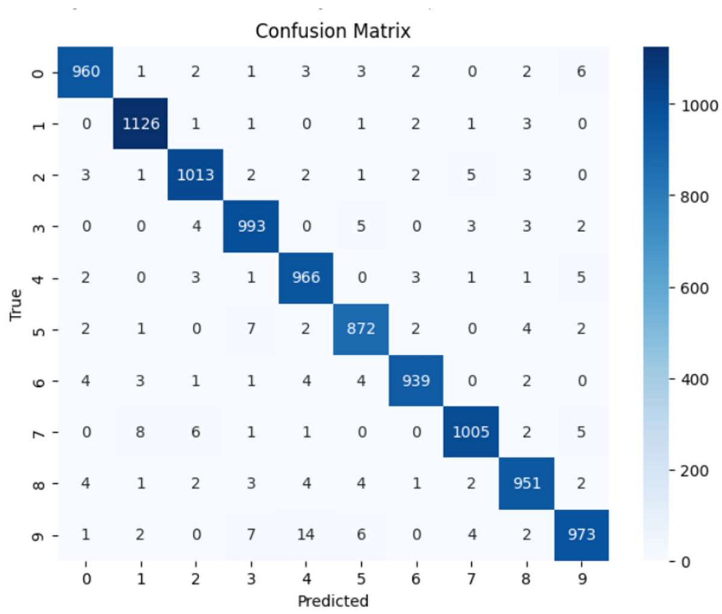
4) This MLP model has 3 layers
5) First layer is of the 256 nodes, 128 nodes and 10 nodes
6) The activation function is RELU
7) Now this algorithm is tested on the test data set
8) Confusion matrix is plotted of the dataset which showcase the accurate answer.
9) This dataset is tested on the random 5 input and their output have been predicted

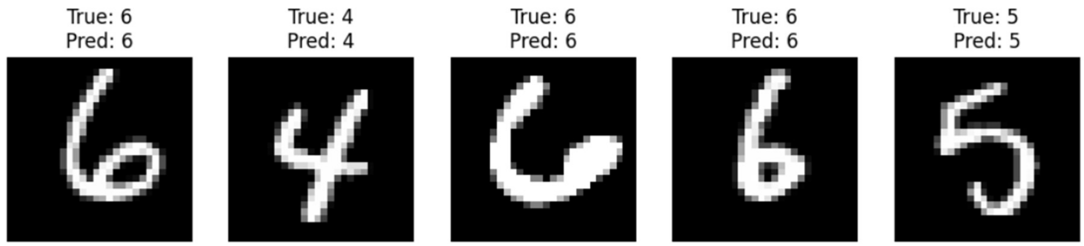
Output:-




```
Test accuracy: 0.9797999858856201
```

Confusion Matrix:-





ResMLP:-

It is a residual neural network which is built on the multi layer perceptron.

Code:-

```
class res_mlp_block(nn.Module):
    def __init__(self, in_features, out_features,
hidden_features=None):
        super(res_mlp_block, self).__init__()
        hidden_features = hidden_features or out_features
        self.fc1 = nn.Linear(in_features, hidden_features)
        self.activation = nn.GELU()
        self.fc2 = nn.Linear(hidden_features, out_features)

    def forward(self, x):
        identity = x
        x = self.fc1(x)
        x = self.activation(x)
        x = self.fc2(x)
        return x + identity

class ResMLP(nn.Module):
    def __init__(self, input_size, hidden_size, output_size,
num_blocks):
        super(ResMLP, self).__init__()
        self.fc_in = nn.Linear(input_size, hidden_size)
        self.blocks = nn.Sequential(*[res_mlp_block(hidden_size,
hidden_size) for _ in range(num_blocks)])
        self.fc_out = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        x = self.fc_in(x)
        x = self.blocks(x)
```

```
        x = self.fc_out(x)
        return x

class MNIST_handwrittern_image_classifier:
    def __init__(self, input_size, hidden_size, output_size,
num_blocks):
        self.device = torch.device("cuda" if
torch.cuda.is_available() else "cpu")
        self.model = ResMLP(input_size, hidden_size, output_size,
num_blocks).to(self.device)
        self.transform = transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize((0.5,), (0.5,))
        ])
        self.res_mlp_train_dataset =
torchvision.datasets.MNIST(root='./data', train=True,
transform=self.transform, download= True)
        self.res_mlp_test_dataset =
torchvision.datasets.MNIST(root='./data', train=False,
transform=self.transform, download= True)
        self.res_mlp_train_loader =
torch.utils.data.DataLoader(dataset=self.res_mlp_train_dataset,
batch_size=64)
        self.res_mlp_test_loader =
torch.utils.data.DataLoader(dataset=self.res_mlp_test_dataset,
batch_size=64)
        self.res_mlp_criterion = nn.CrossEntropyLoss()
        self.res_mlp_optimizer = optim.Adam(self.model.parameters(),
lr=0.001)
        self.num_epochs = 3

    def res_mlp_train_model(self):
        res_mlp_train_loss_ = []
        res_mlp_train_acc_history = []
        res_mlp_train_loss_history = []
        res_mlp_val_acc_history = []
        res_mlp_avg_train_acc_history=[]
        res_mlp_val_loss_history=[]
        mnist_all_Labels=[]
        for epoch in range(self.num_epochs):
            self.model.train()
            for digit_data, data_label in self.res_mlp_train_loader:
```

```
                digit_data, data_label = digit_data.view(-1, 
input_size).to(self.device), data_label.to(self.device)

                self.res_mlp_optimizer.zero_grad()
                res_mlp_output_data = self.model(digit_data)
                loss = self.res_mlp_criterion(res_mlp_output_data, 
data_label)
                loss.backward()
                self.res_mlp_optimizer.step()

            # Evaluate on training set
            self.model.eval()
            res_mlp_total_train, res_mlp_correct_train = 0, 0
            res_mlp_avg_train_loss = 0.0

            with torch.no_grad():
                for digit_data, data_label in 
self.res_mlp_train_loader:
                    digit_data, data_label = digit_data.view(-1, 
input_size).to(self.device), data_label.to(self.device)
                    res_mlp_output_data = self.model(digit_data)
                    _, res_mlp_prediction = 
torch.max(res_mlp_output_data, 1)
                    res_mlp_total_train += data_label.size(0)
                    res_mlp_correct_train += (res_mlp_prediction == 
data_label).sum().item()
                    res_mlp_avg_train_loss += 
self.res_mlp_criterion(res_mlp_output_data, data_label).item()

                res_mlp_train_accuracy = res_mlp_correct_train / 
res_mlp_total_train
                res_mlp_avg_train_loss = res_mlp_avg_train_loss / 
len(self.res_mlp_train_loader)
                res_mlp_train_loss_history.append(res_mlp_avg_train_
loss)
                res_mlp_avg_train_acc_history.append(res_mlp_train_a
ccuracy)

            # Evaluate on validation set
            self.model.eval()
            res_total_val, res_correct_val = 0, 0
            res_val_loss = 0.0
```

```
            with torch.no_grad():
                for digit_data, data_label in
self.res_mlp_test_loader:
                    digit_data, data_label = digit_data.view(-1,
input_size).to(self.device), data_label.to(self.device)
                    res_mlp_output_data = self.model(digit_data)
                    _, res_mlp_prediction =
torch.max(res_mlp_output_data, 1)
                    res_total_val += data_label.size(0)
                    res_correct_val += (res_mlp_prediction ==
data_label).sum().item()
                    res_val_loss +=
self.res_mlp_criterion(res_mlp_output_data, data_label).item()

            res_mlp_val_accuracy = res_correct_val / res_total_val
            res_mlp_avg_val_loss = res_val_loss /
len(self.res_mlp_test_loader)
            res_mlp_val_loss_history.append(res_mlp_avg_val_loss)
            res_mlp_val_acc_history.append(res_mlp_val_accuracy)

            print(f'Epoch [{epoch+1}/{self.num_epochs}], '
                  f'Training Loss: {res_mlp_avg_train_loss:.4f},
Training Accuracy: {100 * res_mlp_train_accuracy:.2f}%, '
                  f'Validation Loss: {res_mlp_avg_val_loss:.4f},
Validation Accuracy: {100 * res_mlp_val_accuracy:.2f}%')
        plt.figure(figsize=(12, 4))
        plt.subplot(1, 2, 1)
        plt.plot(res_mlp_avg_train_acc_history, label='Training
Accuracy')
        plt.plot(res_mlp_val_acc_history, label='Validation
Accuracy')
        plt.xlabel('Epoch')
        plt.ylabel('Accuracy')
        plt.title('Training and Validation Accuracy')
        plt.legend()

        plt.subplot(1, 2, 2)
        plt.plot(res_mlp_train_loss_history, label='Training Loss')
        plt.plot(res_mlp_val_loss_history, label='Validation Loss')
        plt.xlabel('Epoch')
        plt.ylabel('Loss')
```

```
        plt.title('Training and Validation Loss')
        plt.legend()

        plt.show()

    def res_mlp_evaluate_model(self):

        self.model.eval()
        mnist_all_Labels=[]
        mnist_all_predictions=[]
        with torch.no_grad():
            for digit_data, data_label in self.res_mlp_test_loader:
                digit_data, data_label = digit_data.view(-1,
input_size).to(self.device), data_label.to(self.device)
                res_mlp_output_data = self.model(digit_data)
                _, res_mlp_prediction =
torch.max(res_mlp_output_data, 1)
                mnist_all_Labels.extend(data_label.cpu().numpy())
                mnist_all_predictions.extend(res_mlp_prediction.cpu(
).numpy())

        res_mlp_cm = confusion_matrix(mnist_all_Labels,
mnist_all_predictions)
        plt.figure(figsize=(8, 6))
        sns.heatmap(res_mlp_cm, annot=True, fmt='d', cmap='Blues',
xticklabels=range(10), yticklabels=range(10))
        plt.xlabel('res_mlp_prediction')
        plt.ylabel('True')
        plt.title('Confusion Matrix')
        plt.show()

        random_indices =
random.sample(range(len(self.res_mlp_test_dataset)), 5)
        random_images = torch.stack([self.res_mlp_test_dataset[i][0]
for i in random_indices])
        random_labels = [self.res_mlp_test_dataset[i][1] for i in
random_indices]

        self.model.eval()
        with torch.no_grad():
            random_images = random_images.view(-1,
input_size).to(self.device)
```

```
            random_outputs = self.model(random_images)
            _, random_predictions = torch.max(random_outputs, 1)

        plt.figure(figsize=(12, 3))
        for i in range(5):
            plt.subplot(1, 5, i + 1)
            plt.imshow(random_images[i].cpu().view(28, 28),
cmap='gray')
            plt.title(f'True: {random_labels[i]}\nPred:
{random_predictions[i].item()}')
            plt.axis('off')

        plt.show()
        return mnist_all_Labels, mnist_all_predictions

input_size = 28 * 28
hidden_size = 256
output_size = 10
num_blocks = 6

mnist_classifier = MNIST_handwrittern_image_classifier(input_size,
hidden_size, output_size, num_blocks)

mnist_classifier.res_mlp_train_model()

resmlp_labels, resmlp_predictions =
mnist_classifier.res_mlp_evaluate_model()

mlp_precision = precision_score(mlp_labels, mlp_predictions,
average='weighted')
resmlp_precision = precision_score(resmlp_labels,
resmlp_predictions, average='weighted')

mlp_recall = recall_score(mlp_labels, mlp_predictions,
average='weighted')
resmlp_recall = recall_score(resmlp_labels, resmlp_predictions,
average='weighted')

mlp_f1 = f1_score(mlp_labels, mlp_predictions, average='weighted')
resmlp_f1 = f1_score(resmlp_labels, resmlp_predictions,
average='weighted')
```

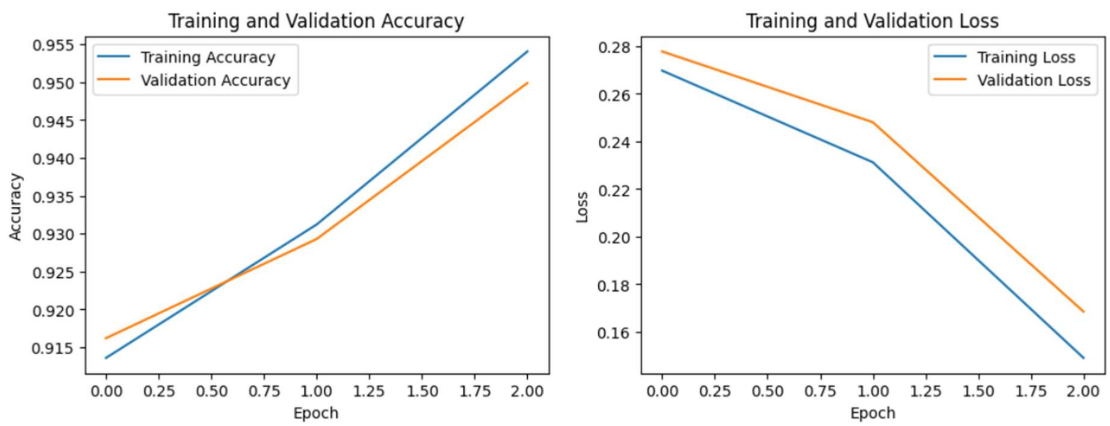
```
print("Precision:")
print(f"MLP: {mlp_precision:.4f}, ResMLP: {resmlp_precision:.4f}")

print("Recall:")
print(f"MLP: {mlp_recall:.4f}, ResMLP: {resmlp_recall:.4f}")

print("F1 Score:")
print(f"MLP: {mlp_f1:.4f}, ResMLP: {resmlp_f1:.4f}")

plt.figure(figsize=(16, 6))

plt.subplot(1, 2, 1)
sns.heatmap(confusion_matrix(mlp_labels, mlp_predictions),
annot=True, fmt='d', cmap='Blues', xticklabels=range(10),
yticklabels=range(10))
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('MLP Confusion Matrix')

plt.subplot(1, 2, 2)
sns.heatmap(confusion_matrix(resmlp_labels, resmlp_predictions),
annot=True, fmt='d', cmap='Blues', xticklabels=range(10),
yticklabels=range(10))
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('ResMLP Confusion Matrix')

plt.show()
```

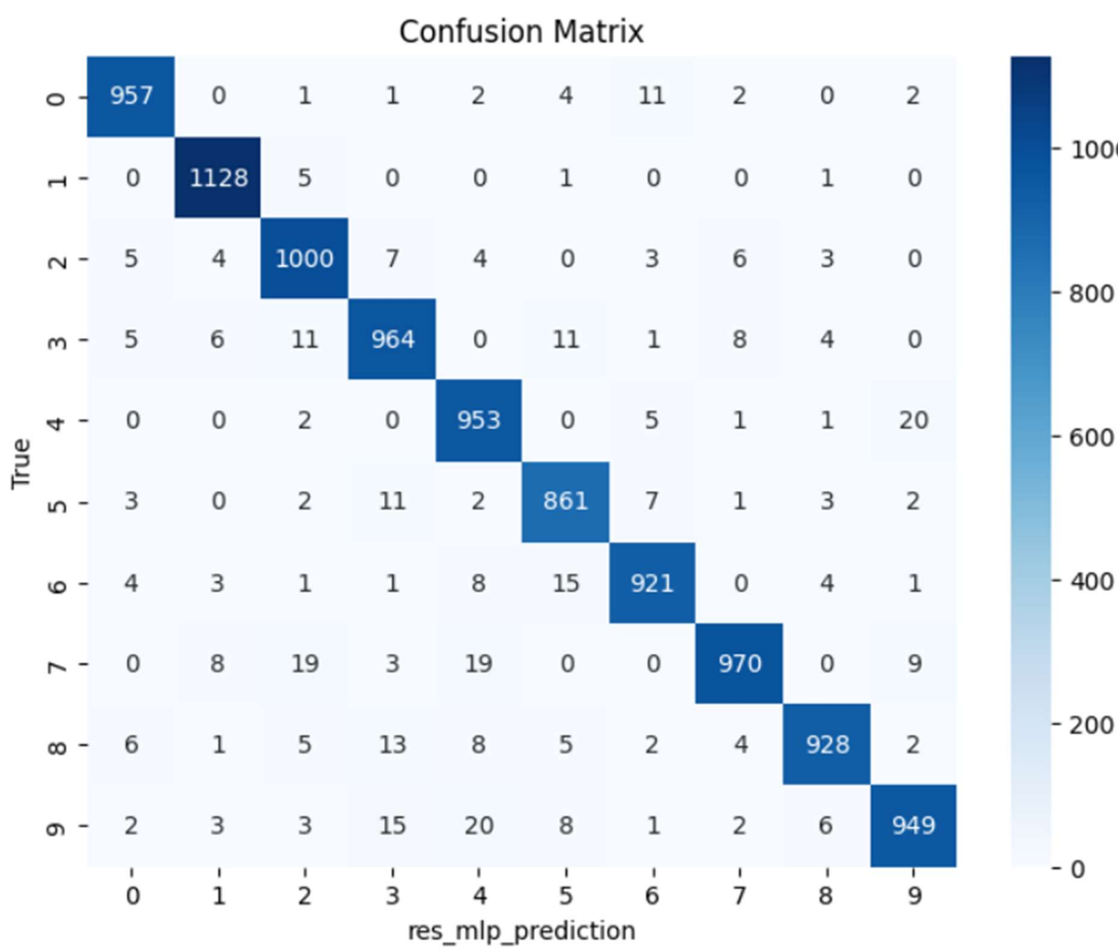
Explanation:-

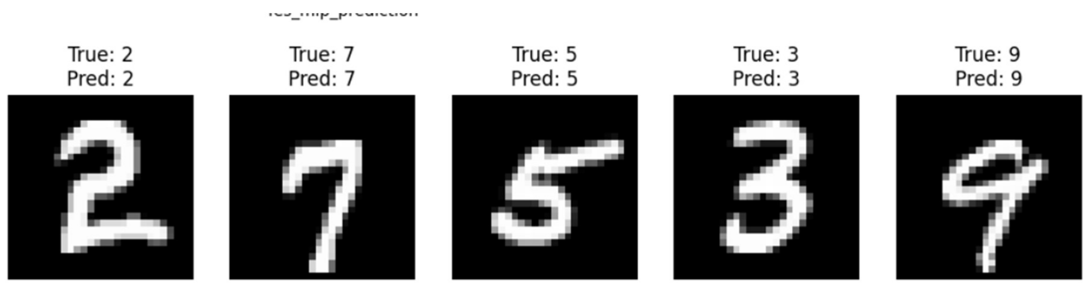
1) Importing the MNIST data from the dataset.
2) Changing the shape of the MNIST dataset
3) Creating the model for the resMLP
4) Making the data in the sequential format and forward function for the algorithm
5) Making the resMLP block
6) Fitting the training data and doing it for 3 epochs
7) Testing the ResMLP on the test data.

8) Plotting confusion matrix of the test data and checking accuracy for the individual number.

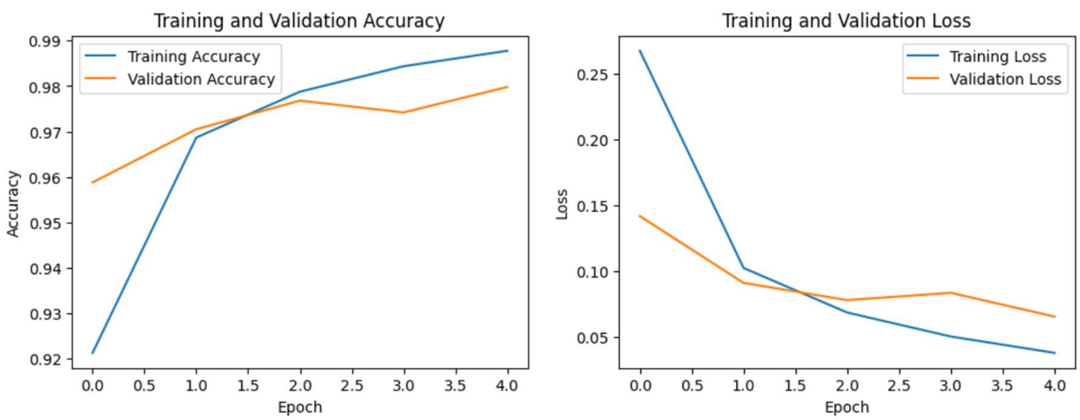
Output:-



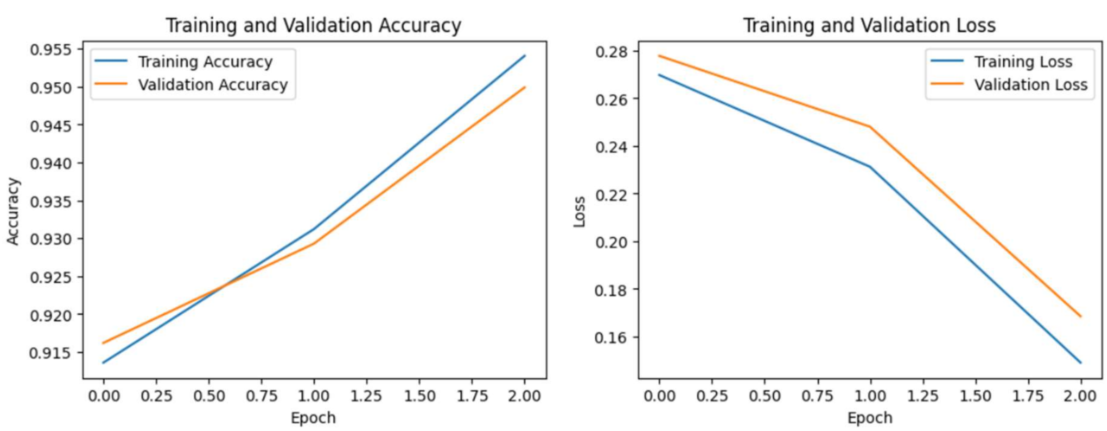




Comparison:-



Training for the Simple MLP



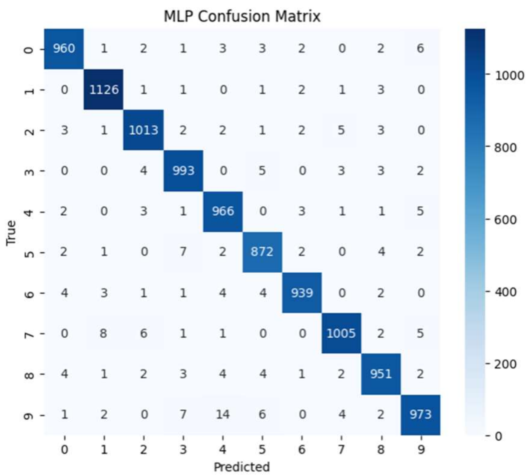
Training for the ResMLP

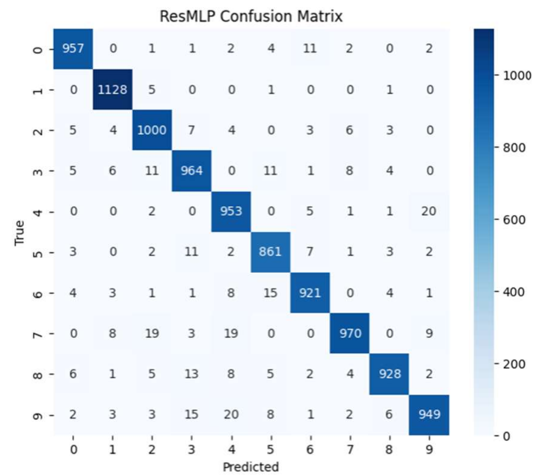
As you can see from the above that the Simple MLP that it performs better than the ResMLP.

After tuning this was the best performance achieved.

```
Precision:
MLP: 0.9798, ResMLP: 0.9633
Recall:
MLP: 0.9798, ResMLP: 0.9631
F1 Score:
MLP: 0.9798, ResMLP: 0.9631
```

From above you can see that the simple MLP performs better than the ResMLP on precision score, Recall score and F1 score.





We can also see similar trends on the confusion matrix. The Simple MLP consistently performed better than the ResMLP.

While working with all the algorithm simple MLP work trained faster than the ResMLP algorithm.

How To run:-

1) **Install Python from the python.org**
2) **Write following in the command prompt**
   pip install seaborn scikit-learn torch torchvision matplotlib tensorflow einops tensorflow-addons seaborn scikit-learn
3) **After installation run assignment1.py or assignment.ipynb on the anaconda**