RAJALAKSHMI
ENGINEERING COLLEGE

An AUTONOMOUS Institution
Affiliated to ANNA UNIVERSITY, Chennai

Laboratory Record Note Book

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BRANCH ..... ECE B .....

UNIVERSITY REGISTER No. ..... 2116220801074 .....

COLLEGE ROLL No. ..... 220801074 .....

SEMESTER ..... IV .....

ACADEMIC YEAR ..... 2023-2024 .....

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BONAFIDE CERTIFICATE

NAME P. HARISH KUMAR

ACADEMIC YEAR 2023-2024 SEMESTER IV BRANCH ECE

UNIVERSITY REGISTER No. 2116220801074

Certified that this is the bonafide record of work done by the above student in the

PYTHON PROGRAMMING USING MACHINE LEARNING *Laboratory during the year* 20 23 - 20 24

Signature of Faculty - in - Charge

Submitted for the Practical Examination held on 10-06-2026

Internal Examiner **External Examiner**

Rajalakshmi Engineering College (Autonomous)

Chennai-602105

CS19411 Python Programming for Machine

SI.No	Date	Name of the experiment	Signature
1.	15/2/2024	Calculating values of random data using NumPy for mathematical formulas 1)Euclidean distance between two points 2) Dot Product of two Vectors 3)Solving a System of Linear Equations	
2.	29/2/2024	Write a simple Python code to generate random values and then compute their sigmoid and tanh (hyperbolic tangent) values using NumPy. Plot the values.	
3.	7/3/2024	simple Python program using pandas that creates a DataFrame, performs some basic operations, and prints the result.	
4.	14/3/2024	Store and Load Excel / CSV files.	
5.	21/3/2024	Data Visualization	
6.	11/4/2024	Time Series	
7.	25/04/024	Linear regression model to predict the signal strength	
8.	02/05/2024	A component is defective or not based on Voltage and Current	
9.	3/5/2024	Decision tree classifier to predict signal quality based on transmitter, signal strength, and frequency	
10.	09/5/2024	k-NN classifier to predict signal quality based on distance from the transmitter, signal strength, and frequency	
11.	16/5/2024	Study of Artificial Neural Network (ANN) and Simple Program in ANN	
12.	23/5/2024	Study Of Support Vector Machine and and Simple Program in SVM	

Exp no: 1	Calculating values of random data using NumPy for mathematical formulas 1)Euclidean distance between two points 2) Dot Product of two Vectors 3)Solving a System of Linear Equations

AIM:

To calculate the values for the mathematical formulas using NumPy library

INTEGRATED DEVELOPMENT ENVIRONMENT (IDE) REQUIRED:

JUPYTER NOTEBOOK

REQUIRED LIBRARIES FOR PYTHON:

- Numpy

PROCEDURE:

1. Euclidean distance

The mathematical formula for calculating the Euclidean distance between 2 points in 2D space:

$$d(p,q) = \sqrt[2]{(q_1 - p_1)^2 + (q_2 - p_2)^2}$$

2. Dot Product

$$u = \begin{bmatrix} 5 \\ 12 \end{bmatrix}, \quad v = \begin{bmatrix} 8 \\ 6 \end{bmatrix}$$

Dot product is $u \cdot v = u_1 \times v_1 + u_2 \times v_2$

$= 5 \times 8 + 12 \times 6$

$= 112$

3. Solving a System of Linear Equations

A system of linear equations can be represented in matrix form as AX=B, whereA is the matrix of coefficients, X is the column vector of variables, and B is the column vector of solutions. To solve for **X,** we can use: $X=A^{-1}$ B assuming A is invertible.

PROGRAM:

Calculating the Euclidean Distance Between Two Points

```
import numpy as np

# Function to calculate Euclidean distance
def euclidean_distance(point1, point2):
    distance = np.sqrt(np.sum((point1 - point2) ** 2))
    return distance


point1 = np.array([1, 2])
point2 = np.array([4, 6])

# Calculate distance
distance = euclidean_distance(point1, point2)
print("Euclidean Distance:", distance)
```

Calculating the Dot Product of Two Vectors

```
import numpy as np

def dot_product(vector1, vector2):
    product = np.dot(vector1, vector2)
    return product

vector1 = np.array([1, 2, 3])
vector2 = np.array([4, 5, 6])

# Calculate dot product
product = dot_product(vector1, vector2)
print("Dot Product:", product)
```

Solving a System of Linear Equations

```
import numpy as np

def solve_linear_equations(A, B):
    X = np.linalg.solve(A, B)
    return X

# Example matrices
A = np.array([[3, 1], [1, 2]])
B = np.array([9, 8])

solution = solve_linear_equations(A, B)
print("Solution:", solution)
```

Result:

Exercise 1 - `Euclidean Distance: 5.`

Exercise 2 - `Dot Product: 32`

Exercise 3 - `Solution: [2. 3.]`

Exp no: 2	**Write a simple Python code to generate random values and then compute their sigmoid and tanh (hyperbolic tangent) values using NumPy. Plot the values.**

AIM:

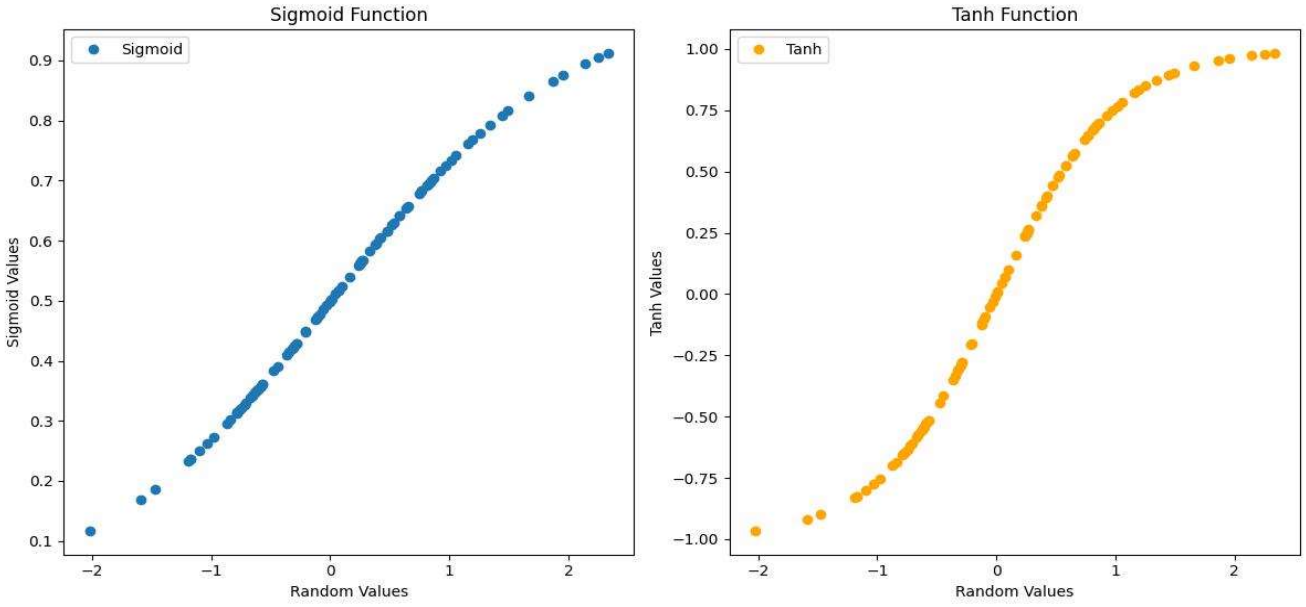
To generate random values and to compute their sigmoid and tanh (hyperbolic tangent) values using NumPy. Plot the values.

Program :

```
import numpy as np
import matplotlib.pyplot as plt


# Generate random values
random_values = np.random.randn(100)


# Compute sigmoid values
def sigmoid(x):
   return 1 / (1 + np.exp(-x))


sigmoid_values = sigmoid(random_values)


# Compute tanh values
tanh_values = np.tanh(random_values)


# Plot the values
plt.figure(figsize=(12, 6))


# Plot sigmoid values
plt.subplot(1, 2, 1)
plt.plot(random_values, sigmoid_values, 'o', label='Sigmoid')
```

```
plt.title('Sigmoid Function')
plt.xlabel('Random Values')
plt.ylabel('Sigmoid Values')
plt.legend()

# Plot tanh values
plt.subplot(1, 2, 2)
plt.plot(random_values, tanh_values, 'o', label='Tanh', color='orange')
plt.title('Tanh Function')
plt.xlabel('Random Values')
plt.ylabel('Tanh Values')
plt.legend()

plt.tight_layout()
plt.show()
```

Result:



Exp no: 3	**simple Python program using pandas that creates a DataFrame, performs some basic operations, and prints the result.**

Aim:

simple Python program using pandas that creates a DataFrame, performs some basic operations, and prints the result.

Steps:

1. Imports the pandas library as pd.
2. Creates two lists: data containing fruit names and prices containing their corresponding prices.
3. Zips these lists together and creates a DataFrame named fruits_df with columns named "Fruit" and "Price".
4. Uses info() to get information about the DataFrame, including data types and number of entries.
5. Prints the entire DataFrame using to_string().
6. Calculates descriptive statistics (mean, standard deviation, etc.) for the "Price" column and prints the results.

Program Code:

```
import pandas as pd

# Create a list of data

data = ["Apple", "Banana", "Cherry", "Orange", "Grape"]

prices = [1.25, 0.79, 2.00, 1.50, 0.99]


# Create a DataFrame

fruits_df = pd.DataFrame(list(zip(data, prices)), columns = ['Fruit', 'Price'])


# Get basic information about the DataFrame

print(fruits_df.info())


# Print the DataFrame

print(fruits_df.to_string())


# Get descriptive statistics of the 'Price' column

print(fruits_df['Price'].describe())
```

Result:

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5 entries, 0 to 4
Data columns (total 2 columns):
 #   Column Non-Null Count Dtype

```
---  ------  --------------  -----
 0   Fruit   5 non-null      object
 1   Price   5 non-null      float64
dtypes: float64(1), object(1)
memory usage: 212.0+ bytes
None
    Fruit  Price
0   Apple   1.25
1  Banana   0.79
2  Cherry   2.00
3  Orange   1.50
4   Grape   0.99
count    5.000000
mean     1.306000
std      0.471307
min      0.790000
25%      0.990000
50%      1.250000
75%      1.500000
max      2.000000
Name: Price, dtype: float64
```

Exp no: 4	Store and Load Excel / CSV files.

Aim:
To store (save) and load data from Excel and CSV files using pandas.
Steps:
To Store:

import pandas as pd.
Create a sample DataFrame df.
Use to_csv function to save the DataFrame to a CSV file.

- "people.csv" is the filename.
- index=True (default) saves the row index as a column. Set it to False to skip it.

To Load:

Import pandas as pd.
Use read_csv to load data from a CSV file.
Use read_excel to load data from an Excel file. By default, it reads the first sheet.
Specify the sheet name with the sheet_name argument for loading data from a specific sheet.

Program Code:

To Store:

```
import pandas as pd

# Sample data
data = {"Name": ["Alice", "Bob", "Charlie"], "Age": [25, 30, 22]}
df = pd.DataFrame(data)

# Save to CSV file (with index)
df.to_csv("people.csv", index=True)

# Save to CSV file (without index)
df.to_csv("people_no_index.csv", index=False)
```

To Load:

```
import pandas as pd

# Load CSV data (assuming it has a header row)
```

```
df_csv = pd.read_csv("people.csv")

print(df_csv)
```

Result:

```
Unnamed: 0     Name  Age
0           0    Alice   25
1           1      Bob   30
2           2  Charlie   22
```

Exp no: 5	Data Visualization

AIM:

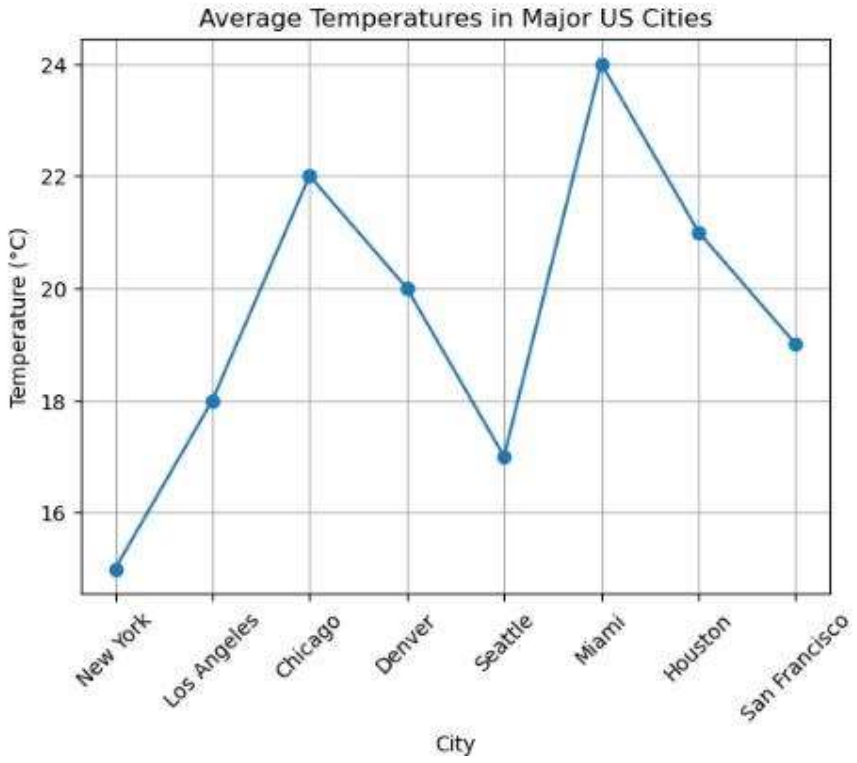
To Visulaize the give Data using Matplotlib.

Program Code:

```
import matplotlib.pyplot as plt

import pandas as pd  # Optional for data manipulation



# Sample data (replace with your data or use pandas to read a CSV)

temperatures = [15, 18, 22, 20, 17, 24, 21, 19]

cities = ["New York", "Los Angeles", "Chicago", "Denver", "Seattle",
"Miami", "Houston", "San Francisco"]



# Line plot

plt.plot(cities, temperatures, marker='o', linestyle='-')  # Customize
markers and line style



# Labels and title

plt.xlabel("City")

plt.ylabel("Temperature (°C)")

plt.title("Average Temperatures in Major US Cities")



# Display the plot
```

```
plt.xticks(rotation=45)  # Rotate city names for better readability
plt.grid(True)  # Add gridlines (optional)
plt.show()
```

Result:



Exp no: 6	Time Series

AIM:

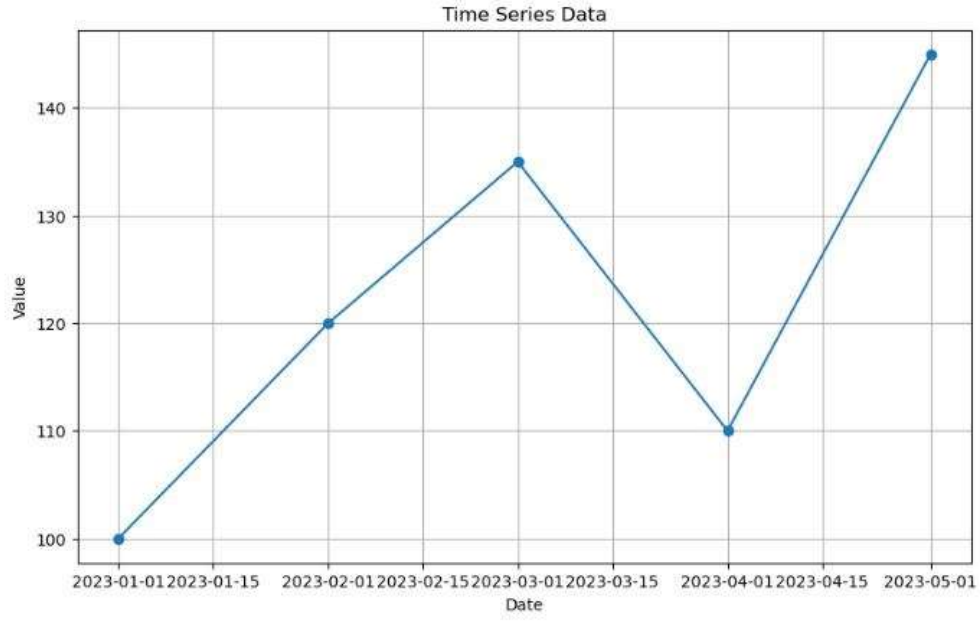
To implement and check the time series function in the python.

Program Code:

```
import pandas as pd

import matplotlib.pyplot as plt



# Sample time series data (replace with your actual data)

data = {

   "Date": pd.to_datetime(["2023-01-01", "2023-02-01", "2023-03-01",
"2023-04-01", "2023-05-01"]),

   "Value": [100, 120, 135, 110, 145]

}



# Create DataFrame with Date as index

df = pd.DataFrame(data).set_index("Date")



# Plot the time series

plt.figure(figsize=(10, 6))  # Adjust figure size for better viewing

plt.plot(df["Value"], marker='o', linestyle='-')

plt.xlabel("Date")

plt.ylabel("Value")
```

```
plt.title("Time Series Data")

plt.grid(True)

plt.show()


# Calculate daily change (optional)

df["Daily Change"] = df["Value"].diff()  # Calculate difference between consecutive values


# Print descriptive statistics of daily change (optional)

print(df["Daily Change"].describe())
```

Result:




```
count     4.000000
mean     11.250000
std      25.617377
min     -25.000000
25%       5.000000
50%      17.500000
75%      23.750000
max      35.000000
Name: Daily Change, dtype: float64
```

Exp no: 7	Linear regression model to predict the signal strength

AIM:

To develop a linear regression model to predict the signal strength based on the distance.

Problem Statement

We have a dataset that records the signal strength (in dBm) at various distances (in meters) from a transmitter. The goal is to develop a linear regression model to predict the signal strength based on the distance.

Steps: pip install numpy pandas scikit-learn matplotlib.

Program Code:

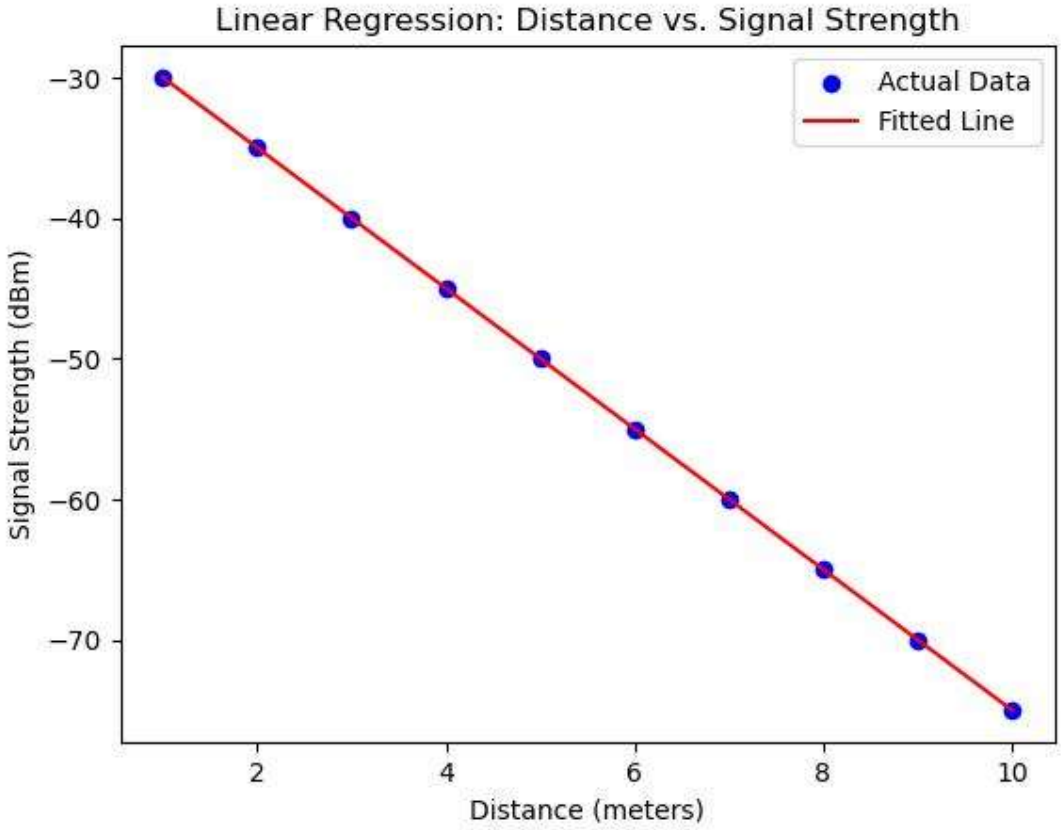
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Example dataset: Distance (meters) vs. Signal Strength (dBm)
data = {
    'Distance': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
    'Signal_Strength': [-30, -35, -40, -45, -50, -55, -60, -65, -70, -75]
}

# Convert the data into a DataFrame
df = pd.DataFrame(data)

# Separate features and target variable
```

```
X = df[['Distance']].values  # Feature: Distance
y = df['Signal_Strength'].values  # Target: Signal Strength

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and train the linear regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse:.2f}')
print(f'R^2 Score: {r2:.2f}')

# Visualize the results
plt.scatter(X, y, color='blue', label='Actual Data')
plt.plot(X, model.predict(X), color='red', label='Fitted Line')
plt.xlabel('Distance (meters)')
plt.ylabel('Signal Strength (dBm)')
plt.title('Linear Regression: Distance vs. Signal Strength')
plt.legend()
plt.show()
```

Result:

Mean Squared Error: 0.00

R^2 Score: 1.00



Exp no: 8	A component is defective or not based on Voltage and Current

Aim :

To classify a component is defective or not based on Voltage and Current

Program Code:

```
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

np.random.seed(0)

defective_data = np.random.normal(loc=[5, 2], scale=[1, 0.5], size=(100, 2))  # Defective components
normal_data = np.random.normal(loc=[8, 4], scale=[1, 0.5], size=(100, 2))  # Normal components

# Concatenate the data and create labels
X = np.concatenate([defective_data, normal_data])
y = np.concatenate([np.zeros(100), np.ones(100)])  # Defective: 0, Normal: 1

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Create and train the logistic regression model
clf = LogisticRegression()
clf.fit(X_train, y_train)

# Make predictions on the test set
```

```
y_pred = clf.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
```

Result:

Accuracy: 1.00

Exp no: 9	**Decision tree classifier to predict signal quality based on transmitter, signal strength, and frequency**

Aim:

create a simple dataset to classify signal quality based on various parameters such as distance from the transmitter, signal strength, and frequency.

Problem Statement:

Dataset that records various parameters affecting the signal quality (Good or Bad). The goal is to develop a decision tree classifier to predict signal quality based on these parameters.

Steps:

1. Dataset:
   - We create a simple dataset with distance from the transmitter, signal strength, frequency, and corresponding signal qua lity (Good or Bad). The dataset is stored in a dictionary and then converted into a pandas DataFrame.
2. Data Prepa ration:
   - Separate the dataset into features (X) and the target variable (y).
   - Encode the target variable Signal_Quality from categorical values ('Good', 'Bad') to numerical values using LabelEncoder.
3. Model Training:
   - Split the data into training and testing sets using train_test_split.
   - Create an instance of DecisionTreeClassifier and train the model on the training data using the fit method.
4. Prediction and Evaluation:
   - Use the trained model to make predictions on the test data.
   - Calculate the accuracy score and generate a classification report to evaluate the model's performance.
5. Visualization:
   - Visualize the decision tree using plot_tree to understand how the model makes decisions based on the input features.

Program Code:

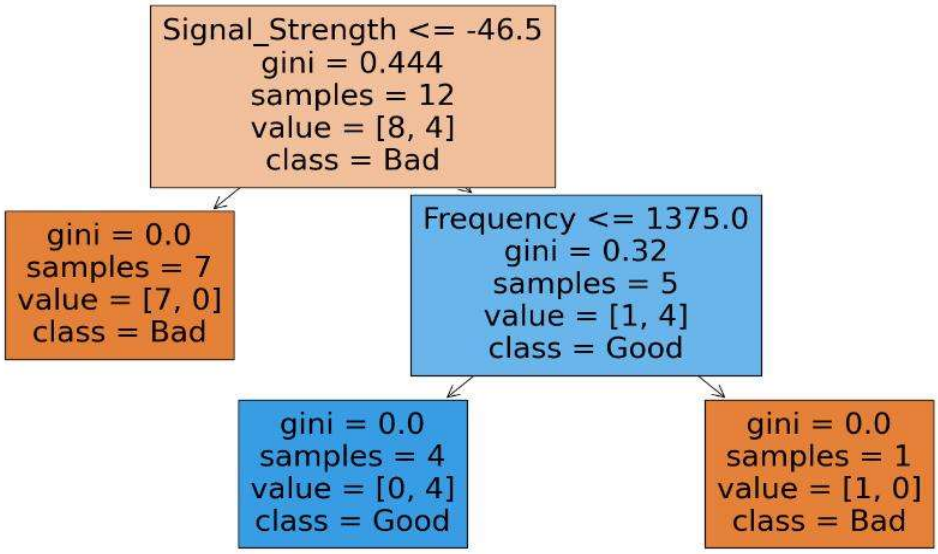
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

```
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import accuracy_score, classification_report

# Example dataset: Distance (meters), Signal Strength (dBm), Frequency (MHz) vs. Signal Quality
data = {
    'Distance': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 2, 3, 4, 5, 6],
    'Signal_Strength': [-30, -35, -40, -45, -50, -55, -60, -65, -70, -75, -33, -38, -43, -48, -53],
    'Frequency': [850, 850, 850, 850, 850, 1900, 1900, 1900, 1900, 1900, 850, 850, 1900, 1900, 1900],
    'Signal_Quality': ['Good', 'Good', 'Good', 'Good', 'Bad', 'Bad', 'Bad', 'Bad', 'Bad', 'Bad', 'Good', 'Good', 'Bad', 'Bad', 'Bad']
}

# Convert the data into a DataFrame
df = pd.DataFrame(data)

# Separate features and target variable
X = df[['Distance', 'Signal_Strength', 'Frequency']].values  # Features
y = df['Signal_Quality'].values  # Target

# Encode the target variable
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y = le.fit_transform(y)  # 'Good' -> 1, 'Bad' -> 0

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and train the decision tree classifier
model = DecisionTreeClassifier(random_state=42)
model.fit(X  train, y  train)
```

```
# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred, target_names=['Bad', 'Good'])

print(f'Accuracy: {accuracy:.2f}')
print('Classification Report:')
print(report)

# Visualize the decision tree
plt.figure(figsize=(20,10))
plot_tree(model, feature_names=['Distance', 'Signal_Strength', 'Frequency'], class_names=['Bad',
'Good'], filled=True)
plt.show()
```

Output:

```
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

         Bad       1.00      1.00      1.00         1
        Good       1.00      1.00      1.00         2

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3
```



k-NN classifier to predict signal quality based on distance from the transmitter, signal strength, and frequency

Exp no: 10	**k-NN classifier to predict signal quality based on distance from the transmitter, signal strength, and frequency**

Aim:

To classify signal quality based on various parameters such as distance from the transmitter, signal strength, and frequency.

Prerequisite:

pip install numpy pandas scikit-learn matplotlib

Problem Statement

A dataset that records various parameters affecting the signal quality (Good or Bad). The goal is to develop a k-NN classifier to predict signal quality based on these parameters.

Program Code:

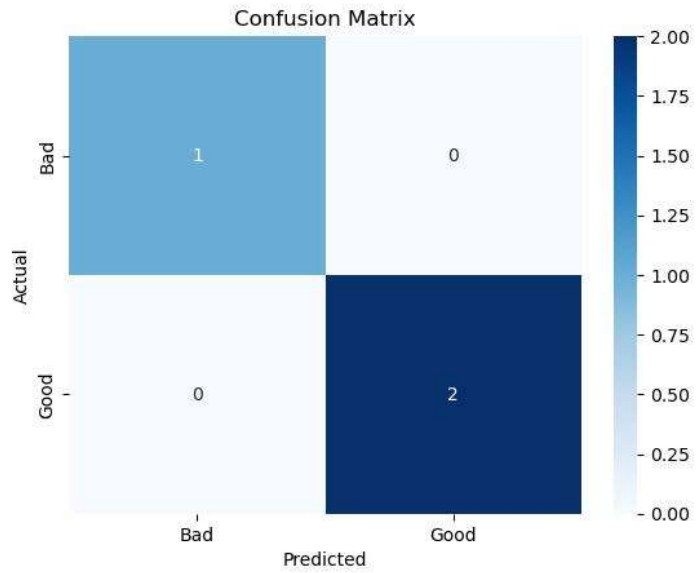
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import seaborn as sns

# Example dataset: Distance (meters), Signal Strength (dBm), Frequency (MHz) vs. Signal Quality
data = {
    'Distance': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 2, 3, 4, 5, 6],
    'Signal_Strength': [-30, -35, -40, -45, -50, -55, -60, -65, -70, -75, -33, -38, -43, -48, -53],
    'Frequency': [850, 850, 850, 850, 850, 1900, 1900, 1900, 1900, 1900, 850, 850, 1900, 1900, 1900],
    'Signal_Quality': ['Good', 'Good', 'Good', 'Good', 'Bad', 'Bad', 'Bad', 'Bad', 'Bad', 'Bad', 'Good', 'Good', 'Bad', 'Bad', 'Bad']
}
```

```
# Convert the data into a DataFrame
df = pd.DataFrame(data)

# Separate features and target variable
X = df[['Distance', 'Signal_Strength', 'Frequency']].values  # Features
y = df['Signal_Quality'].values  # Target

# Encode the target variable
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
y = le.fit_transform(y)  # 'Good' -> 1, 'Bad' -> 0

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Create and train the k-NN classifier
k = 3  # Number of neighbors
model = KNeighborsClassifier(n_neighbors=k)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification  report(y  test, y  pred, target  names=['Bad', 'Good'])
```

```
print(f'Accuracy: {accuracy:.2f}')
print('Classification Report:')
print(report)

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Bad', 'Good'],
yticklabels=['Bad', 'Good'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

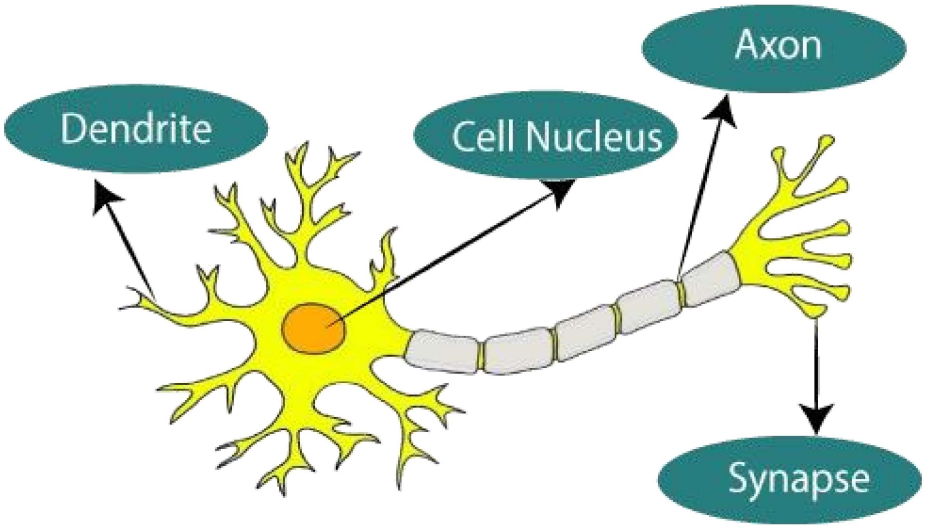
Output:

```
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

         Bad       1.00      1.00      1.00         1
        Good       1.00      1.00      1.00         2

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3
```



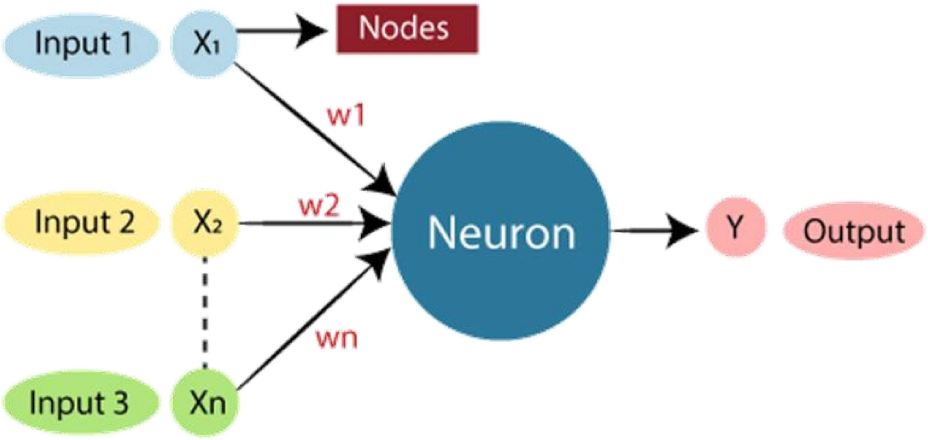
Exp no: 11	Study of Artificial Neural Network (ANN) and Simple Program in ANN

Artificial Neural Networks (ANNs) are computational models inspired by the human brain's neural networks.



The given figure illustrates the typical diagram of Biological Neural Network.

The typical Artificial Neural Network looks something like the given figure.



Dendrites from Biological Neural Network represent inputs in Artificial Neural Networks, cell nucleus represents Nodes, synapse represents Weights, and Axon represents Output.

Relationship between Biological neural network and artificial neural network:

Biological Neural Network	Artificial Neural Network
Dendrites	Inputs
Cell nucleus	Nodes
Synapse	Weights
Axon	Output

They are used in various applications, from image and speech recognition to game playing and medical diagnosis. Here's a concise guide on the study of ANNs, covering key concepts, components, types, and applications.

Key Concepts

Neuron (Perceptron): The basic unit of an ANN, analogous to a biological neuron. It takes multiple inputs, applies weights to them, sums them up, and passes the result through an activation function to produce an output.

Weights: Parameters that adjust the strength of the connection between neurons. They are crucial in learning and adjusting the network during training.

Activation Function: A function applied to the input sum of a neuron to introduce non-linearity. Common functions include sigmoid, tanh, and ReLU (Rectified Linear Unit).

Layers: Neurons are organized into layers. The main types are:

Input Layer: Receives initial data.

Hidden Layers: Intermediate layers that process inputs from the input layer. Deep networks have multiple hidden layers.

Output Layer: Produces the final result.

Forward Propagation: The process of passing inputs through the network to get the output.

Backpropagation: A training method where errors are propagated back through the network to update weights. It involves computing the gradient of the loss function with respect to each weight.

Loss Function: A function that measures the difference between the network's output and the actual target values. Common loss functions include Mean Squared Error (MSE) for regression and Cross-Entropy for classification.

Types of Neural Networks

Feedforward Neural Networks (FNNs): The simplest type where connections between the nodes do not form a cycle. Information moves in one direction from input to output.

Convolutional Neural Networks (CNNs): Specialized for processing data with a grid-like topology, such as images. They use convolutional layers to automatically detect spatial hierarchies in data.

Recurrent Neural Networks (RNNs): Designed for sequential data, such as time series or natural language. They have connections that form directed cycles, allowing them to maintain a memory of previous inputs.

Long Short-Term Memory Networks (LSTMs): A type of RNN designed to overcome the limitations of traditional RNNs in learning long-term dependencies.

Generative Adversarial Networks (GANs): Consist of two networks, a generator and a discriminator, that compete against each other to produce high-quality synthetic data.

Applications

Image and Speech Recognition: CNNs are extensively used in image recognition, while RNNs and LSTMs are used in speech recognition and natural language processing.

Medical Diagnosis: ANNs help in diagnosing diseases by analyzing medical images, genetics, and patient data.

Autonomous Vehicles: Used for object detection, lane detection, and decision-making in self-driving cars.

Financial Services: Applications include fraud detection, algorithmic trading, and risk management.

Gaming: ANNs have been used to develop agents that can play games at a superhuman level.

Program code:

```
import numpy as np

# Define the sigmoid activation function
def sigmoid(x):
  return 1 / (1 + np.exp(-x))

# Initialize weights with random values
weights = np.random.rand(2, 1)  # 2 inputs, 1 output neuron

# Training data (inputs and desired outputs)
inputs = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
outputs = np.array([[0], [1], [1], [1]])

# Learning rate
learning_rate = 0.1

# Training loop (multiple iterations)
for epoch in range(1000):
  # Forward propagation
  z = np.dot(inputs, weights)  # Dot product of inputs and weights
  predictions = sigmoid(z)

  # Calculate the error
  error = outputs - predictions

  # Backpropagation
  delta = error * predictions * (1 - predictions)
  weight_delta = np.dot(inputs.T, delta)

  # Update weights
  weights += learning_rate * weight_delta
```

```
# Test the network with a new input
new_input = np.array([1, 0])
prediction = sigmoid(np.dot(new_input, weights))

print("Predicted output for [1, 0]:", prediction)
```

Result:

```
Predicted output for [1, 0]: [0.92406673]
```

Exp no: 12	Study Of Support Vector Machine and and Simple Program in SVM

Support Vector Machines (SVMs) are a powerful set of supervised learning algorithms used for classification, regression, and outliers detection. They are particularly well-known for their application in classification problems. Here's a comprehensive guide to understanding SVMs:

Basics of SVM

1. Objective: SVM aims to find the best boundary (hyperplane) that separates data points of different classes with the maximum margin. The margin is the distance between the hyperplane and the nearest data point from either class.
2. Hyperplane: In a two-dimensional space, this is a line, but in higher dimensions, it becomes a plane or hyperplane. The goal is to identify the hyperplane that best separates the classes.
3. Support Vectors: These are the data points closest to the hyperplane and are critical in defining the position and orientation of the hyperplane. The model's performance is highly dependent on these support vectors.

Mathematical Formulation

1. **Linear SVM**: For linearly separable data, SVM aims to find a hyperplane defined by $w \cdot x + b = 0$ where w is the weight vector, x is the feature vector, and b is the bias. The goal is to maximize the margin $2/||w||$, subject to the constraint that all points are correctly classified.

2. **Optimization Problem**:

$$\min_{w,b} \frac{1}{2}||w||^2$$

Subject to:

$$y_i(w \cdot x_i + b) \geq 1 \quad \forall i$$

where y_i are the class labels (either +1 or -1).

3. **Soft Margin SVM**: For non-linearly separable data, a slack variable ξ_i is introduced to allow some misclassifications:

$$\min_{w,b,\xi} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \xi_i$$

Subject to:

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i \quad \forall i$$

Here, C is a regularization parameter that balances margin maximization and classification error.

Kernel Trick

For datasets that are not linearly separable, SVM can be extended to handle this using the kernel trick. Kernels map the original input space into a higher-dimensional space where a linear separation is possible. Common kernels include:

1. **Linear Kernel:** $K(x_i, x_j) = x_i \cdot x_j$
2. **Polynomial Kernel:** $K(x_i, x_j) = (x_i \cdot x_j + c)^d$
3. **Radial Basis Function (RBF) Kernel:** $K(x_i, x_j) = \exp(-\gamma ||x_i - x_j||^2)$
4. **Sigmoid Kernel:** $K(x_i, x_j) = \tanh(\alpha x_i \cdot x_j + c)$

SVM for Regression (SVR)

Support Vector Regression (SVR) uses the same principles as SVM for classification but adapts them for regression. Instead of finding a hyperplane that separates the data, SVR finds a function that deviates from the actual data points by a value no greater than a certain threshold (epsilon).

Applications of SVM

1. Text and Hypertext Categorization: Due to their capability to handle high-dimensional spaces efficiently.
2. Image Classification: SVMs are often used for face detection and other image classification tasks.
3. Bioinformatics: For protein classification and gene expression data analysis.
4. Handwriting Recognition: Classifying characters in handwriting recognition systems.

Advantages and Disadvantages

Advantages:

- Effective in high-dimensional spaces.
- Still effective when the number of dimensions is greater than the number of samples.
- Memory efficient due to the use of support vectors.
- Versatile with different kernel functions.

Disadvantages:

- Not suitable for large datasets as the training time can be high.
- Less effective on noisy data where classes are not well-separated.
- Choice of kernel and parameters (such as C and γ) requires careful tuning and cross-validation.

Import Libraries:

from sklearn import datasets

from sklearn.model_selection import train_test_split

from sklearn.svm import SVC

from sklearn.metrics import accuracy_score

datasets: This module from Scikit-learn provides various built-in datasets like the Iris dataset.

train_test_split: This function is used to split the dataset into training and testing sets.

SVC: This is the SVM classifier class.

accuracy_score: This function computes the accuracy of the predictions.

Load Dataset:

iris = datasets.load_iris()

X = iris.data

y = iris.target

datasets.load_iris(): Loads the Iris dataset, which is a classic dataset in machine learning with 150 samples of iris flowers. Each sample has four features (sepal length, sepal width, petal length, petal width) and a corresponding class label (0, 1, or 2) representing three species of iris flowers.

X = iris.data : Assigns the features (input data) to X.

y = iris.target : Assigns the labels (target data) to y.

Split the Dataset:

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

train_test_split(X, y, test_size=0.3, random_state=42): Splits the data into training and testing sets. test_size=0.3 means 30% of the data will be used for testing, and random_state=42 ensures reproducibility of the split.

Create a SVM Classifier:

clf = SVC(kernel='linear', C=1)

SVC(kernel='linear', C=1): Initializes the SVM classifier with a linear kernel and a regularization parameter C set to 1. The kernel='linear' means it will use a linear hyperplane for classification. The parameter C controls the trade-off between achieving a low error on the training data and minimizing the norm of the weights (i.e., the margin).

Train the Classifier:

clf.fit(X_train, y_train)

clf.fit(X_train, y_train): Trains the SVM classifier using the training data (X_train and y_train).

Make Predictions:

y_pred = clf.predict(X_test)

y_pred = clf.predict(X_test): Uses the trained classifier to make predictions on the test data (X_test). The predictions are stored in y_pred.

Evaluate the Model:

accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')

accuracy = accuracy_score(y_test, y_pred): Computes the accuracy of the model by comparing the true labels (y_test) with the predicted labels (y_pred).
print(f'Accuracy: {accuracy:.2f}'): Prints the accuracy score, formatted to two decimal places.

Result:

The experiment successfully demonstrated the application of SVM for classification, showcasing its strengths in handling high-dimensional spaces and providing a clear understanding of its working mechanism.