R.M.K. COLLEGE OF ENGINEERING AND TECHNOLOGY

(An Autonomous Institution)

R.S.M. Nagar, PUDUVOYAL-601 206

Approved by AICTE, New Delhi /Affiliated to Anna University, Chennai

Accredited by NBA, New Delhi (All Eligible Courses)/ NAAC with 'A' Grade

An ISO 21001:2018 Certified Institution

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

LAB RECORD

22AI401 - MACHINE LEARNING

(LAB INTEGRATED)

Academic Year	**:**	**2025-2026**
Regulations	**:**	**2022**
Batch	**:**	**2023-2027**
Year / Semester	**:**	**III / V**

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Institute Vision and Mission

Vision

To be knowledge hub of providing quality technical education and promoting research for building up of our nation and its contribution for the betterment of humanity

Mission

- To make the best use of state-of-the-art infrastructure to ensure quality technical education
- To develop industrial collaborations to promote innovation and research capabilities
- To inculcate values and ethics to serve humanity

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Vision

To be a source of knowledge in the field of Computer Science and Engineering to cater to the growing need of industry and society

Mission

- To avail state-of-the art infrastructure for adopting cutting edge technologies and encouraging research activities
- To promote industrial collaborations for professional competency
- To nurture social responsibility and ethics to become worthy citizens

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Program Educational Objectives (PEOs)

Graduates of Computer Science and Engineering Program will

1. Become a globally competent professional in all spheres and pursue higher education world over.
2. Successfully carry forward domain knowledge in computing and allied areas to solve complex real world engineering problems.
3. Continuously upgrade their technical knowledge and expertise to keep pace with the technological revolution.
4. Serve the humanity with social responsibility combined with ethics.

Program Specific Outcomes (PSOs)

Graduates of Computer Science and Engineering Program will be able to:

- Analyze, design and develop computing solutions by applying foundational concepts of Computer Science and Engineering.
- Apply software engineering principles and practices for developing quality software for scientific and business applications.
- Implement cost-effective solutions for the betterment of both industry and society with the technological skills acquired through the Centres of Excellence.

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

Program Outcome

1. **Engineering Knowledge**: Apply knowledge of mathematics, science, engineering fundamentals and an engineering specialization to the solution of complex engineering problems.
2. **Problem Analysis**: Identify, formulate, research literature and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences and engineering sciences.
3. **Design/ Development of Solutions**: Design solutions for complex engineering problems and design system components or processes that meet specified needs with appropriate consideration for public health and safety, cultural, societal and environmental considerations.
4. **Conduct investigations of complex problems** using research-based knowledge and research methods including design of experiments, analysis and interpretation of data and synthesis of information to provide valid conclusions.
5. **Modern Tool Usage**: Create, select and apply appropriate techniques, resources and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
6. **The Engineer and Society**: Apply reasoning informed by contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to professional engineering practice.
7. **Environment and Sustainability**: Understand the impact of professional engineering solutions in societal and environmental contexts and demonstrate knowledge of and need for sustainable development.
8. **Ethics**: Apply ethical principles and commit to professional ethics and responsibilities and norms of engineering practice.
9. **Individual and Team Work**: Function effectively as an individual, and as a member or leader in diverse teams and in multi-disciplinary settings.
10. **Communication**: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as being able to comprehend and write effective reports and design documentation, make effective presentations and give and receive clear instructions.
11. **Project Management and Finance**: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12. **Life-long Learning**: Recognize the need for and have the preparation and ability to Engage in independent and life- long learning in the broadest context of technological Change.

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22AI401	**MACHINE LEARNING**	**L**	**T**	**P**	**C**
	(Lab Integrated)	**3**	**0**	**2**	**4**

COURSE OBJECTIVES:

- To discuss the basics of Machine Learning and model evaluation.
- To study dimensionality reduction techniques.
- To understand the various classification algorithms.
- To elaborate on unsupervised learning techniques.
- To discuss the basics of neural networks and various types of learning.

UNIT I	**INTRODUCTION**	**9+6**

Machine Learning – Types – Applications – Preparing to Model – Activities – Data – Exploring structure of Data – Data Quality and Remediation – Data Pre-processing – Modelling and Evaluation: Selecting a Model -Training a Model – Model representation and Interpretability – Evaluating Performance of a Model – Improving Performance.

Lab Programs:

1. Implementation of Candidate Elimination algorithm
2. Implementation of ML model evaluation techniques (R-Squared/Adjusted R-Squared/Mean Absolute Error/Mean Squared Error)
3. Implementation of ML model evaluation techniques (Confusion Matrix/F1 Score/AUC-ROC Curve)

UNIT II	**FEATURE ENGINEERING AND DIMENSIONALITY REDUCTION**	**9+6**

Feature Engineering – Feature Transformation – Feature Subset Selection - Principle Component Analysis – Feature Embedding – Factor Analysis – Singular value decomposition and Matrix Factorization – Multidimensional scaling – Linear Discriminant Analysis – Canonical Correlation Analysis – Isomap – Locally linear Embedding – Laplacian Eigenmaps.

Lab Programs:

1. Write python code to identify feature co-relations (PCA)
2. Interpret Canonical Covariates with Heatmap
3. Feature Engineering is the way of extracting features from data and transforming them into formats that are suitable for Machine Learning algorithms. Implement python code for Feature Selection/ Feature Transformation/ Feature Extraction.
4. Mini Project – Feature Subset Selection

UNIT III	**SUPERVISED LEARNING**	**9+6**

Linear Regression -Relation between two variables – Steps – Evaluation – Logistic Regression – Decision Tree – Algorithms – Construction – Classification using Decision Tree – Issues – Rule - based Classification – Pruning the Rule Set – Support Vector Machines – Linear SVM – Optimal Hyperplane – Radial Basis Functions – Naïve Bayes Classifier – Bayesian Belief Networks.

Lab Programs:

1. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select the appropriate data set for your experiment and draw graphs.
2. Implement and demonstrate the working of the decision tree-based ID3 algorithm
3. Build a Simple Support Vector Machines using a data set

UNIT IV	UNSUPERVISED LEARNING	9+6

Clustering – Types – Applications - Partitioning Methods – K-means Algorithm – K-Medoids – Hierarchical methods – Density based methods DBSCAN – Finding patterns using Association Rules – Hidden Markov Model.

Lab Programs:

1. Implement a k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions
2. Implement market basket analysis using association rules

Mini Project using Clustering analysis.

UNIT V	NEURAL NETWORKS AND TYPES OF LEARNING	9+6

Biological Neuron – Artificial Neuron – Types of Activation function – Implementations of ANN – Architectures of Neural Networks – Learning Process in ANN – Back propagation – Deep Learning – Representation Learning – Active Learning – Instance based Learning – Association Rule Learning – Ensemble Learning Algorithm – Regularization Algorithm- Reinforcement Learning – Elements- Model-based- Temporal Difference Learning.

Lab Programs:

1. Build an ANN by implementing the Single-layer Perceptron. Test it using appropriate data sets.
2. Implement Multi-layer Perceptron and test the same using appropriate data sets.
3. Build a RBF Network to calculate the fitness function with five neurons.

Mini Project – Face recognition,

TOTAL: 45 +30=75 PERIODS

OUTCOMES:

Upon completion of the course, the students will be able to:

CO1: Explain the basics of Machine Learning and model evaluation.
CO2: Study dimensionality reduction techniques.
CO3: Understand and implement various classification algorithms.
CO4: Understand and implement various unsupervised learning techniques.
CO5: Build Neural Networks and understand the different types of learning.
CO6: Develop simple projects using machine learning concepts

TEXTBOOKS:

1. Saikat Dutt, Subramanian Chandramouli, Amit Kumar Das, “Machine Learning”, Pearson,2019. (Unit 1 – chap 1,2,3/ Unit 2 – Chap 4 / Unit 4 – 9 / Unit 5 – Chap 10, 11)
2. Ethem Alpaydin, “Introduction to Machine Learning, Adaptive Computation and Machine Learning

Series", Third Edition, MIT Press, 2014. (Unit 2 – Chap 6 / Unit 4 – chap 8.2.3/ Unit 5 – Chap 18)

REFERENCES:

1. Anuradha Srinivasaraghavan,Vincy Joseph, "Machine Learning", First Edition, Wiley, 2019.(Unit 3 – Chap 7,8,9,10,11 / Unit 4 – 13, 11.4, 11.5,12)
2. Peter Harrington, "Machine Learning in Action", Manning Publications, 2012.
3. Stephen Marsland, "Machine Learning – An Algorithmic Perspective", Second Edition,
4. Chapman and Hall/CRC Machine Learning and Pattern Recognition Series, 2014.
5. Tom M Mitchell, "Machine Learning", First Edition, McGraw Hill Education, 2013.
6. Christoph Molnar, "Interpretable Machine Learning - A Guide for Making Black Box Models Explainable", Creative Commons License, 2020.
7. NPTEL Courses:
   a. Introduction to Machine Learning - https://onlinecourses.nptel.ac.in/noc23_cs18/preview

SOFTWARE REQUIREMENTS:

Systems with Anaconda, Jupyter Notebook, Python, Pytorch, scikit-learn, Tensorflow, Colab

Course Articulation Matrix

Course Code/ Course Name: 22AI401/ Machine Learning (Lab Integrated)

COURSE OUTCOMES	
CO1	Explain the basics of Machine Learning and model evaluation.
CO2	Study dimensionality reduction techniques
CO3	Understand and implement various classification algorithms.
CO4	Understand and implement various unsupervised learning techniques.
CO5	Build Neural Networks and understand the different types of learning.
CO6	Develop simple projects using machine learning concepts.

Course Outcome – Program Outcome & Program Specific Outcome Mapping:

Course Outcomes (COs)	Program Outcomes (POs), Program Specific Outcomes (PSOs)														
	PO1	**PO2**	**PO3**	**PO4**	**PO5**	**PO6**	**PO7**	**PO8**	**PO9**	**PO10**	**PO11**	**PO12**	**PSO1**	**PSO2**	**PSO3**
CO1	3	3	2	-	2	-	-	-	-	-	-	2	3	2	-
CO2	3	2	2	-	2	-	-	1	-	-	-	2	3	3	-
CO3	3	2	2	-	2	-	-	1	-	-	-	2	3	2	-
CO4	3	2	2	-	2	-	-	1	-	-	-	2	3	2	-
CO5	3	3	3	-	2	-	-	1	-	-	-	2	3	2	-
CO6	3	3	2	-	2	-	-	1	-	-	-	2	3	2	-

EXPERIMENTS WITH MAPPED CO

S.NO	NAME OF THE EXERCISE	Mapped CO
1	Implementation of Candidate Elimination algorithm	CO1
2	Implementation of ML model evaluation techniques (R-Squared/Adjusted R-Squared/Mean Absolute Error/Mean Squared Error)	CO1
3	Implementation of ML model evaluation techniques (Confusion Matrix/F1 Score/AUC-ROC Curve)	CO1
4	Write python code to identify feature co-relations (PCA)	CO2
5	Interpret Canonical Covariates with Heatmap	CO2
6	Feature Engineering is the way of extracting features from data and transforming them into formats that are suitable for Machine Learning algorithms. Implement python code for Feature Selection/ Feature Transformation/ Feature Extraction	CO2
7	Mini Project – Feature Subset Selection	CO2
8	Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select the appropriate data set for your experiment and draw graphs.	CO3
9	Implement and demonstrate the working of the decision tree-based ID3 algorithm	CO3
10	Build a Simple Support Vector Machines using a data set	CO3
11	Implement a k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions	CO3
12	Implement market basket analysis using association rules	CO4
13	Mini Project using Clustering analysis.	CO4
14	Build an ANN by implementing the Single-layer Perceptron. Test it using appropriate data sets.	CO5
15	Implement Multi-layer Perceptron and test the same using appropriate data sets.	CO5
16	Build a RBF Network to calculate the fitness function with five neurons.	CO5
17	Mini Project – Face recognition,	CO1, CO2, CO5,CO6

VIVA QUESTIONS

1. Candidate Elimination Algorithm

1. What is the Candidate Elimination algorithm?
2. Define Version Space.
3. What are the specific and general boundaries?
4. What is the hypothesis space?
5. Why is Candidate Elimination sensitive to noise?
6. What type of learning does it support?
7. What happens when a positive example is encountered?
8. What is the role of the general hypothesis?
9. How is consistency maintained in hypotheses?
10. What is the limitation of this algorithm?

2. Model Evaluation (R^2, Adjusted R^2, MAE, MSE)

1. What does R^2 value indicate?
2. What is the range of R^2?
3. How is Adjusted R^2 calculated?
4. When would Adjusted R^2 be more useful than R^2?
5. Define Mean Absolute Error.
6. Define Mean Squared Error.
7. Which is more sensitive to outliers, MAE or MSE?
8. What is a good R^2 value?
9. How do you interpret a negative R^2?
10. What does a low MAE signify?

3. Classification Evaluation (Confusion Matrix, F1, AUC-ROC)

1. What is a confusion matrix?
2. Define TP, TN, FP, FN.
3. What is the accuracy metric?
4. What is precision?
5. What is recall?

6. What is the F1 score?
7. Why is F1 score important?
8. What is an ROC curve?
9. What does AUC represent?
10. How can you improve the AUC score?

4. PCA for Feature Correlation

1. What is Principal Component Analysis?
2. What is the purpose of PCA?
3. What are eigenvectors and eigenvalues?
4. Why is standardization important in PCA?
5. What is dimensionality reduction?
6. How many components should be selected?
7. Can PCA be used on categorical data?
8. What is the explained variance ratio?
9. How does PCA handle multicollinearity?
10. What are the limitations of PCA?

5. Canonical Covariates with Heatmap

1. What are canonical covariates?
2. What is a heatmap?
3. What does a heatmap show?
4. How do you interpret color in a heatmap?
5. What does a correlation coefficient of +1 mean?
6. What does -1 correlation indicate?
7. How is a heatmap useful in ML?
8. How do you calculate correlation?
9. What is covariance?
10. Difference between correlation and covariance?

6. Feature Engineering (Selection, Transformation, Extraction)

1. What is feature engineering?
2. Why is feature engineering important?
3. What is feature selection?
4. What is feature transformation?
5. What is feature extraction?
6. Name any two feature selection methods.
7. What is normalization?
8. What is standardization?
9. What is one-hot encoding?
10. How does PCA help in feature extraction?

7. Mini Project – Feature Subset Selection

1. What is subset selection in ML?
2. Why is it necessary to reduce features?
3. What is Recursive Feature Elimination (RFE)?
4. What is a wrapper method?
5. What is a filter method?
6. What is a hybrid method?
7. How is model performance affected by irrelevant features?
8. What is overfitting and how does it relate to features?
9. How to evaluate selected features?
10. Difference between feature selection and dimensionality reduction?

8. Locally Weighted Regression

1. What is Locally Weighted Regression (LWR)?
2. How is LWR different from Linear Regression?
3. What does the bandwidth parameter (tau) control?
4. Is LWR parametric or non-parametric?
5. What kernel function is used in LWR?
6. What is the role of weights in LWR?
7. When would you prefer LWR over linear regression?

8. What is the time complexity of LWR?
9. Can LWR handle non-linear data?
10. What is the main drawback of LWR?

9. Decision Tree (ID3 Algorithm)

1. What is a decision tree?
2. What is the ID3 algorithm?
3. Define entropy.
4. Define information gain.
5. Why is ID3 suitable for categorical data?
6. How does ID3 build the tree?
7. What are the limitations of ID3?
8. How can overfitting be avoided in decision trees?
9. What is pruning?
10. What are leaf nodes in decision trees?

10. Support Vector Machines (SVM)

1. What is the basic idea behind SVM?
2. What is a hyperplane?
3. What are support vectors?
4. What is the kernel trick?
5. Name different types of kernels.
6. What does the C parameter control?
7. What is the margin in SVM?
8. How does SVM handle outliers?
9. Can SVM be used for regression?
10. What are advantages and disadvantages of SVM?

11. k-Nearest Neighbour (k-NN)

1. What is k-NN?

2. How is the value of k selected?
3. What is a lazy learner?
4. What distance metrics are used in k-NN?
5. Is k-NN sensitive to irrelevant features?
6. How does k-NN handle missing values?
7. What is the time complexity of k-NN?

8. Can k-NN be used for regression?
9. How does k-NN work for multi-class classification?
10. What is the effect of high-dimensional data on k-NN?

12. Market Basket Analysis (Association Rules)

1. What is Market Basket Analysis?
2. What is support?
3. What is confidence?
4. What is lift?
5. What does lift > 1 indicate?
6. Name algorithms for association rule mining.
7. What are frequent itemsets?
8. What is the Apriori principle?
9. What is FP-Growth algorithm?
10. What are real-life applications of association rules?

13. Mini Project – Clustering Analysis

1. What is clustering?
2. Is clustering supervised or unsupervised?
3. What is the KMeans algorithm?
4. What is the Elbow method?
5. What is hierarchical clustering?
6. What is DBSCAN?
7. What is the silhouette score?

8. What is centroid in KMeans?
9. How do you choose the number of clusters?
10. Applications of clustering in real life?

14. Single-layer Perceptron

1. What is a perceptron?
2. Who invented the perceptron?
3. What activation function is used?
4. What type of data can a perceptron classify?
5. Can a single-layer perceptron solve XOR?
6. What is the perceptron learning rule?
7. What is the bias term?
8. What are the weights in a perceptron?
9. What is a threshold function?
10. What is the limitation of single-layer perceptrons?

15. Multi-layer Perceptron (MLP)

1. What is an MLP?
2. What is the structure of MLP?
3. What is backpropagation?
4. What activation functions are used?
5. What is the vanishing gradient problem?
6. What is the difference between MLP and logistic regression?
7. How many hidden layers should be used?
8. What is the cost function in MLP?
9. What is epoch in training?
10. What libraries are used to implement MLP in Python?

16. Radial Basis Function (RBF) Network

1. What is an RBF network?
2. What activation function is used in RBF?

3. What is the difference between RBF and MLP?
4. What is the role of centers in RBF?
5. What is the Gaussian function?
6. What is the spread (sigma) in RBF?
7. How are weights calculated in RBF?
8. What are the advantages of RBF?
9. What are limitations of RBF networks?
10. Where are RBF networks used?

17. Mini Project – Face Recognition

1. What is face recognition?
2. What features are extracted from face images?
3. What is Eigenface?
4. How does PCA help in face recognition?
5. What is LBP (Local Binary Pattern)?
6. What challenges exist in face recognition?
7. What is the difference between face detection and face recognition?
8. What is a distance threshold in recognition?
9. What is OpenCV?
10. What real-time applications use face recognition?

ubrics for Assessment

	Excellent	**Good**	**Average**	**Poor**
Problem Understanding & Logic Design	Clear understanding with efficient logic (3 marks)	Good logic with minor issues (2 marks)	Partial understanding (1 mark)	unclear understanding (0 mark)
Code Implementation	Error-free, well-structured, meets all requirements (3 marks)	Minor errors, mostly meets objectives (2 marks)	Major errors (1 mark)	incomplete implementation (0 mark)
Output & Viva Explanation	All test cases passed, confident explanation (4 marks)	Some test cases passed, fair explanation (3 marks)	Few test cases passed, weak explanation (2 marks)	Attempted, no test cases passed, no explanation (1 mark)

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LIST OF EXPERIMENTS

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4	Write python code to identify feature co-relations (PCA)
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6	Feature Engineering is the way of extracting features from data and transforming them into formats that are suitable for Machine Learning algorithms. Implement python code for Feature Selection/ Feature
7	Mini Project – Feature Subset Selection
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13	Mini Project using Clustering analysis.
14	Build an ANN by implementing the Single-layer Perceptron. Test it using appropriate data sets.
15	Implement Multi-layer Perceptron and test the same using appropriate datasets.
16	Build a RBF Network to calculate the fitness function with five neurons.
17	Mini Project – Face recognition,

EXP NO: 01 **CANDIDATE ELIMINATION ALGORITHM**

DATE:

Aim:

The Candidate Elimination Algorithm learns from examples to identify concepts. It does this by refining a set of possible descriptions (hypotheses) based on whether examples are positive matches or not.

Algorithm :

Step1: Load Data set

Step2: Initialize General Hypothesis and Specific Hypothesis.

Step3: For each training example

Step4: If example is positive example

if attribute_value == hypothesis_value:

Do nothing

else:

replace attribute value with '?' (Basically generalizing it)

Step5: If example is Negative example

Make generalize hypothesis more specific.

Program:

```
import numpy as np

import pandas as pd

data = pd.read_csv('EnjoySport.csv')

concepts = np.array(data.iloc[:,0:-1])

print("\nInstances are:\n",concepts)

target = np.array(data.iloc[:,-1])

print("\nTarget Values are: ",target)

def learn(concepts, target):

    specific_h = concepts[0].copy()

    print("\nInitialization of specific_h and genearal_h")

    print("\nSpecific Boundary: ", specific_h)

    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]

     print("\nGeneric Boundary: ",general_h)
```

```
    for i, h in enumerate(concepts):
        print("\nInstance", i+1 , "is ", h)
        if target[i] == "yes":
            print("Instance is Positive ")
            for x in range(len(specific_h)):
                if h[x]!= specific_h[x]:
                    specific_h[x] ='?'
                    general_h[x][x] ='?'
        if target[i] == "no":
            print("Instance is Negative ")
            for x in range(len(specific_h)):
                if h[x]!= specific_h[x]:
                    general_h[x][x] = specific_h[x]
                else:
                    general_h[x][x] = '?'

        print("Specific Bundary after ", i+1, "Instance is ", specific_h)
        print("Generic Boundary after ", i+1, "Instance is ", general_h)
        print("\n")

    indices = [i for i, val in enumerate(general_h) if val == ['?', '?', '?', '?', '?', '?']]
    for i in indices:
        general_h.remove(['?', '?', '?', '?', '?', '?'])
    return specific_h, general_h
s_final, g_final = learn(concepts, target)
print("Final Specific_h: ", s_final, sep="\n")
print("Final General_h: ", g_final, sep="\n")
```

Output:

```
Instances are:
 [['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]

Target Values are:  ['yes' 'yes' 'no' 'yes']

Initialization of specific_h and genearal_h

Specific Boundary:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Generic Boundary:  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?',
'?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Instance 1 is  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
Instance is Positive
Specific Bundary after  1 Instance is  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
Generic Boundary after  1 Instance is  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]



Instance 2 is  ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
Instance is Positive
Specific Bundary after  2 Instance is  ['sunny' 'warm' '?' 'strong' 'warm' 'same']
Generic Boundary after  2 Instance is  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?',
'?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]



Instance 3 is  ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
Instance is Negative
Specific Bundary after  3 Instance is  ['sunny' 'warm' '?' 'strong' 'warm' 'same']
Generic Boundary after  3 Instance is  [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?',
'?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'same']]



Instance 4 is  ['sunny' 'warm' 'high' 'strong' 'cool' 'change']
Instance is Positive
Specific Bundary after  4 Instance is  ['sunny' 'warm' '?' 'strong' '?' '?']
Generic Boundary after  4 Instance is  [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?',
'?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]


Final Specific_h:
['sunny' 'warm' '?' 'strong' '?' '?']
Final General_h:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

The Candidate Elimination algorithm was successfully implemented and executed. The version space was updated correctly based on positive and negative training examples, resulting in a specific and general hypothesis that is consistent with the training data.

EXP NO: 02 **2A. R-Squared Error**

DATE:

Aim:

To write a program to implement model evaluation technique R-Squared Error.

Algorithm:

1. First, calculate the mean of the target/dependent variable y and we denote it by $\bar{y}$

2. Calculate the Total Sum of Squares (TSS) by subtracting each observation yi from $\bar{y}$, then squaring it and summing these square differences across all the values. It is denoted by

$$\mathbf{TSS} = \sum_{i=1}^{n}(y_i - \bar{y})^2$$

3. We estimate the model parameter using a suitable regression model such as Linear Regression or SVM Regressor

4. We calculate the Sum of squares due to regression which is denoted by RSS. This is calculated by subtracting each predicted value of y denoted by y_predi from yi squaring these differences and then summing all the n terms.

Calculate the regression sum of squares (RSS).

$$RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

3. Calculate R-squared using the formula: R^2 = 1 - (RSS / TSS).

Program:

```
val1 = (1 - (2.5 * 1 + (-2)))**2

val2 = (2 - (2.5 * 2 + (-2)))**2

val3 = (3 - (2.5 * 2 + (-2)))**2

val4 = (6 - (2.5 * 3 + (-2)))**2

rss = val1 + val2 + val3 + val4

print("\n")

print("RSS", val1, val2, val3, val4)

y = [1, 2, 3, 6]

y_mean = sum(y) / len(y)
```

```
y_var = sum((yi - y_mean)**2 for yi in y)

tss = y_var

r_squared = 1 - (rss / tss)

print("Error", r_squared)
```

Output:

```
RSS 0.25 1.0 0.0 0.25
Error 0.8928571428571429
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Thus the above program has been Executed Successfully.

B. Adjusted RSquared

Aim:

To write a program to implement Adjusted R-Squared error model evaluation technique.

Algorithm:

1. First, calculate the mean of the target/dependent variable y and we denote it by $\bar{y}$

2. Calculate the Total Sum of Squares (TSS) by subtracting each observation yi from $\bar{y}$, then squaring it and summing these square differences across all the values. It is denoted by

$$\text{TSS} = \sum_{i=1}^{n}(y_i - \bar{y})^2$$

2. We calculate the Sum of squares due to regression which is denoted by RSS. This is calculated by subtracting each predicted value of y denoted by y_predi from yi squaring these differences and then summing all the n terms.

Calculate the regression sum of squares (RSS).

$$RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

3. Calculate the number of predictors (p) in the model.

4. Determine the number of observations(n).

5. Calculate the adjusted R-squared using the formula:

Adjusted R^2 = 1 - ((1 - R^2) * ((n - 1) / (n - p - 1))).

Program:

```
def adjusted_r_squared(r_squared, n, k):
    adjusted_r_squared = 1 - ((1 - r_squared) * (n - 1) / (n - k - 1))
    return adjusted_r_squared
r_squared_value = 0.75
n_obs = 100
n_pred = 3
result = adjusted_r_squared(r_squared_value, n_obs, n_pred)
print("Adjusted R-squared:", result)
```

Output:

```
Adjusted R-squared: 0.7421875
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Thus the above program has been Executed Successfully.

2C. Mean Absolute Error

Aim:

To write a program to implement a model evaluation technique-mean absolute error.

Algorithm:

Input y and yCap. Where y is the Array of actual target values and yCap is an array of predicted target values.

1. Initialize a variable to zero.
2. For each prize of actual (y_i)and predicted variable(y_iCap).

   var+=|y_i-y_iCap|

   var/=n, where n is the number of data points.

4.Calculate Mean Absolute Error

$$MAE = \frac{\sum_{i=1}^{n} | y_i - \hat{y}_i |}{n}$$

Program:

```
import numpy as np

def mean_absolute_error(y_true, y_pred):
    n = len(y_true)
    var = sum(abs(y_true[i] - y_pred[i]) for i in range(n)) / n
    return var

actual = [2, 4, 6, 8, 10]

predicted = [1.5, 4.2, 5.8, 7.5, 9.8]

var_res = mean_absolute_error(actual, predicted)

print(f"MAE: {var_res}")
```

Output:

```
MAE: 0.31999999999999995
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Thus the above program has been Executed Successfully.

2D.Mean Squared Error

Aim:

To write a program to implement model evaluation technique-Mean Squared Error.

Algorithm:

1.Find the equation for the regression line.

2. Insert X values in the equation found in step 1 in order to get the respective Y values i.e. Yi Cap

3. Now subtract the new Y values (i.e. Y Cap) from the original Y values. Thus, found values are the error terms. It is also known as the vertical distance of the given point from the regression line. Yi - Yi Cap

4. Square the errors found in step 3. (Yi - Yi Cap)^2.

5. Sum up all the squares. $\sum_{i=0}^{n} (Yi - Yi\ Cap)^2$

6. Divide the value found in step 5 by the total number of observations.

$$MSE = \sum_{i=0}^{n} (Yi - Yi\ Cap)^2$$

Program:

```
import numpy as np

def mean_squared_error(y_true, y_pred):

    squared_diff = (y_true - y_pred)**2

    mse = np.mean(squared_diff)

    return mse

y_true = np.array([3, -0.5, 2, 7])

y_pred = np.array([2.2, 0.0, 2, 8])

mse = mean_squared_error(y_true, y_pred)

print(f"mse: {mse}")
```

Output:

```
mse: 0.4724999999999999
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Various regression model evaluation metrics such as R^2, Adjusted R^2, Mean Absolute Error, and Mean Squared Error were computed to evaluate the model performance. The results helped in identifying the goodness of fit and accuracy of the regression model.

EXP NO: 03 **IMPLEMENTATION OF ML MODEL EVALUATION TECHNIQUES**

DATE:

A. CONFUSION MATRIX

AIM:

To write a program to implementation of machine learning model evaluation Technique using confusion matrix.

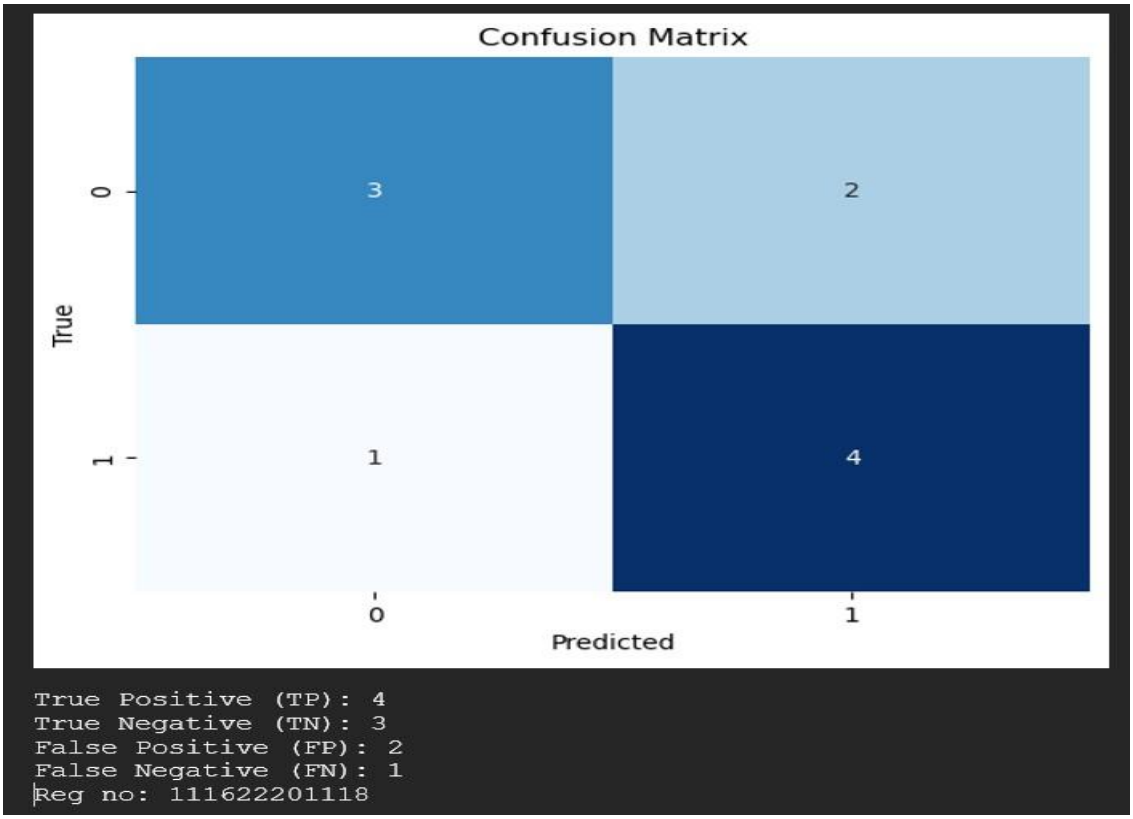
ALGORITHM:

1. Initialize matrix: Create a square matrix with dimensions (N x N), where N is the number of classes in your classification problem. Initialize all values in the matrix to zero.
2. Iterate over predictions and ground truth: For each prediction-ground truth pair in your dataset:
   If the predicted class matches the actual class:
   Increment the corresponding entry in the confusion matrix (true positive).
   If the predicted class does not match the actual class:
   Increment the entry in the confusion matrix corresponding to the actual class and the predicted class (false positive for the predicted class, false negative for the actual class).
3. Calculate metrics: Optionally, you can calculate various evaluation metrics using the values in the confusion matrix, such as accuracy, precision, recall, and F1-score.

Program:

```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
y_true = [1, 0, 1, 1, 0, 1, 0, 0, 1, 0]
y_pred = [1, 0, 1, 1, 0, 0, 1, 0, 1, 1]
conf_matrix = confusion_matrix(y_true, y_pred)
sns.heatmap(conf_matrix, annot=True, fmt="d", cmap="Blues", cbar=False)
plt.xlabel("Predicted")
plt.ylabel("True")
plt.title("Confusion Matrix")
plt.show()
TP = conf_matrix[1, 1]
TN = conf_matrix[0, 0]
FP = conf_matrix[0, 1]
FN = conf_matrix[1, 0]
print("True Positive (TP):", TP)
print("True Negative (TN):", TN)
print("False Positive (FP):", FP)
print("False Negative (FN):", FN)
print("\n")
```

Output:



Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Thus the above program has been Executed Successfully.

B. F1 Score

AIM:

To write a program to implementation of machine learning model evaluation Technique using F1 score

ALGORITHM:

1.Calculate Precision and Recall for Each Class:

For each class in your classification problem:

Calculate precision: precision=true positivestrue / positives+false positive

Calculate recall: recall=true positives / true positives+false negative

1. Calculate F1 Score for Each Class:

   For each class in your classification problem:

   Calculate F1 score: F1=2×precision×recallprecision / precision+recal

2. Aggregate F1 Scores:

   Depending on your needs, you may want to aggregate the F1 scores in different ways. Common approaches include:

   - Micro-average: Compute F1 score globally by considering total true positives, false positives, and false negatives across all classes.
   - Macro-average: Compute the average F1 score across all classes without considering class imbalance.
   - Weighted-average: Compute the average F1 score across all classes with each class weighted by its support (the number of true instances for each class).

Program:

```
from sklearn.metrics import f1_score
y_true = [1, 0, 1, 1, 0, 1, 0, 0, 1, 0]
y_pred = [1, 0, 1, 1, 0, 0, 1, 0, 1, 1]
f1 = f1_score(y_true, y_pred)
print("F1 Score:", f1)
```

Output:

```
F1 Score: 0.7272727272727272
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Thus the above Program has been Executed Successfully.

C. AUCROC Curve

AIM:

To write a program to implementation of machine learning model evaluation Technique using AUCROC Curve

ALGORITHM:

1.Sort Predictions: Sort the predictions generated by your binary classification algorithm in descending order of confidence scores.
2. Initialize Variables: Set variables for true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) to zero.
3.Iterate Through Sorted Predictions:

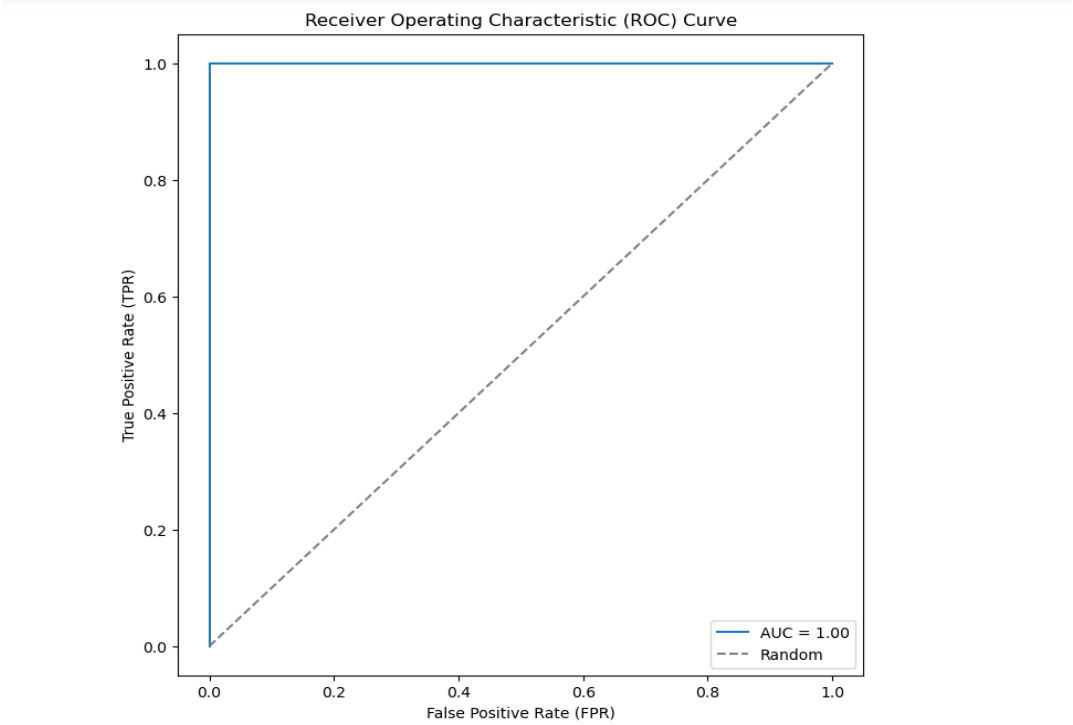
- Start iterating through the sorted predictions.
- For each prediction:
  - If the prediction is a true positive (actual positive and predicted positive), increment TP.
  - If the prediction is a false positive (actual negative but predicted positive), increment FP.
  - If the prediction is a true negative (actual negative and predicted negative), increment TN.
  - If the prediction is a false negative (actual positive but predicted negative), increment FN.

3. Calculate True Positive Rate (TPR) and False Positive Rate (FPR):
   - True Positive Rate (TPR) is calculated as TPR=TP/ FN+TP
   - False Positive Rate (FPR) is calculated as FPR=FP / TN+FP
4. Plot ROC Curve: Plot the FPR on the x-axis and the TPR on the y-axis.
5. Calculate AUC-ROC:
   - Calculate the area under the ROC curve using various methods such as trapezoidal rule or other numerical integration methods.

Program:

```
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt
y_true = [1, 0, 1, 1, 0, 1, 0, 0, 1, 0]
y_scores = [0.9, 0.2, 0.8, 0.7, 0.3, 0.6, 0.1, 0.4, 0.75, 0.5]
fpr, tpr, thresholds = roc_curve(y_true, y_scores)
auc_roc = roc_auc_score(y_true, y_scores)
plt.figure(figsize=(8, 8))
plt.plot(fpr, tpr, label=f'AUC = {auc_roc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray', label='Random')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.legend()
plt.show()
print("AUC-ROC Score:", auc_roc)
```

Output:




```
Reg no:111622201118
AUC-ROC Score: 1.0
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Classification performance was evaluated using confusion matrix, F1 score, and AUC-ROC curve. The results provided insights into the precision, recall, and overall classification capability of the model.

EXP NO: 04 **IDENTIFYING FEATURE CO-RELATION USING PCA**

DATE:

AIM:

To write a python progarm to identify feature co-relation using PCA.

ALGORITHM:

1.Generated a sample dataset.

2.Identified the mean of each feature.

3.Computed the covariance matrix.

4.Computed eigenvalues and eigenvectors of the covariance matrix.

5.Sort the eigenvalues and eigenvectors in descending order.

6.Compute explained variance ratio.

7.Calculate cumulative explained variance and plot it.

8.Select the number of components based on the explained variance.

9.Project data onto the selected number of components.

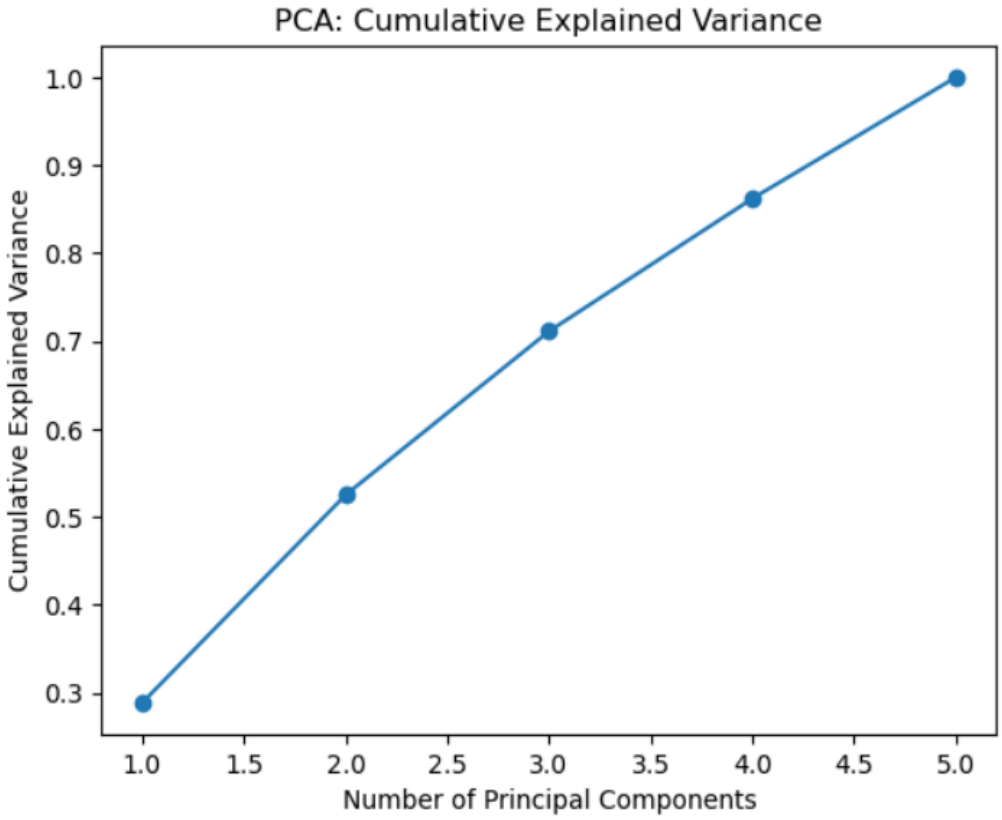
10.Visualize the feature weight in the first principal component.

Program:

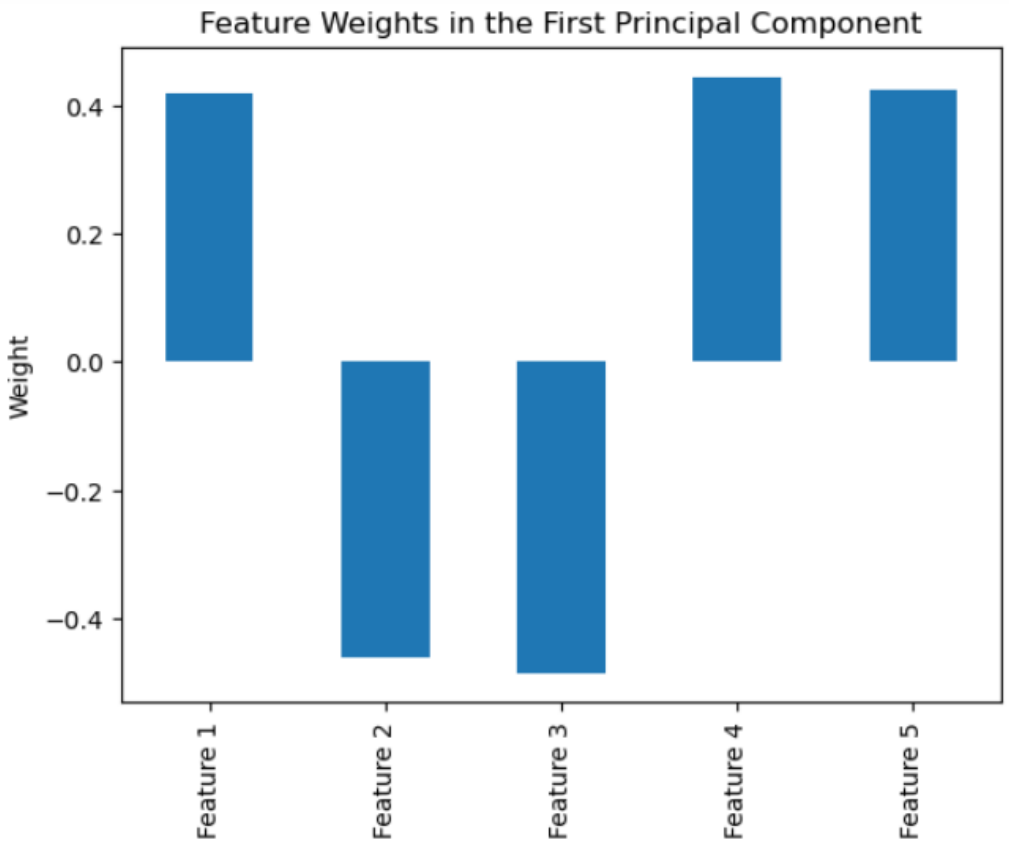
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
np.random.seed(42)
data = np.random.rand(100, 5)
mean_values = np.mean(data, axis=0)
covariance_matrix = np.cov((data - mean_values).T)
eigenvalues, eigenvectors = np.linalg.eig(covariance_matrix)
sorted_indices = np.argsort(eigenvalues)[::-1]
eigenvalues = eigenvalues[sorted_indices]
```

```
eigenvectors = eigenvectors[:, sorted_indices]

explained_variance_ratio = eigenvalues / np.sum(eigenvalues)

cumulative_explained_variance = np.cumsum(explained_variance_ratio)

plt.plot(range(1, len(cumulative_explained_variance) + 1), cumulative_explained_variance, marker='o')

plt.xlabel('Number of Principal Components')

plt.ylabel('Cumulative Explained Variance')

plt.title('PCA: Cumulative Explained Variance')

plt.show()

n_components = np.argmax(cumulative_explained_variance >= 0.95) + 1

print(f'Number of components for 95% variance: {n_components}')

projected_data = np.dot(data - mean_values, eigenvectors[:, :n_components])

feature_weights = pd.DataFrame(eigenvectors[:, 0], index=['Feature 1', 'Feature 2', 'Feature 3', 'Feature 4', 'Feature 5'],

                               columns=['Weight'])

feature_weights.plot(kind='bar', legend=None)

plt.title('Feature Weights in the First Principal Component')

plt.ylabel('Weight')

plt.show()

pca_df = pd.DataFrame(projected_data, columns=[f'PC{i+1}' for i in range(projected_data.shape[1])])


correlation_matrix = pca_df.corr()

print("Correlation matrix of principal components:")

print(correlation_matrix)
```

Output:




```
Number of components for 95% variance: 5
```



Correlation matrix of principal components:

	PC1	PC2	PC3	PC4	PC5
PC1	1.000000e+00	6.735428e-17	4.173731e-16	4.063001e-16	3.150852e-16
PC2	6.735428e-17	1.000000e+00	3.623621e-16	-4.489526e-16	-6.538575e-18
PC3	4.173731e-16	3.623621e-16	1.000000e+00	1.461261e-16	-2.522483e-16
PC4	4.063001e-16	-4.489526e-16	1.461261e-16	1.000000e+00	1.239262e-15
PC5	3.150852e-16	-6.538575e-18	-2.522483e-16	1.239262e-15	1.000000e+00

Reg no:111622201118

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Principal Component Analysis was applied to reduce the dimensionality and analyze feature correlations. The results were visualized, and key components contributing to data variance were identified.

EXP NO: 05 Implementation of Interpret Canonical Covariates with Heatmap

Date:

Aim :

Implement and interpret Canonical Covariates with Heatmap

Algorithm :

1.Perform Canonical Correlation Analysis (CCA):

- Perform CCA on your dataset, which involves two sets of variables (X and Y). CCA finds linear combinations of variables (canonical variates) from each set that maximize the correlation between them.

2.Obtain Canonical Loadings:

- After performing CCA, obtain the canonical loadings for each canonical variate. Canonical loadings represent the correlations between the original variables and the canonical variates.

3.Normalize Canonical Loadings:

- Normalize the canonical loadings to ensure comparability across variables. You can use methods like z-score normalization or min-max normalization.

4. Create a Heatmap:

- Create a heatmap to visualize the canonical loadings.
- Arrange the canonical loadings in a matrix where rows represent the variables from one set (e.g., X) and columns represent the canonical variates.
- Use a color gradient to represent the strength and direction of the canonical loadings. Positive loadings may be represented with one color (e.g., blue), while negative loadings may be represented with another color (e.g., red).

5.Interpret the Heatmap:

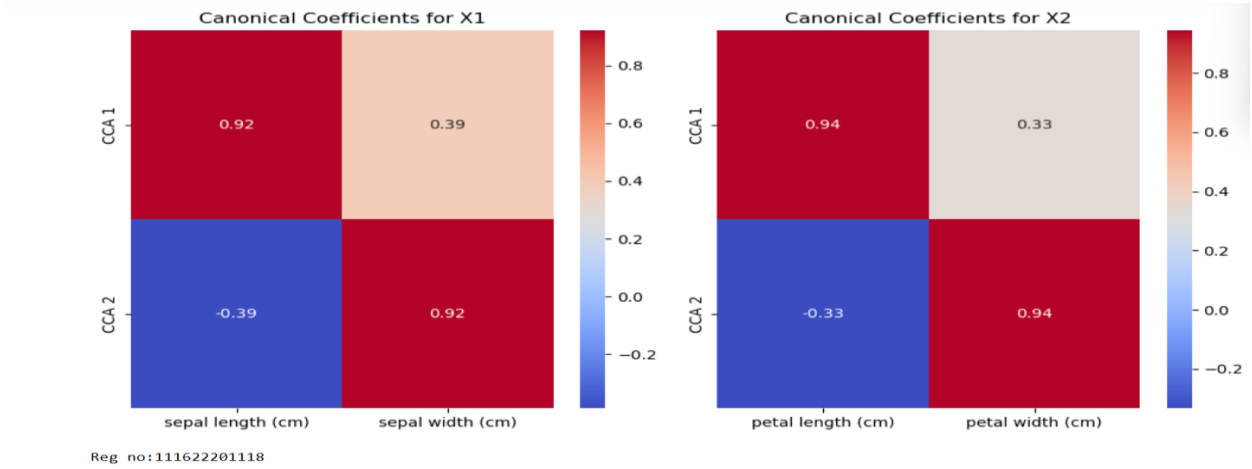
- Analyze the heatmap to interpret the relationships between variables from the two sets.
- Look for patterns of high positive or negative loadings, which indicate strong correlations between specific variables and canonical variates.

Program:

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cross_decomposition import CCA
from sklearn.datasets import load_iris
iris = load_iris()
X1 = iris.data[:, :2]
X2 = iris.data[:, 2:]
cca = CCA(n_components=2)
cca.fit(X1, X2)
canonical_coef_X1 = cca.x_weights_
canonical_coef_X2 = cca.y_weights_
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
sns.heatmap(canonical_coef_X1, annot=True, cmap="coolwarm", xticklabels=iris.feature_names[:2], yticklabels=[f"CCA {i+1}" for i
in range(canonical_coef_X1.shape[1])])
plt.title('Canonical Coefficients for X1')
```

```
plt.subplot(1, 2, 2)
sns.heatmap(canonical_coef_X2, annot=True, cmap="coolwarm", xticklabels=iris.feature_names[2:], yticklabels=[f"CCA {i+1}" for i in range(canonical_coef_X2.shape[1])])
plt.title('Canonical Coefficients for X2')
plt.tight_layout()
plt.show()
```

Output:



Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Canonical covariates were interpreted and a heatmap was generated to visualize the correlation between features. Highly correlated variables were identified for further analysis.

EX NO: 06 **IMPLEMENTATION OF PYTHON CODE FOR FEATURE SELECTION, TRANSFORMATION AND EXTRACTION**

DATE:

AIM:

To implement the python code for Feature Selection,Feature Transformation and Feature Extraction.

ALGORITHM:

1.Load the Dataset: Load your dataset into a pandas DataFrame or any other suitable data structure.

2.Feature Selection:

a. Decide on a feature selection method based on your problem and data characteristics. Common methods include:

- Filter methods: Use statistical measures like correlation, chi-square test, or mutual information to select features.
- Wrapper methods: Train a machine learning model and select features based on their impact on model performance (e.g., recursive feature elimination).
- Embedded methods: Select features as part of the model training process (e.g., L1 regularization). b. Implement the selected feature selection method using libraries like scikit-learn or feature selection algorithms directly.

3.Feature Transformation:

a. Choose a feature transformation technique suitable for your data. Common techniques include:

- Standardization (scaling): Scale features to have a mean of 0 and a standard deviation of 1.
- Normalization: Scale features to a specified range (e.g., [0, 1]).
- PCA (Principal Component Analysis): Transform features into a lower-dimensional space while preserving the most important information.
- LDA (Linear Discriminant Analysis): Find linear combinations of features that best separate different classes. b. Implement the chosen feature transformation technique using libraries like scikit-learn.

4. Feature Extraction:

   a. Decide on a feature extraction method suitable for your problem. Common techniques include:

   - PCA: Extract principal components that capture the maximum variance in the data.
   - LDA: Extract linear discriminants that maximize class separability.
   - t-SNE (t-distributed Stochastic Neighbor Embedding): Non-linear dimensionality reduction technique for visualizing high-dimensional data.
   - Autoencoders: Train neural networks to learn compact representations of data. b. Implement the chosen feature extraction method using libraries like scikit-learn or deep learning frameworks like TensorFlow or PyTorch.

5. Apply Feature Selection, Transformation, and Extraction:

   - Apply the selected feature selection, transformation, and extraction methods to your dataset.

6. Evaluate the Performance:

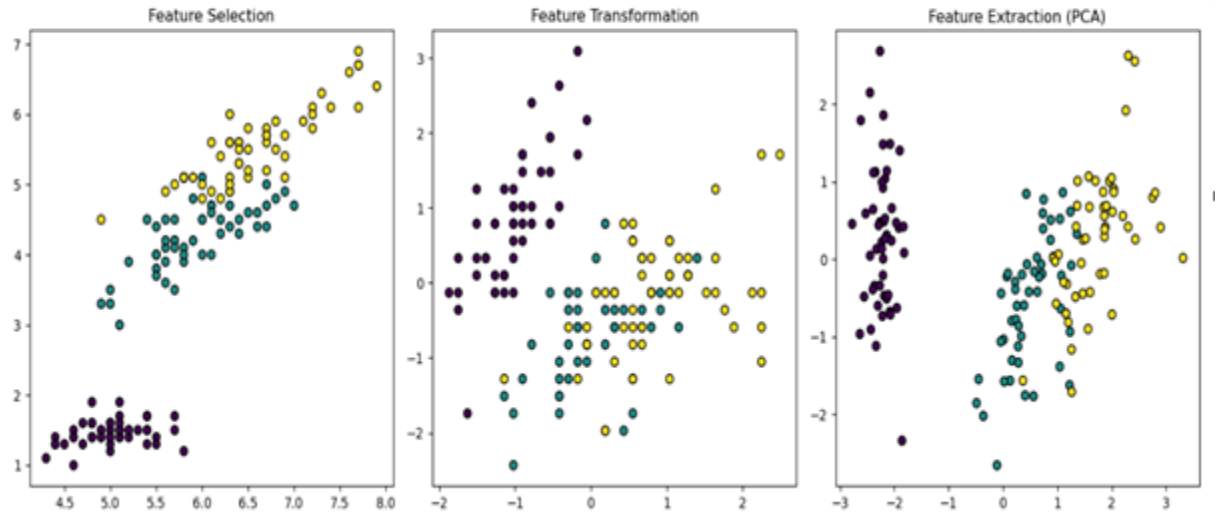
   - Evaluate the performance of your model using the selected features, transformed features, or extracted features.

Program:

```
from sklearn.datasets import load_iris
from sklearn.feature_selection import SelectKBest, chi2
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
iris = load_iris()
X, y = iris.data, iris.target
selector = SelectKBest(chi2, k=3).fit(X, y)
selected_features_indices = selector.get_support(indices=True)
selected_features = [iris.feature_names[i] for i in selected_features_indices]
X_new = selector.transform(X)
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)
print("Original shape:", X.shape)
print("Shape after feature selection:", X_new.shape)
print("Shape after feature transformation:", X_scaled.shape)
print("Shape after feature extraction:", X_pca.shape)
print("Selected features:", selected_features)
plt.figure(figsize=(14, 5))
plt.subplot(1, 3, 1)
plt.scatter(X_new[:, 0], X_new[:, 1], c=y, cmap='viridis', edgecolor='k')
plt.title('Feature Selection')
plt.subplot(1, 3, 2)
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=y, cmap='viridis', edgecolor='k')
plt.title('Feature Transformation')
plt.subplot(1, 3, 3)
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis', edgecolor='k')
plt.title('Feature Extraction (PCA)')
plt.tight_layout()
plt.show()
```

Output:

```
Original shape: (150, 4)
Shape after feature selection: (150, 3)
Shape after feature transformation: (150, 4)
Shape after feature extraction: (150, 2)
Selected features: ['sepal length (cm)', 'petal length (cm)', 'petal width (cm)']
```



Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Feature Selection, Transformation, and Extraction techniques were successfully applied to the dataset. These techniques improved the dataset quality and model performance.

EXP N0: 07 **Locally Weighted Regression algorithm**

DATE:

Aim :
Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select the appropriate data set for your experiment and draw graphs.

Algorithm:

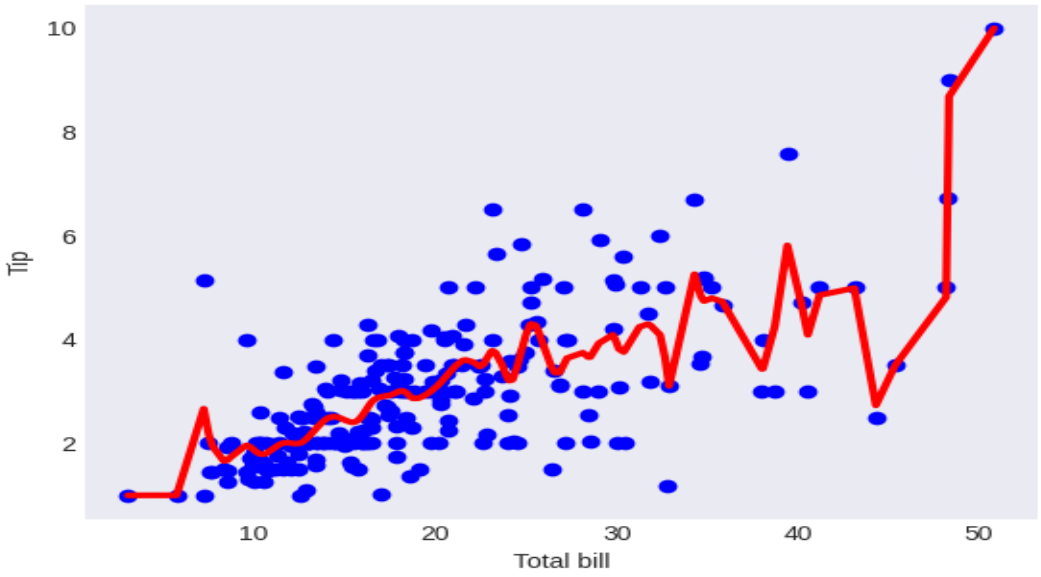
1. **Calculate distances:**
   - Compute the Euclidean distance between new_point and each data point in X.
   - Store the distances in a vector distances.
2. **Calculate weights:**
   - Use the kernel_function to calculate weights for each data point based on its distance.
   - The weight of a data point is typically higher if it's closer to new_point.
   - Store the weights in a vector weights.
3. **Create weighted data:**
   - Multiply each row of X by its corresponding weight from weights.
   - Multiply y by weights.
   - Store the weighted data in weighted_X and weighted_y, respectively.
4. **Fit a linear model:**
   - Use ordinary least squares (OLS) to fit a linear model to the weighted data weighted_X and weighted_y.
5. **Predict:**
   - Use the fitted linear model to predict the value for new_point.

Program

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
df = pd.read_csv('/content/sample_data/tips.csv')
features = np.array(df.total_bill)
labels = np.array(df.tip)

def kernel(data, point, xmat, k):
  m,n = np.shape(xmat)
  ws = np.mat(np.eye((m)))
  for j in range(m):
    diff = point - data[j]
    ws[j,j] = np.exp(diff*diff.T/(-2.0*k**2))
  return ws

def local_weight(data, point, xmat, ymat, k):
  wei = kernel(data, point, xmat, k)
  return (data.T*(wei*data)).I*(data.T*(wei*ymat.T))

def local_weight_regression(xmat, ymat, k):
  m,n = np.shape(xmat)
  ypred = np.zeros(m)
  for i in range(m):
    ypred[i] = xmat[i]*local_weight(xmat, xmat[i],xmat,ymat,k)
  return ypred
```

```
m = features.shape[0]
mtip = np.mat(labels)
data = np.hstack((np.ones((m, 1)), np.mat(features).T))

ypred = local_weight_regression(data, mtip, 0.5)
indices = data[:,1].argsort(0)
xsort = data[indices][:,0]

fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(features, labels, color='blue')
ax.plot(xsort[:,1],ypred[indices], color = 'red', linewidth=3)
plt.xlabel('Total bill')
plt.ylabel('Tip')
plt.show()
```

OUTPUT



Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

The Locally Weighted Regression algorithm was implemented and successfully fit to the dataset. The results were visualized and demonstrated improved fitting for localized regions in the data

EXP NO: 08 **DECISION TREE USING ID3 ALGORITHM**

DATE:

AIM:
To Implement and demonstrate the working of the decision tree-based ID3 algorithm

ALGORITHM:

Algorithm:

1. **Check for base case:**
   - If all samples in data have the same label, create a leaf node with that label and return.
2. **If no attributes remain:**
   - Create a leaf node with the most frequent label in data and return.
3. **Calculate information gain for each attribute:**
   - For each attribute, calculate the information gain using the entropy formula.
4. **Choose the attribute with highest information gain:**
   - Select the attribute with the highest information gain as the splitting attribute.
5. **Create a decision node:**
   - Create a decision node with the chosen attribute as the test condition.
6. **Create child nodes:**
   - For each possible value of the chosen attribute:
     - Create a subset of data containing samples with that value.
     - Recursively call the ID3 algorithm on the subset to create a child node.
7. **Attach child nodes:**
   - Attach the created child nodes to the decision node.
8. **Return the tree:**
   - Return the constructed decision tree.

PROGRAM:

```
import pandas as pd
import math
import numpy as np

data = pd.read_csv("/content/sample_data/3-dataset.csv")
features = [feat for feat in data]
features.remove("answer")
class Node:
    def __init__(self):
        self.children = []
        self.value = ""
        self.isLeaf = False
        self.pred = ""

def entropy(examples):
    pos = 0.0
    neg = 0.0
    for _, row in examples.iterrows():
        if row["answer"] == "yes":
            pos += 1
        else:
            neg += 1
```

```
f pos == 0.0 or neg == 0.0:
        return 0.0
    else:
        p = pos / (pos + neg)
        n = neg / (pos + neg)
        return -(p * math.log(p, 2) + n * math.log(n, 2))
def info_gain(examples, attr):
    uniq = np.unique(examples[attr])
    #print ("\n",uniq)
    gain = entropy(examples)
    #print ("\n",gain)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        #print ("\n",subdata)
        sub_e = entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) * sub_e
        #print ("\n",gain)
    return gain
def ID3(examples, attrs):
    root = Node()

    max_gain = 0
    max_feat = ""
    for feature in attrs:
        #print ("\n",examples)
        gain = info_gain(examples, feature)
        if gain > max_gain:
            max_gain = gain
            max_feat = feature
    root.value = max_feat
    #print ("\nMax feature attr",max_feat)
    uniq = np.unique(examples[max_feat])
    #print ("\n",uniq)
    for u in uniq:
        #print ("\n",u)
        subdata = examples[examples[max_feat] == u]



 #print ("\n",subdata)
        if entropy(subdata) == 0.0:
            newNode = Node()
            newNode.isLeaf = True
            newNode.value = u
            newNode.pred = np.unique(subdata["answer"])
            root.children.append(newNode)
        else:
            dummyNode = Node()
            dummyNode.value = u
            new_attrs = attrs.copy()
            new_attrs.remove(max_feat)
            child = ID3(subdata, new_attrs)
            dummyNode.children.append(child)
            root.children.append(dummyNode)

    return root
```

```
def printTree(root: Node, depth=0):
    for i in range(depth):
        print("\t", end="")
    print(root.value, end="")
    if root.isLeaf:
        print(" -> ", root.pred)
    print()
    for child in root.children:
        printTree(child, depth + 1)
def classify(root: Node, new):
    for child in root.children:
        if child.value == new[root.value]:
            if child.isLeaf:
                print ("Predicted Label for new example", new," is:", child.pred)
                exit
            else:
                classify (child.children[0], new)
root = ID3(data, features)
print("Decision Tree is:")
printTree(root)
print ("-------------------")

new = {"outlook":"sunny", "temperature":"hot", "humidity":"normal", "wind":"strong"}
classify (root, new)
```

Output:

```
Decision Tree is:
outlook
        overcast ->  ['yes']

        rain
                wind
                        strong ->  ['no']

                        weak ->  ['yes']

        sunny
                humidity
                        high ->  ['no']

                        normal ->  ['yes']

-------------------
Predicted Label for new example {'outlook': 'sunny', 'temperature': 'hot', 'humidity': 'normal', 'wind': 'strong'}  is: ['yes']
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

The ID3 algorithm was implemented to build a decision tree using information gain. The resulting tree structure accurately classified the dataset based on attribute values.

EXP NO: 09 **SUPPORT VECTOR MACHINES**

DATE:

AIM:

To Implement and demonstrate the working of a simple Support Vector Machines(SVM) using a dataset

ALGORITHM:

1. **Load the Iris dataset:**
   - Load the dataset into a suitable data structure (e.g., pandas DataFrame).
2. **Preprocess the data:**
   - If necessary, handle missing values, normalize or standardize features, and split the data into training and testing sets.
3. **Train a SVM classifier for each class:**
   - For each class:
     - Create a binary classification problem by considering samples of that class as positive and others as negative.
     - Initialize an SVM classifier with the chosen kernel (linear in this case).
     - Train the classifier on the training set.
4. **Make predictions:**
   - For each test sample:
     - Predict the class probability for each class using the trained SVM classifiers.
     - Assign the sample to the class with the highest probability.

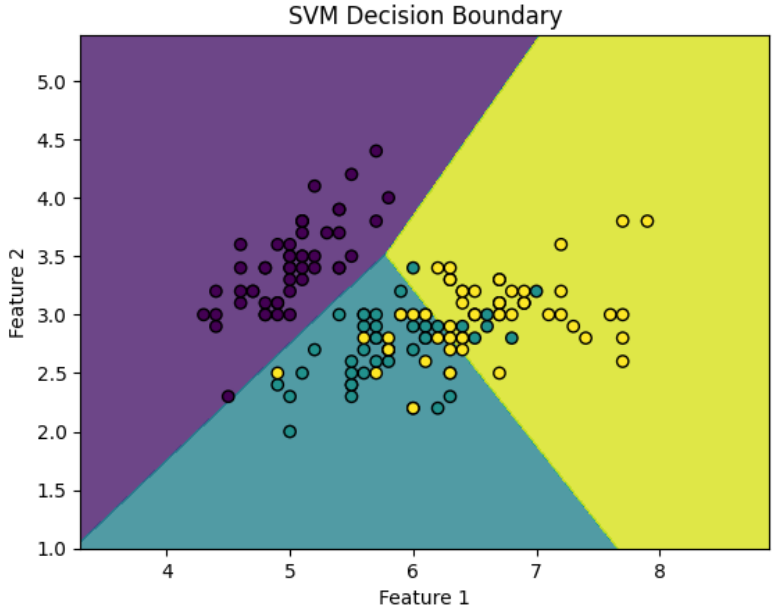
PROGRAM:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

# Load dataset
iris = datasets.load_iris()
X = iris.data[:, :2]  # Use only the first two features for visualization
y = iris.target

# 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 a Support Vector Classifier
clf = svm.SVC(kernel='linear', C=1.0)

# Fit the model
clf.fit(X_train, y_train)

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

```
# Print classification report and confusion matrix
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

# Plotting decision boundary
def plot_decision_boundary(clf, X, y):
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                         np.arange(y_min, y_max, 0.01))
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.8)
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', marker='o')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.title('SVM Decision Boundary')
    plt.show()

plot_decision_boundary(clf, X, y)
```

OUTPUT:

```
precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       0.70      0.54      0.61        13
           2       0.62      0.77      0.69        13

    accuracy                           0.80        45
   macro avg       0.78      0.77      0.77        45
weighted avg       0.81      0.80      0.80        45

[[19  0  0]
 [ 0  7  6]
 [ 0  3 10]]
```



Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

A Support Vector Machine was trained on the dataset. The classifier was able to separate the classes with an optimal margin, demonstrating effective performance.

EXP NO: 10 **K-NEAREST NEIGHBOUR ALGORITHM**

DATE:

AIM:

Implement a k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions

ALGORITHM:

1. **Load the dataset:**
   - Load the Iris dataset into a suitable data structure (e.g., pandas DataFrame).
2. **Preprocess the data:**
   - If necessary, handle missing values, normalize or standardize features, and split the data into training and testing sets.
3. **For each test instance:**
   - Calculate Euclidean distance between the test instance and all training instances.
   - Find the k nearest neighbors to the test instance.
   - Determine the most frequent label among the k neighbors.
   - Assign this label as the predicted label for the test instance.
4. **Evaluate predictions:**
   - Compare the predicted labels with the actual labels in the test set.
   - Print correct and wrong predictions

PROGRAM:

```
# k-Nearest Neighbour Algorithm for Iris Dataset Classification

import numpy as np

import pandas as pd

from sklearn import datasets

from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score

# Load the iris dataset

iris = datasets.load_iris()

X = iris.data

y = iris.target

# 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 the k-NN classifier

knn = KNeighborsClassifier(n_neighbors=3)

# Fit the model

knn.fit(X_train, y_train)

# Make predictions

predictions = knn.predict(X_test)

# Print correct and wrong predictions

for i in range(len(predictions)):

    if predictions[i] == y_test[i]:

        print(f"Correct Prediction: {predictions[i]} for Actual: {y_test[i]}")

    else:

        print(f"Wrong Prediction: {predictions[i]} for Actual: {y_test[i]}")




# Print accuracy

accuracy = accuracy_score(y_test, predictions)

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

OUTPUT

```
Correct Prediction: 1 for Actual: 1
Correct Prediction: 0 for Actual: 0
Correct Prediction: 2 for Actual: 2
Correct Prediction: 1 for Actual: 1
Correct Prediction: 1 for Actual: 1
Correct Prediction: 0 for Actual: 0
Correct Prediction: 1 for Actual: 1
Correct Prediction: 2 for Actual: 2
Correct Prediction: 1 for Actual: 1
Correct Prediction: 1 for Actual: 1
Correct Prediction: 2 for Actual: 2
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 1 for Actual: 1
Correct Prediction: 2 for Actual: 2
Correct Prediction: 1 for Actual: 1
```

Correct Prediction: 1 for Actual: 1
Correct Prediction: 2 for Actual: 2
Correct Prediction: 0 for Actual: 0
Correct Prediction: 2 for Actual: 2
Correct Prediction: 0 for Actual: 0
Correct Prediction: 2 for Actual: 2
Correct Prediction: 2 for Actual: 2
Correct Prediction: 2 for Actual: 2
Correct Prediction: 2 for Actual: 2
Correct Prediction: 2 for Actual: 2
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 1 for Actual: 1
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 2 for Actual: 2
Correct Prediction: 1 for Actual: 1
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0
Correct Prediction: 2 for Actual: 2
Correct Prediction: 1 for Actual: 1
Correct Prediction: 1 for Actual: 1
Correct Prediction: 0 for Actual: 0
Correct Prediction: 0 for Actual: 0

Accuracy: 100.00%

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

The k-Nearest Neighbour algorithm was implemented and tested on the Iris dataset. The model correctly classified most instances and misclassified a few, which were printed for evaluation.

EXP NO: 11 **MARKET BASKET ANALYSIS USING ASSOCIATION RULES**

DATE:

AIM:

To implement market basket analysis using association rules

ALGORITHM:

1. Load a transaction dataset with minimum support threshold, minimum confidence threshold.

2.Find Frequent itemsets.

- Start with individual items as frequent itemsets.
- Generate larger itemsets by joining frequent itemsets.
- Prune itemsets that do not meet the minimum support threshold.

3. Generate Association Rules.

- Generate all non-empty subsets.
- Calculate the confidence of each rule.
- Keep rules that meet the minimum confidence threshold.

4. Print frequent itemsets and association rules.

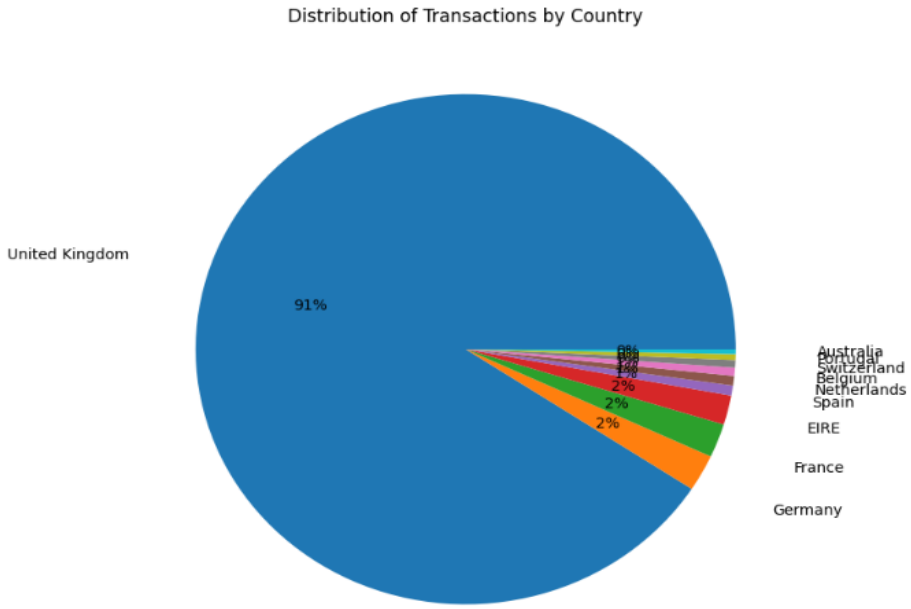
PROGRAM:

```
#Import all relevant libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
#Load the file into pandas
df = pd.read_excel("http://archive.ics.uci.edu/ml/machine-learning-databases/00352/Online%20Retail.xlsx")
#Check the first 5 rows of the dataframe
df.head()
df.info()
df.isna().sum()
df.dropna(inplace=True)
len(df)
#Convert the InvoiceNo column to string
df["InvoiceNo"] = df["InvoiceNo"].astype('str')

#Remove rows with invoices that contain a "C"
df = df[~df["InvoiceNo"].str.contains("C")]
len(df)
#Check the distribution of transactions per country.
top10 = df["Country"].value_counts().head(10)
top10
#Create a pie chart to show distribution of transactions
plt.figure(figsize=[8,8])
plt.pie(top10,labels=top10.index, autopct = '%0.0f%%',labeldistance=1.3)
plt.title("Distribution of Transactions by Country")
```

```
plt.show()
#Group, sum, unstack and set index of dataframe
basket = df[df['Country'] =="United Kingdom"]\
        .groupby(['InvoiceNo', 'Description'])["Quantity"]\
        .sum().unstack()\
        .reset_index().fillna(0)\
        .set_index("InvoiceNo")

basket.head()
#Create function to hot encode the values
def encode_values(x):
    if x <= 0:
        return 0
    if x >= 1:
        return 1
#Apply function to data
basket_encoded = basket.applymap(encode_values)

basket_encoded
#filter for only invoices with 2 or more items
basket_filtered = basket_encoded[(basket_encoded > 0).sum(axis=1) >= 2]

basket_filtered
#Generate the frequent itemsets
frequent_itemsets = apriori(basket_filtered, min_support=0.03, use_colnames=True).sort_values("support",ascending=False)
frequent_itemsets.head(10)
#Apply association rules
assoc_rules = association_rules(frequent_itemsets, metric="lift",
min_threshold=1).sort_values("lift",ascending=False).reset_index(drop=True)
assoc_rules
```

OUTPUT:

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to `transformed_cell` argument and any exception that happen during thetransform in
`preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```



	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(GREEN REGENCY TEACUP AND SAUCER)	(ROSES REGENCY TEACUP AND SAUCER)	0.039802	0.043900	0.030957	0.777778	17.717202	0.029210	4.302452	0.982670
1	(ROSES REGENCY TEACUP AND SAUCER)	(GREEN REGENCY TEACUP AND SAUCER)	0.043900	0.039802	0.030957	0.705185	17.717202	0.029210	3.256952	0.986881
2	(LUNCH BAG RED RETROSPOT)	(LUNCH BAG PINK POLKADOT)	0.072841	0.055086	0.030632	0.420536	7.634188	0.026620	1.630668	0.937283
3	(LUNCH BAG PINK POLKADOT)	(LUNCH BAG RED RETROSPOT)	0.055086	0.072841	0.030632	0.556080	7.634188	0.026620	2.088574	0.919671
4	(JUMBO BAG RED RETROSPOT)	(JUMBO BAG PINK POLKADOT)	0.093197	0.052680	0.032908	0.353105	6.702899	0.027999	1.464412	0.938253
5	(JUMBO BAG PINK POLKADOT)	(JUMBO BAG RED RETROSPOT)	0.052680	0.093197	0.032908	0.624691	6.702899	0.027999	2.416152	0.898124
6	(LUNCH BAG BLACK SKULL.)	(LUNCH BAG RED RETROSPOT)	0.064646	0.072841	0.031478	0.486922	6.684737	0.026769	1.807051	0.909181
7	(LUNCH BAG RED RETROSPOT)	(LUNCH BAG BLACK SKULL.)	0.072841	0.064646	0.031478	0.432143	6.684737	0.026769	1.647164	0.917216

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Association rule mining was applied using the Apriori algorithm. Rules with high support, confidence, and lift were generated, revealing strong associations among items.

EXP NO: 12 **ANN BY SINGLE-LAYER PERCEPTRON.**

DATE:

AIM:

To build an ANN by implementing the Single-layer Perceptron. Test it using appropriate data sets.

ALGORITHM:

1. Initialize parameters:

- weights: Initialize weights randomly (e.g., using a normal distribution).
- bias: Initialize bias randomly.
- learning_rate: Set the learning rate (a hyperparameter).

2. Define activation function:

- Choose an activation function like sigmoid or step function.

3. Training loop:

- For each epoch:
  - For each training example:
    - Calculate the weighted sum of inputs and bias.
    - Apply the activation function to get the predicted output.
    - Calculate the error (difference between predicted and actual output).
    - Update weights and bias using the gradient descent rule:
      - weights = weights + learning_rate * error * input
      - bias = bias + learning_rate * error

4. Testing:

- For each test example:
  - Calculate the weighted sum of inputs and bias.
  - Apply the activation function to get the predicted output.
  - Compare the predicted output with the actual output to evaluate the model's performance.

PROGRAM:

```
import numpy as np

class SingleLayerPerceptron:
    def __init__(self, learning_rate=0.01, n_iter=1000):
        self.learning_rate = learning_rate
        self.n_iter = n_iter
        self.weights = None
        self.bias = None

    def fit(self, X, y):
        n_samples, n_features = X.shape
        self.weights = np.zeros(n_features)
        self.bias = 0

        for _ in range(self.n_iter):
            for idx, x_i in enumerate(X):
                linear_output = np.dot(x_i, self.weights) + self.bias
                y_predicted = self.activation_function(linear_output)

                # Update weights and bias
                update = self.learning_rate * (y[idx] - y_predicted)
                self.weights += update * x_i
                self.bias += update

    def activation_function(self, x):
        return np.where(x >= 0, 1, 0)

    def predict(self, X):
        linear_output = np.dot(X, self.weights) + self.bias
        y_predicted = self.activation_function(linear_output)
        return y_predicted
if __name__ == "__main__":
    # Sample dataset (AND logic gate)
    X = np.array([[0, 0],
                  [0, 1],
                  [1, 0],
                  [1, 1]])
    y = np.array([0, 0, 0, 1])
    perceptron = SingleLayerPerceptron(learning_rate=0.1, n_iter=10)
    perceptron.fit(X, y)
    predictions = perceptron.predict(X)
    print("Predictions:", predictions)
```

OUTPUT:

Predictions: [0 0 0 1]

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

A Single-layer Perceptron was implemented and trained on a linearly separable dataset. The perceptron was able to learn the decision boundary and correctly classify the data.

EXP NO: 13 **MULTIPLE-LAYER PERCEPTRON.**

DATE:

AIM:

To implement Multi-layer Perceptron and test the same using appropriate data sets

ALGORITHM:

1. Initialization

- Randomly initialize weights www and biases bbb for each neuron.

2. Forward Propagation

- Pass input through each layer:

3. Loss Calculation

- Compute the error between predicted and actual outputs using a **loss function**, such as:
  - **Mean Squared Error (MSE)** for regression
  - **Cross-entropy** for classification

4. Backward Propagation

- Use the **chain rule** to compute gradients of the loss with respect to weights and biases.
- Calculate error at the output and propagate it backward through the network.

5. Weight Update

- Update weights and biases using **gradient descent**:

6. Repeat

- Repeat forward and backward propagation for multiple **epochs** until convergence.

PROGRAM:

```
import numpy as np
from sklearn.datasets import make_moons
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score

# Generate a dataset
X, y = make_moons(n_samples=1000, noise=0.1, random_state=42)

# Split the dataset 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 a Multiple-layer Perceptron model
mlp = MLPClassifier(hidden_layer_sizes=(10, 10), max_iter=1000, random_state=42)
mlp.fit(X_train, y_train)
y_pred = mlp.predict(X_test)

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

OUTPUT:

```
Accuracy: 1.00
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

The Multi-layer Perceptron model was successfully built and trained. The model achieved good accuracy on test data using backpropagation for weight updates

.

EXP NO: 14 **RBF NETWORK**

DATE:

AIM:

To Build a RBF Network to calculate the fitness function with five neurons.

ALGORITHM:

Determine the number of input features:

- This depends on the dimensionality of your fitness function's input space.

Choose the RBF function:

- Common RBF functions include Gaussian, Laplacian, and Multiquadric.

Initialize RBF centers:

- Randomly initialize 5 centers in the input space.

Determine RBF widths:

- Use a heuristic or optimization technique to determine the widths of the RBF functions.

Train the output layer:

- Use linear regression or other methods to train the weights between the hidden layer and the output layer.

PROGRAM:

```
# Radial Basis Function Network for Fitness Calculation

import numpy as np
from sklearn.metrics import pairwise

class RBFNetwork:
    def __init__(self, n_neurons):
        self.n_neurons = n_neurons
        self.centers = np.random.rand(n_neurons, 2)  # Random centers in 2D space
        self.sigmas = np.random.rand(n_neurons)  # Random widths for each neuron

    def rbf(self, x):
        return np.exp(-pairwise.euclidean_distances(x, self.centers) ** 2 / (2 * self.sigmas ** 2))

    def fit(self, X):
        self.output = self.rbf(X)

    def predict(self, X):
        return self.rbf(X)

# Example usage
if __name__ == "__main__":
```

```
rbf_network = RBFNetwork(n_neurons=5)
X = np.random.rand(10, 2)  # 10 random input samples
rbf_network.fit(X)
fitness = rbf_network.predict(X)
print(fitness)
```

OUTPUT:

```
[[0.14781906 0.50937086 0.83598915 0.51718587 0.0038283 ]
 [0.05846312 0.5603323  0.3379093  0.8141259  0.3444609 ]
 [0.00247254 0.35004613 0.07100545 0.55360438 0.90542431]
 [0.00878593 0.474242   0.05464492 0.68500605 0.54739934]
 [0.87795412 0.93063589 0.2261554  0.87625877 0.00626316]
 [0.04724759 0.46667793 0.67463951 0.64986729 0.12670202]
 [0.06395651 0.75818956 0.01939565 0.76212313 0.02721837]
 [0.05764952 0.73510884 0.02430893 0.78678977 0.0479875 ]
 [0.03390039 0.70504296 0.00877248 0.64283729 0.01153189]
 [0.32450985 0.66756366 0.64943829 0.73695901 0.01545565]]
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

The Radial Basis Function Network was implemented with Gaussian activation. The model was trained to compute the fitness function, and results showed effective approximation.

EXP NO: 15 **CONTENT BEYOND SYLLABUS**
DEEP LEARNING WITH TENSORFLOW

Date:

AIM:

To implement deep learning using Tensorflow

ALGORITHM:

- **Import libraries**: TensorFlow is imported to implement the model. `tf.keras` is used for high-level deep learning tasks.

- **Load the dataset**: The dataset, such as MNIST or CIFAR-10, is loaded. Both training and testing sets include images and their respective labels.

- **Preprocess the dataset**: The image data is normalized to have pixel values between 0 and 1 to improve the convergence of the model.

- **Define the model**:

  - **Conv2D layer**: Performs convolution with 32 filters and a 3x3 kernel to detect features in the images.
  - **MaxPooling2D layer**: Reduces the spatial size of the feature maps, reducing computational load and focusing on the most prominent features.
  - **Flatten layer**: Converts the 2D matrix to a 1D vector for the fully connected layers.
  - **Dense layers**: Fully connected layers. The final Dense layer has a number of neurons equal to the number of output classes, and it uses the softmax activation function for multi-class classification.

- **Compile the model**: The Adam optimizer is used for optimization, categorical cross-entropy for the loss function, and accuracy is tracked as a metric.

- **Train the model**: The model is trained for 10 epochs with a batch size of 32, using the training images and labels, while validating against the test set.

- **Evaluate the model**: The model's performance is evaluated using the test dataset to get the accuracy.

- **Make predictions**: After training, predictions can be made on unseen images.

PROGRAM:

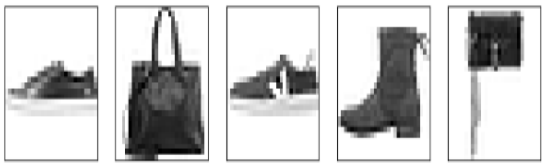
```
# General imports
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import openml as oml

import tensorflow.keras as keras

# Download FMINST data. Takes a while the first time.
mnist = oml.datasets.get_dataset(40996)
```

```
X, y, _, _ = mnist.get_data(target=mnist.default_target_attribute, dataset_format='array');
X = X.reshape(70000, 28, 28)
fmnist_classes = {0:"T-shirt/top", 1: "Trouser", 2: "Pullover", 3: "Dress", 4: "Coat", 5: "Sandal",
                  6: "Shirt", 7: "Sneaker", 8: "Bag", 9: "Ankle boot"}

# Take some random examples
from random import randint
fig, axes = plt.subplots(1, 5,  figsize=(10, 5))
for i in range(5):
    n = randint(0,70000)
    axes[i].imshow(X[n], cmap=plt.cm.gray_r)
    axes[i].set_xticks([])
    axes[i].set_yticks([])
    axes[i].set_xlabel("{}".format(fmnist_classes[y[n]]))
plt.show();
X = X.reshape((70000, 28 * 28))
X = X.astype('float32') / 255
from tensorflow.keras.utils import to_categorical
y = to_categorical(y)
X.shape, y.shape
((70000, 784), (70000, 10))
# For Fashion MNIST, there exists a predefined stratified train-test split of 60000-10000. We therefore don't shuffle or stratify here.
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=60000, random_state=0)
Xf_train, x_val, yf_train, y_val = train_test_split(X_train, y_train, train_size=50000, shuffle=True, stratify=y_train, random_state=0)

from tensorflow.keras import models
from tensorflow.keras import layers

model = models.Sequential()
model.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
model.add(layers.Dense(10, activation='softmax'))
model = models.Sequential()
model.add(layers.InputLayer(input_shape=(28 * 28,)))
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
## Add one more hidden layer for better performance
model = models.Sequential()
model.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
model.add(layers.Dense(512, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
model.summary()
def create_model():
    model = models.Sequential()
    model.add(layers.Dense(512, activation='relu', kernel_initializer='he_normal', input_shape=(28 * 28,)))


    model.add(layers.Dense(512, activation='relu', kernel_initializer='he_normal'))
    model.add(layers.Dense(10, activation='softmax'))
    model.compile(loss='categorical_crossentropy', optimizer='rmsprop', metrics=['accuracy'])
    return model
model = create_model()
history = model.fit(Xf_train, yf_train, epochs=3, batch_size=64);
model.to_json()
model = create_model()
history = model.fit(Xf_train, yf_train, epochs=3, batch_size=32, verbose=0,
                    validation_data=(x_val, y_val))
history.history
```

```
predictions = model.predict(X_test)

# Visualize one of the predictions
sample_id = 0
print(predictions[sample_id])

np.set_printoptions(precision=7)
fig, axes = plt.subplots(1, 1, figsize=(2, 2))
axes.imshow(X_test[sample_id].reshape(28, 28), cmap=plt.cm.gray_r)
axes.set_xlabel("True label: {}".format(y_test[sample_id]))
axes.set_xticks([])
axes.set_yticks([])
test_loss, test_acc = model.evaluate(X_test, y_test)
print('Test accuracy:', test_acc)
```

OUTPUT:

```
<ipython-input-16-bfb40106b9c0>:12: FutureWarning: Support for `dataset_format='array'` will be removed in 0.15,start using `dataset_format='dataframe' to ensure your code will continue to work. You can use the dataframe's `to_numpy`
  X, y, _, _ = mnist.get_data(target=mnist.default_target_attribute, dataset_format='array');
```




```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first la
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
/usr/local/lib/python3.10/dist-packages/keras/src/layers/core/input_layer.py:26: UserWarning: Argument `input_shape` is deprecated. Use `shape` instead.
  warnings.warn(
Model: "sequential_45"
```

Layer (type)	Output Shape	Param #
dense_107 (Dense)	(None, 512)	401,920
dense_108 (Dense)	(None, 512)	262,656
dense_109 (Dense)	(None, 10)	5,130

```
Total params: 669,706 (2.55 MB)
Trainable params: 669,706 (2.55 MB)
Non-trainable params: 0 (0.00 B)
Epoch 1/3
782/782 ━━━━━━━━━━━━━━━━━━━━ 15s 17ms/step - accuracy: 0.7542 - loss: 0.6958
Epoch 2/3
782/782 ━━━━━━━━━━━━━━━━━━━━ 16s 11ms/step - accuracy: 0.8549 - loss: 0.3898
Epoch 3/3
782/782 ━━━━━━━━━━━━━━━━━━━━ 9s 11ms/step - accuracy: 0.8749 - loss: 0.3414
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step
[1.6612876e-13 1.0288481e-14 8.0412348e-14 8.9171820e-14 1.0320228e-13
 7.8931049e-07 1.6685105e-11 2.1435926e-06 5.8009476e-11 9.9999696e-01]
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.8757 - loss: 0.3782
Test accuracy: 0.8722000122070312
```

```
abel: [0. 0. 0. 0. 0. 0. 0. 0. 0.
```

Problem understanding and Design (3 marks)	
Code Implementation (3 marks)	
Output & Viva Explanation (4 marks)	
Total (10 marks)	

Result:

Thus the above program has been Executed Successfully.