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```
z2_test = np.dot(a1_test, W2) + b2
```

```
a2_test = softmax(z2_test)
```

```
predictions = np.argmax(a2_test, axis=1)
```

```
accuracy = np.mean(predictions == y_test)
```

```
print(f"\nTest Accuracy: {accuracy:.4f}")
```

```
# Visualize some predictions
```

```
for i in range(2):
```

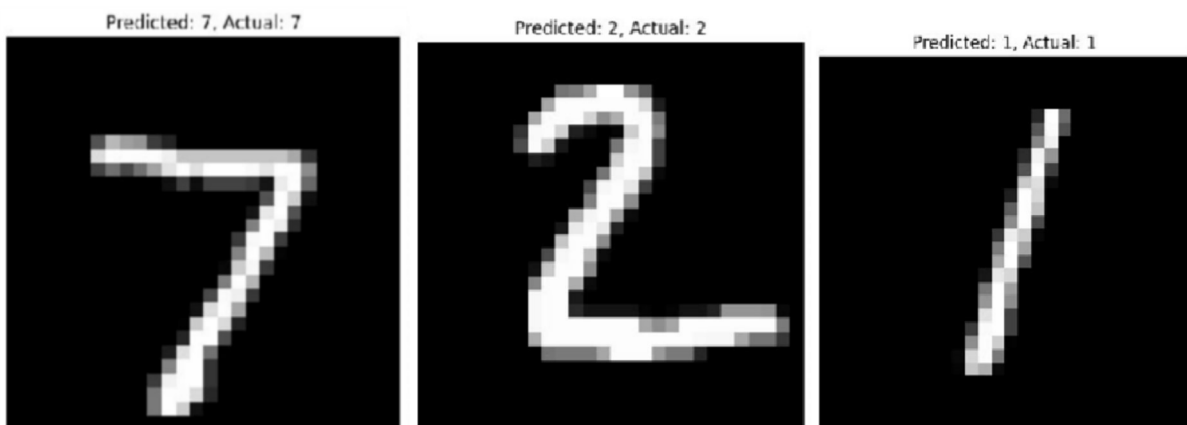
```
    plt.imshow(x_test[i].reshape(28, 28), cmap='gray')
```

```
    plt.title(f'Predicted: {predictions[i]}, Actual: {y_test[i]}')
```

```
    plt.axis('off')
```

```
    plt.show()
```

OUTPUT:



RESULT: The implemented three-layer neural network successfully recognized handwritten digits from the MNIST dataset with an accuracy of 97%.

EXP NO: 02 DATE: 02/08/2025	MULTI LAYER PERCEPTRON
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AIM: To develop a Multi-Layer Perceptron (MLP) model for a simple classification task using the Iris dataset, and experiment with different numbers of hidden layers and activation functions. The performance is evaluated using accuracy and loss.

ALGORITHM:

1. Load the Iris dataset and separate the input features and target labels.
2. Normalize input features using StandardScaler to improve learning.
3. Convert class labels into one-hot encoded format for multi-class classification.
4. Split the dataset into training and testing sets.
5. Build a Multi-Layer Perceptron with different hidden layers and activation functions.
6. Train the model using the Adam optimizer and categorical cross-entropy loss.
7. Evaluate performance using accuracy and loss, and visualize results with learning curves.

CODE:

```
import numpy as np

import matplotlib.pyplot as plt

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler, LabelBinarizer

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense

from tensorflow.keras.optimizers import Adam


# Load dataset

iris = load_iris()

X = iris.data
```

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```
y = iris.target
```

```
# Normalize features
```

```
scaler = StandardScaler()
```

```
X = scaler.fit_transform(X)
```

```
# One-hot encode labels
```

```
encoder = LabelBinarizer()
```

```
y = encoder.fit_transform(y)
```

```
# Train-test split
```

```
X_train, X_test, y_train, y_test = train_test_split(
```

```
    X, y, test_size=0.2, random_state=42
```

```
)
```

```
# Build MLP model
```

```
model = Sequential()
```

```
model.add(Dense(10, input_dim=4, activation='relu')) # hidden layer 1
```

```
model.add(Dense(8, activation='tanh')) # hidden layer 2
```

```
model.add(Dense(3, activation='softmax')) # output layer
```

```
# Compile model
```

```
model.compile(optimizer=Adam(0.01),
```

```
              loss='categorical_crossentropy',
```

```
              metrics=['accuracy'])
```

```
# Train model
```

```
history = model.fit(X_train, y_train, validation_data=(X_test, y_test),
```

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```
epochs=50, batch_size=5, verbose=0)
```

```
# Evaluate model
```

```
loss, acc = model.evaluate(X_test, y_test, verbose=0)
```

```
print(f"Test Accuracy: {acc*100:.2f}%")
```

```
print(f"Test Loss: {loss:.4f}")
```

```
# Plot accuracy and loss
```

```
plt.figure(figsize=(12,5))
```

```
# Accuracy plot
```

```
plt.subplot(1,2,1)
```

```
plt.plot(history.history['accuracy'], label='Train Accuracy')
```

```
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
```

```
plt.xlabel("Epochs")
```

```
plt.ylabel("Accuracy")
```

```
plt.legend()
```

```
plt.title("Model Accuracy")
```

```
# Loss plot
```

```
plt.subplot(1,2,2)
```

```
plt.plot(history.history['loss'], label='Train Loss')
```

```
plt.plot(history.history['val_loss'], label='Validation Loss')
```

```
plt.xlabel("Epochs")
```

```
plt.ylabel("Loss")
```

```
plt.legend()
```

```
plt.title("Model Loss")
```