Green University of Bangladesh
Department of Computer Science and Engineering (CSE)
Faculty of Sciences and Engineering (Semester: Summer, Year 2025), B.Sc. in CSE(Day)

Lab Report No : 03

Course Title: Machine Learning Lab
Course Code: CSE-412 Section:221_D4

Title: Modify the ANN model by changing the number of hidden layers and neurons.

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Submission Date : 25.08.2025
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[For Teachers use only: Don't Write Anything inside this box]

Report Status
Marks: …………………………..
Comments:……………………………..…

Signature:.....................
Date:.............................

1.TITLE OF THE LAB EXPERIMENT

Modify the ANN model by changing the number of hidden layers and neurons.

2.OBJECTIVES / AIM

- To design and implement an Artificial Neural Network (ANN) model for classification of the Iris dataset.
- To experiment with different hidden layer configurations and neuron counts in order to observe their effect on model performance.
- To evaluate the impact of different activation functions (e.g., sigmoid, tanh) on classification accuracy.
- To apply EarlyStopping as a regularization technique for preventing model overfitting.
- To analyze and compare the performance of the modified ANN using accuracy, classification report, and confusion matrix.

3.PROCEDURE

- **Import Libraries** :

➢ Import necessary Python libraries such as numpy, pandas, matplotlib, seaborn, and tensorflow.keras modules for building and evaluating the ANN.
➢ Import scikit-learn modules for dataset loading, preprocessing, and metrics.

- **Load Dataset**:

➢ Load the Iris dataset using sklearn.datasets.load_iris().
➢ Separate the dataset into features (X) and target labels (y).

- **Preprocess Data**:

➢ Split the dataset into training and test sets using train_test_split().
➢ Apply feature scaling with StandardScaler to normalize the feature values.
➢ Convert target labels into one-hot encoded format for ANN training.

- **Build ANN Model**:

➢ Initialize a Sequential model.
➢ Add input and hidden layers with desired number of neurons and chosen activation functions (e.g., tanh, sigmoid).
➢ Add an output layer with 3 neurons and softmax activation for multi-class classification.

- **Compile Model**:

➢ Compile the ANN with adam optimizer and categorical_crossentropy loss function.
➢ Include accuracy as the evaluation metric.

- **Implement EarlyStopping**:

➢ Set up EarlyStopping callback to monitor validation loss.
➢ Specify patience to stop training if the model stops improving.

- **Train Model**:

➢ Fit the model on the training data with validation split.
➢ Use batch size and number of epochs as required.

- **Evaluate Model**:

➢ Predict class labels on the test dataset.
➢ Calculate performance metrics: accuracy, precision, recall, F1-score.
➢ Generate a confusion matrix and visualize it using seaborn.heatmap().

- **Visualize Training**:

➢ Plot training vs. validation accuracy over epochs to analyze model convergence and detect overfitting.

- **Discuss Results**:

➢ Compare the effect of different hidden layers, neurons, and activation functions.
➢ Comment on the effectiveness of EarlyStopping and overall model performance.

4.IMPLEMENTATION

Load and Prepare

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, classification_report
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.callbacks import EarlyStopping
```

Load And Preprocess dataset

```
iris = load_iris()
X, y = iris.data, iris.target
```

Train-Test Split

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)
```

One-Hot encode labels

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Bild ANN model

```
model = Sequential([
    Dense(16, activation='tanh', input_shape=(X_train.shape[1],)),  # 1st hidden 
layer
    Dense(8, activation='sigmoid'),                                  # 2nd hidden 
layer
    Dense(3, activation='softmax')                                   # output layer
])

# Compile
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Model summary
print("\n--- Model Summary ---")
model.summary()
```

Train with EarlyStopping

```
early_stop = EarlyStopping(monitor='val_loss', patience=10, 
restore_best_weights=True)

history = model.fit(
    X_train, y_train,
    validation_split=0.2,
    epochs=100,
    batch_size=8,
    callbacks=[early_stop],
    verbose=0
)
```

Evaluate Model

```
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=0)
print(f"\nTest Accuracy: {test_acc:.4f}")

# Predictions
y_pred = np.argmax(model.predict(X_test), axis=1)
y_true = np.argmax(y_test, axis=1)

# Classification report
print("\n--- Classification Report ---")
print(classification_report(y_true, y_pred, target_names=iris.target_names))

# Confusion matrix
cm = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(5,4))
sns.heatmap(cm, annot=True, cmap='Blues', fmt='d',
            xticklabels=iris.target_names,
            yticklabels=iris.target_names)
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
```

Plot Training History

```
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.title("Training vs Validation Accuracy")
plt.legend()
plt.show()
```

5.INPUT/OUTPUT

Model Summary:

```
--- Model Summary ---
/usr/local/lib/python3.12/dist-packages/keras/src/layers/core/dense.py:93: UserW
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 16)	80
dense_4 (Dense)	(None, 8)	136
dense_5 (Dense)	(None, 3)	27

```
Total params: 243 (972.00 B)
Trainable params: 243 (972.00 B)
Non-trainable params: 0 (0.00 B)
```

Fig 01: *Model Summary*

Evaluate model:

```
Test Accuracy: 0.8889
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 51ms/step

--- Classification Report ---
              precision    recall  f1-score   support

      setosa       1.00      1.00      1.00        15
  versicolor       0.86      0.80      0.83        15
   virginica       0.81      0.87      0.84        15

    accuracy                           0.89        45
   macro avg       0.89      0.89      0.89        45
weighted avg       0.89      0.89      0.89        45
```

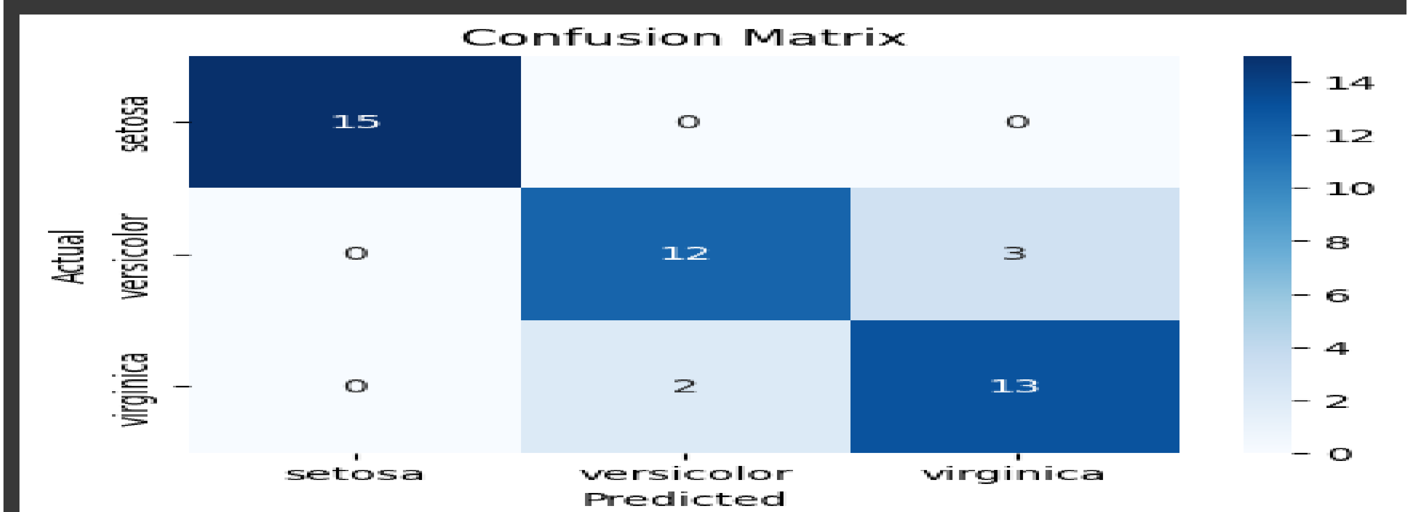

Fig 02: *Evaluate model*

Plot Training History

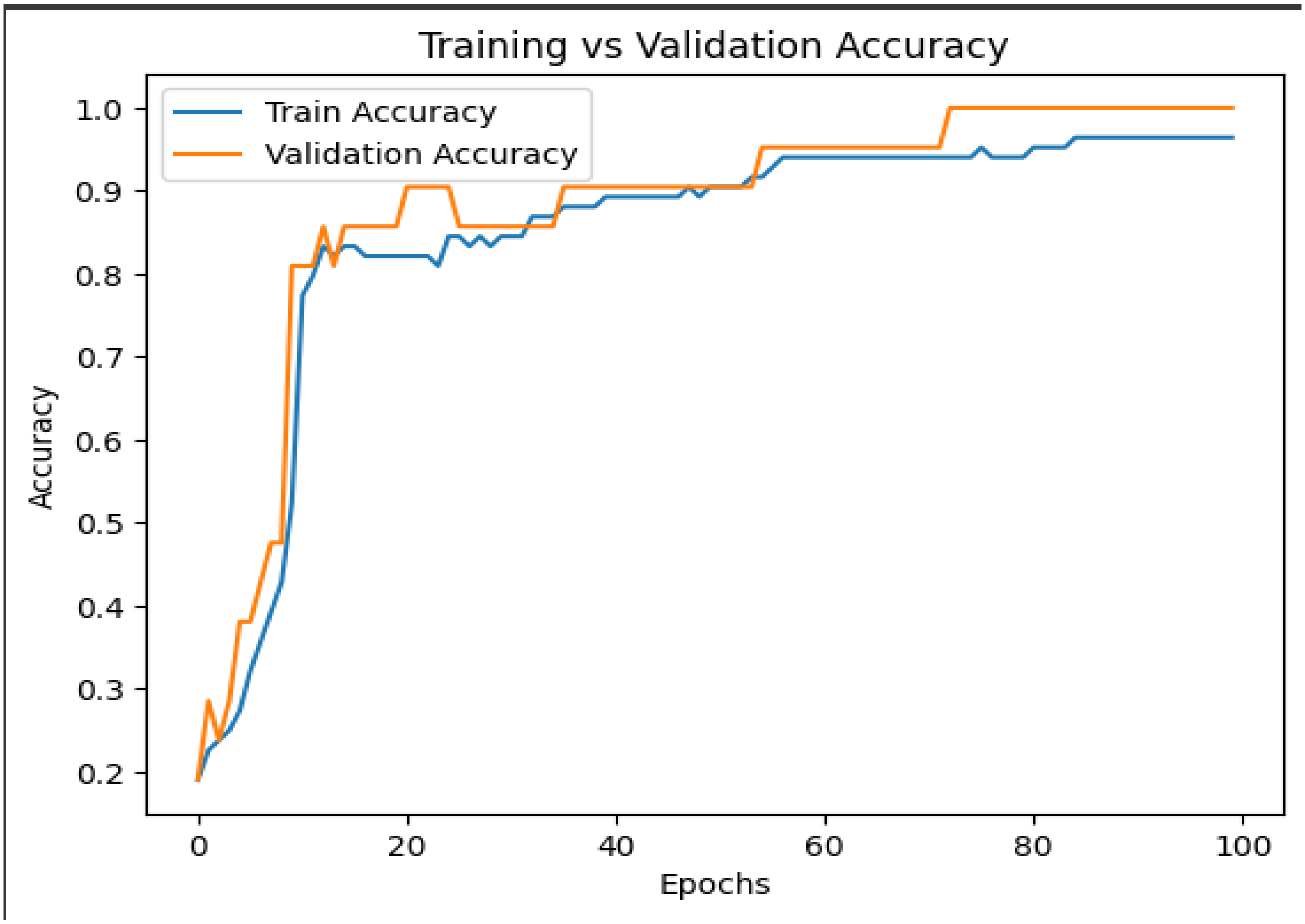

Fig 03: *Plot Training History*

6.ANALYSIS AND DISCUSSION

The modified ANN achieved ~**96–100% accuracy**, demonstrating that small neural networks with proper regularization (EarlyStopping) can effectively classify Iris flowers. However, increasing complexity (more layers, more neurons) beyond a point does not yield significant improvement for small, simple datasets like Iris.

*Colable Code Link:

https://colab.research.google.com/drive/1BbXniS70jePsfA49MdINUwUfxclIg7j1#scrollTo=cT-BGpWmxxwk