

<b>Exp No: 6</b>	<b>Feedforward and Convolutional Neural Networks</b>
<b>Date : 11/9/25</b>	

**Aim:**

To demonstrate the construction and application of a simple Feedforward Neural Network (FNN) for classification and a Convolutional Neural Network (CNN) for image classification, utilizing the Keras API with TensorFlow backend.

**Algorithm:****1. Feedforward Neural Network (FNN)**

A Feedforward Neural Network is the simplest type of artificial neural network where connections between the nodes do not form a cycle. It consists of an input layer, one or more hidden layers, and an output layer. Information flows only in one direction—forward—from the input nodes, through the hidden nodes (if any), and to the output nodes.

**Steps:**

1. Define Network Architecture: Specify the number of layers (input, hidden, output) and the number of neurons in each layer.
2. Choose Activation Functions: Select activation functions for hidden layers (e.g., ReLU) and the output layer (e.g., Sigmoid for binary classification, Softmax for multi-class classification).
3. Define Loss Function: Choose a loss function appropriate for the task (e.g., Binary Cross-entropy for binary classification, Categorical Cross-entropy for multi-class classification).
4. Choose Optimizer: Select an optimization algorithm (e.g., Adam, SGD) to update network weights during training.
5. Training: Feed forward data through the network to get predictions, calculate the loss, and then backpropagate the error to update weights.
6. Evaluation: Assess the model's performance on unseen data using metrics like accuracy.

**2. Convolutional Neural Network (CNN)**

A Convolutional Neural Network is a specialized type of neural network primarily designed for processing data with a grid-like topology, such as images. Key components include convolutional layers, pooling layers, and fully connected layers.

**Steps:**

1. Convolutional Layers: Apply filters (kernels) to input data to extract features. Each filter detects a specific pattern (e.g., edges, textures).
2. Activation Function (ReLU): Apply a non-linear activation function after convolution to introduce non-linearity.

3. Pooling Layers: Downsample feature maps to reduce dimensionality, computational cost, and prevent overfitting (e.g., Max Pooling).
4. Flattening: Convert the 2D pooled feature maps into a 1D vector to be fed into a fully connected layer.
5. Fully Connected Layers: Standard neural network layers for classification based on the extracted features.
6. Output Layer: Final layer with an activation function (e.g., Softmax) to output class probabilities.
7. Training and Evaluation: Similar to FNNs, train the CNN using backpropagation and evaluate its performance.

### **CODE:**

```
# Import necessary libraries
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.datasets import mnist, fashion_mnist
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns

# Suppress TensorFlow warnings for cleaner output
tf.keras.utils.disable_interactive_logging()

# --- Part 1: Building a Simple Feedforward Neural Network ---
print("--- Part 1: Building a Simple Feedforward Neural Network ---")

# 1. Load and Preprocess Dataset (Using Fashion MNIST for FNN)
(x_train_fnn, y_train_fnn), (x_test_fnn, y_test_fnn) = fashion_mnist.load_data()

print(f"\nOriginal FNN training data shape: {x_train_fnn.shape}")
print(f"Original FNN test data shape: {x_test_fnn.shape}")

# Flatten images to 1D array
x_train_fnn_flat = x_train_fnn.reshape(-1, 28 * 28)
x_test_fnn_flat = x_test_fnn.reshape(-1, 28 * 28)

# Normalize pixel values
x_train_fnn_norm = x_train_fnn_flat / 255.0
x_test_fnn_norm = x_test_fnn_flat / 255.0

print(f"Flattened & Normalized FNN training data shape: {x_train_fnn_norm.shape}")
print(f"Flattened & Normalized FNN test data shape: {x_test_fnn_norm.shape}")
```

## # 2. Build FNN Model

```
model_fnn = keras.Sequential([
    layers.Dense(128, activation='relu', input_shape=(784,)),
    layers.Dropout(0.2),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])
```

## # 3. Compile Model

```
model_fnn.compile(optimizer='adam',
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])
```

```
print("\n--- FNN Model Summary ---")
model_fnn.summary()
```

## # 4. Train Model

```
print("\n--- Training FNN Model ---")
history_fnn = model_fnn.fit(x_train_fnn_norm, y_train_fnn, epochs=10,
                           validation_split=0.1, verbose=1)
```

## # 5. Evaluate Model

```
print("\n--- Evaluating FNN Model ---")
loss_fnn, accuracy_fnn = model_fnn.evaluate(x_test_fnn_norm, y_test_fnn, verbose=0)
print(f"FNN Test Loss: {loss_fnn:.4f}")
print(f"FNN Test Accuracy: {accuracy_fnn:.4f}")
```

## # Classification report & confusion matrix

```
y_pred_fnn = np.argmax(model_fnn.predict(x_test_fnn_norm), axis=-1)
print("\n--- FNN Classification Report ---")
print(classification_report(y_test_fnn, y_pred_fnn))
```

## print("\n--- FNN Confusion Matrix ---")

```
cm_fnn = confusion_matrix(y_test_fnn, y_pred_fnn)
plt.figure(figsize=(10, 8))
sns.heatmap(cm_fnn, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.title("FNN Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

## # Plot Accuracy & Loss

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

```
plt.subplot(1, 2, 1)
plt.plot(history_fnn.history['accuracy'], label='Training Accuracy')
plt.plot(history_fnn.history['val_accuracy'], label='Validation Accuracy')
plt.title('FNN Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)
```

```
plt.subplot(1, 2, 2)
plt.plot(history_fnn.history['loss'], label='Training Loss')
plt.plot(history_fnn.history['val_loss'], label='Validation Loss')
plt.title('FNN Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
# --- Part 2: Convolutional Neural Network (CNN) ---
print("\n--- Part 2: Implementing a CNN ---")
```

```
# 1. Load MNIST for CNN
```

```
(x_train_cnn, y_train_cnn), (x_test_cnn, y_test_cnn) = mnist.load_data()
print(f"\nOriginal CNN training data shape: {x_train_cnn.shape}")
print(f"Original CNN test data shape: {x_test_cnn.shape}")
```

```
# Reshape for channel dimension
```

```
x_train_cnn = x_train_cnn.reshape(x_train_cnn.shape[0], 28, 28, 1)
x_test_cnn = x_test_cnn.reshape(x_test_cnn.shape[0], 28, 28, 1)
```

```
# Normalize
```

```
x_train_cnn = x_train_cnn.astype('float32') / 255.0
x_test_cnn = x_test_cnn.astype('float32') / 255.0
```

```
print(f"Reshaped & Normalized CNN training data shape: {x_train_cnn.shape}")
print(f"Reshaped & Normalized CNN test data shape: {x_test_cnn.shape}")
```

```
num_classes_cnn = 10
```

```
# 2. Build CNN Model
```

```
model_cnn = keras.Sequential([
    layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)),
```

```
layers.MaxPooling2D((2, 2)),
layers.Conv2D(64, (3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Flatten(),
layers.Dense(128, activation='relu'),
layers.Dropout(0.5),
layers.Dense(num_classes_cnn, activation='softmax')
])
```

### # 3. Compile Model

```
model_cnn.compile(optimizer='adam',
                  loss='sparse_categorical_crossentropy',
                  metrics=['accuracy'])
```

```
print("\n--- CNN Model Summary ---")
model_cnn.summary()
```

### # 4. Train Model

```
print("\n--- Training CNN Model ---")
history_cnn = model_cnn.fit(x_train_cnn, y_train_cnn, epochs=10,
                           validation_split=0.1, verbose=1)
```

### # 5. Evaluate Model

```
print("\n--- Evaluating CNN Model ---")
loss_cnn, accuracy_cnn = model_cnn.evaluate(x_test_cnn, y_test_cnn, verbose=0)
print(f"CNN Test Loss: {loss_cnn:.4f}")
print(f"CNN Test Accuracy: {accuracy_cnn:.4f}")
```

### # Classification report & confusion matrix

```
y_pred_cnn = np.argmax(model_cnn.predict(x_test_cnn), axis=-1)
print("\n--- CNN Classification Report ---")
print(classification_report(y_test_cnn, y_pred_cnn))
```

```
print("\n--- CNN Confusion Matrix ---")
```

```
cm_cnn = confusion_matrix(y_test_cnn, y_pred_cnn)
plt.figure(figsize=(10, 8))
sns.heatmap(cm_cnn, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.title("CNN Confusion Matrix")
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()
```

### # Plot Accuracy & Loss

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

```

plt.subplot(1, 2, 1)
plt.plot(history_cnn.history['accuracy'], label='Training Accuracy')
plt.plot(history_cnn.history['val_accuracy'], label='Validation Accuracy')
plt.title('CNN Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

plt.subplot(1, 2, 2)
plt.plot(history_cnn.history['loss'], label='Training Loss')
plt.plot(history_cnn.history['val_loss'], label='Validation Loss')
plt.title('CNN Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()

# Optional: Visualize predictions
print("\n--- Sample CNN Predictions ---")
class_names_mnist = [str(i) for i in range(10)]
plt.figure(figsize=(10, 10))
for i in range(25):
    plt.subplot(5, 5, i + 1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(x_test_cnn[i].reshape(28, 28), cmap=plt.cm.binary)
    true_label = y_test_cnn[i]
    predicted_label = y_pred_cnn[i]
    color = 'green' if true_label == predicted_label else 'red'
    plt.xlabel(f"True: {class_names_mnist[true_label]} \n Pred: {class_names_mnist[predicted_label]}", color=color)
plt.suptitle("Sample CNN Predictions (Green: Correct, Red: Incorrect)", y=1.02, fontsize=16)
plt.tight_layout(rect=[0, 0, 1, 0.98])
plt.show()

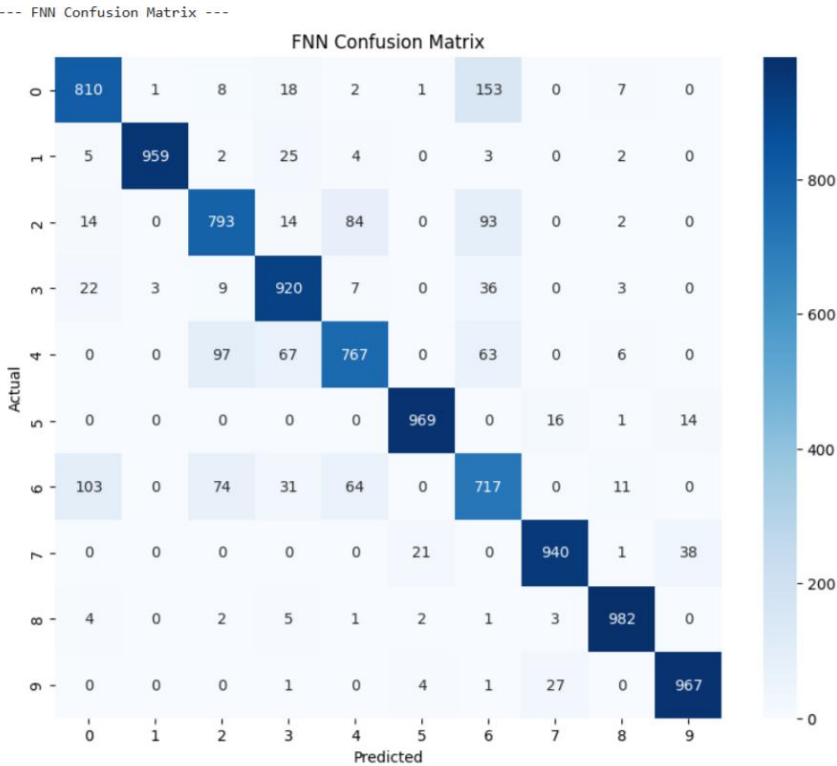
```

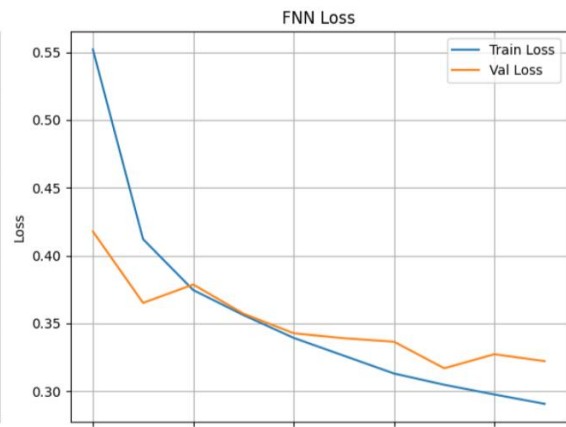
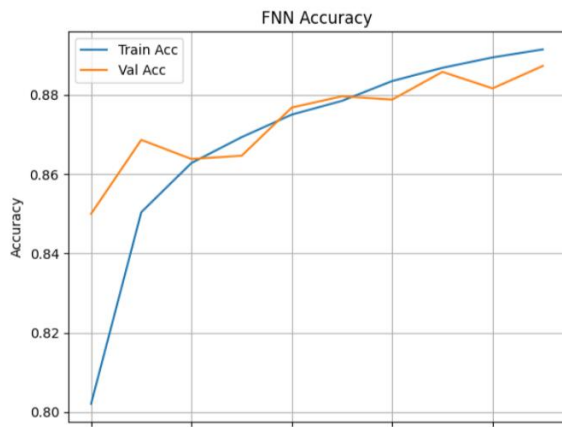
**OUTPUT:**

FNN Test Loss: 0.3404  
FNN Test Accuracy: 0.8824

--- FNN Classification Report ---

	precision	recall	f1-score	support
0	0.85	0.81	0.83	1000
1	1.00	0.96	0.98	1000
2	0.81	0.79	0.80	1000
3	0.85	0.92	0.88	1000
4	0.83	0.77	0.80	1000
5	0.97	0.97	0.97	1000
6	0.67	0.72	0.69	1000
7	0.95	0.94	0.95	1000
8	0.97	0.98	0.97	1000
9	0.95	0.97	0.96	1000
accuracy			0.88	10000
macro avg	0.88	0.88	0.88	10000
weighted avg	0.88	0.88	0.88	10000

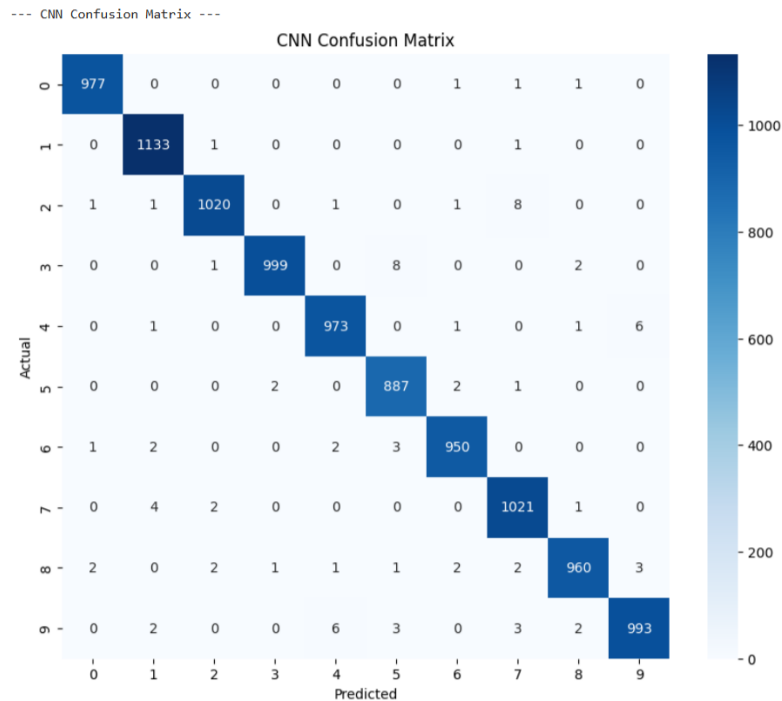




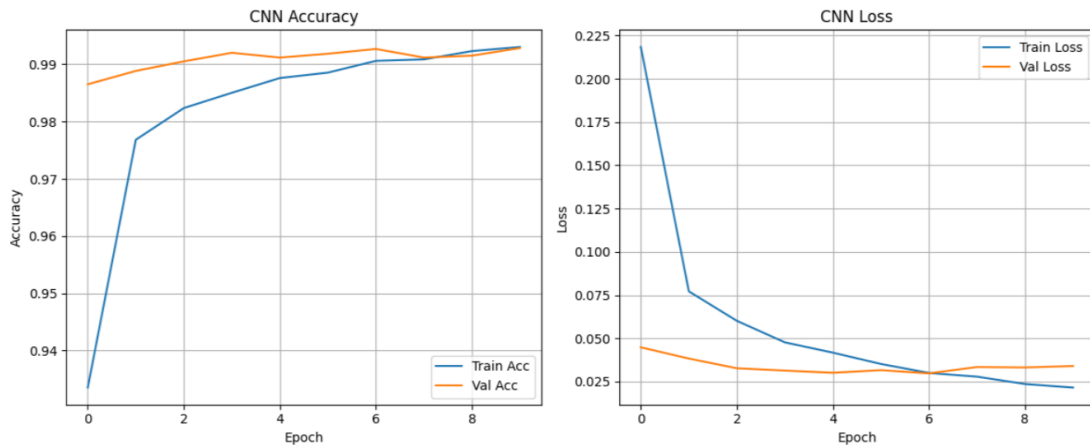
CNN Test Loss: 0.0285  
 CNN Test Accuracy: 0.9913

--- CNN Classification Report ---

	precision	recall	f1-score	support
0	1.00	1.00	1.00	980
1	0.99	1.00	0.99	1135
2	0.99	0.99	0.99	1032
3	1.00	0.99	0.99	1010
4	0.99	0.99	0.99	982
5	0.98	0.99	0.99	892
6	0.99	0.99	0.99	958
7	0.98	0.99	0.99	1028
8	0.99	0.99	0.99	974
9	0.99	0.98	0.99	1009
accuracy			0.99	10000
macro avg	0.99	0.99	0.99	10000
weighted avg	0.99	0.99	0.99	10000

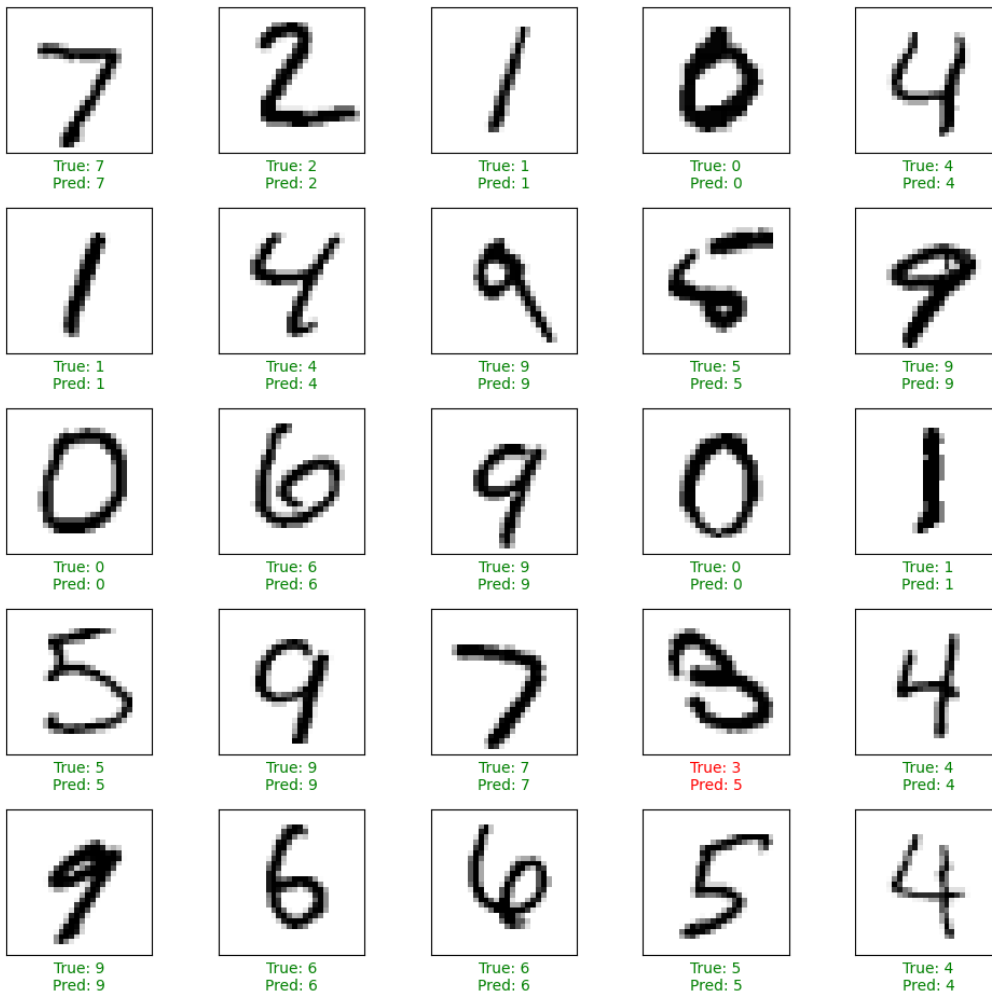






--- Sample CNN Predictions ---

CNN Predictions (Green = Correct, Red = Incorrect)



**Result:**

The Feedforward and Convolutional Neural Networks were successfully implemented. The FNN performed well on Fashion MNIST, while the CNN achieved higher accuracy on MNIST, proving its efficiency in image classification.