SSN COLLEGE OF ENGINEERING
KALAVAKKAM - 603 110

Department of Computer Science and Engineering

UCS2604 PRINCIPLES OF MACHINE LEARNING

Assignment 2

E-commerce Customer Data for Behavior Analysis

Madhumitha E- 3122 22 5001 068

Muthuselvi K - 3122 22 5001 074

Nandhine A - 3122 22 5001 076

I.Aim:

1. Implement the Dimensionality reduction techniques to improve the model performance.
2. Identify the hyper-parameters and model parameters to be tuned.
3. Implement the Random / Grid search to optimize the hyper-parameters of the model.
4. Develop the model with the optimized parameters.
5. Tabulate the analyze the results of the model prior to and post hyper parameter tuning and optimization techniques
6. Compare the performance of the models with and without optimizing the parameters

II.Proposed system:

1. Data Collection:

The dataset is obtained from an e-commerce platform containing customer information, purchase history, and satisfaction levels.

Data includes demographic details (age, gender, city), transaction details (total spend, items purchased), and behavioral metrics (average rating, discount applied, days since last purchase).

2.Data Preprocessing:

a.Feature Engineering:

Categorical variables (e.g., gender, city, membership type) are encoded using label encoding and one-hot encoding.

Boolean attributes (e.g., discount applied) are converted into numerical values.

b.Handling Missing Values:

Rows with missing target values (Satisfaction Level) are removed.

c.Class Imbalance Handling:

The Synthetic Minority Over-sampling Technique (SMOTE) is applied to balance the dataset.

d.Feature Scaling:

Standardization is performed using StandardScaler to normalize numeric attributes.

3.Dimensionality Reduction (PCA):

- Principal Component Analysis (PCA) is used to reduce feature dimensions while preserving essential variance in the dataset.

- The top contributing features for each principal component are identified.

4.Model Selection and Training:

- Three machine learning models are implemented:

  a.Logistic Regression

  b.Support Vector Machine (SVM)

  c.Random Forest Classifier

The dataset is split into training and testing sets (80-20 split).

5.Hyperparameter Tuning:

GridSearchCV is used to optimize model parameters for better accuracy.

6.Model Evaluation:

Performance metrics such as accuracy, precision, recall, and F1-score are calculated.

A confusion matrix is generated to visualize classification performance.

III.Implementation

1.Importing the necessary packages

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, GridSearchCV, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE
```

2.Load the dataset

```
[ ] from google.colab import drive
    drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
[ ] file_path = '/content/drive/MyDrive/E-commerce Customer Behavior - Sheet1.csv'
    df = pd.read_csv(file_path)
    print(df.head())
    print("\nShape: ",df.shape)
```

]

3.Exploratory Data Analysis

```
print("\nShape: ",df.shape)
```

```
   Customer ID  Gender  Age           City Membership Type  Total Spend  \
0          101  Female   29       New York            Gold      1120.20
1          102    Male   34    Los Angeles          Silver       780.50
2          103  Female   43        Chicago          Bronze       510.75
3          104    Male   30  San Francisco            Gold      1480.30
4          105    Male   27          Miami          Silver       720.40

   Items Purchased  Average Rating  Discount Applied  \
0               14             4.6              True
1               11             4.1             False
2                9             3.4              True
3               19             4.7             False
4               13             4.0              True

   Days Since Last Purchase Satisfaction Level
0                        25          Satisfied
1                        18            Neutral
2                        42        Unsatisfied
3                        12          Satisfied
4                        55        Unsatisfied

Shape:  (350, 11)
```

```
[ ] df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 350 entries, 0 to 349
Data columns (total 11 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Customer ID               350 non-null    int64
 1   Gender                    350 non-null    object
 2   Age                       350 non-null    int64
 3   City                      350 non-null    object
 4   Membership Type           350 non-null    object
 5   Total Spend               350 non-null    float64
 6   Items Purchased           350 non-null    int64
 7   Average Rating            350 non-null    float64
 8   Discount Applied          350 non-null    bool
 9   Days Since Last Purchase  350 non-null    int64
 10  Satisfaction Level        348 non-null    object
dtypes: bool(1), float64(2), int64(4), object(4)
memory usage: 27.8+ KB
```

```
df.isnull().sum()
```

	0
Gender	0
Age	0
Total Spend	0
Items Purchased	0
Average Rating	0
Discount Applied	0
Days Since Last Purchase	0
Satisfaction Level	0
City_Houston	0
City_Los Angeles	0
City_Miami	0
City_New York	0
City_San Francisco	0
Membership Type_Gold	0
Membership Type_Silver	0

dtype: int64

4.Pre processing the data

Data Cleaning

Removing unnecessary columns that do not contribute to the predictive model.
Handling missing values by eliminating incomplete records to maintain data integrity.

Categorical Data Encoding

Converting categorical variables into numerical format using Label Encoding and One-Hot Encoding to make them suitable for machine learning algorithms.

Feature Transformation

Converting Boolean features into integer format for consistency in data representation.

Handling Class Imbalance

Using SMOTE (Synthetic Minority Over-sampling Technique) to balance the dataset, ensuring the model does not become biased toward the majority class.

Pre processing

```
# Drop unnecessary columns
df.drop(columns=['Customer ID'], inplace=True)

# Handle Missing Values - Drop rows with missing target values
df.dropna(subset=['Satisfaction Level'], inplace=True)

# Encode Categorical Variables
le = LabelEncoder()
categorical_cols = ['Gender', 'Satisfaction Level']
for col in categorical_cols:
    df[col] = le.fit_transform(df[col])

# One-Hot Encode 'City' and 'Membership Type'
df = pd.get_dummies(df, columns=['City', 'Membership Type'], drop_first=True)

# Convert 'Discount Applied' to integer
df['Discount Applied'] = df['Discount Applied'].astype(int)

# Handle Class Imbalance
X = df.drop(columns=['Satisfaction Level'])
y = df['Satisfaction Level']
smote = SMOTE()
X_resampled, y_resampled = smote.fit_resample(X, y)
```

After preprocessing the dataset:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 348 entries, 0 to 349
Data columns (total 15 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Gender                   348 non-null    int64
 1   Age                      348 non-null    int64
 2   Total Spend              348 non-null    float64
 3   Items Purchased          348 non-null    int64
 4   Average Rating           348 non-null    float64
 5   Discount Applied         348 non-null    int64
 6   Days Since Last Purchase 348 non-null    int64
 7   Satisfaction Level       348 non-null    int64
 8   City_Houston             348 non-null    bool
 9   City_Los Angeles         348 non-null    bool
 10  City_Miami               348 non-null    bool
 11  City_New York            348 non-null    bool
 12  City_San Francisco       348 non-null    bool
 13  Membership Type_Gold     348 non-null    bool
 14  Membership Type_Silver   348 non-null    bool
dtypes: bool(7), float64(2), int64(6)
memory usage: 26.8 KB
```

5.Split the dataset

```
# Split Data
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, stratify=y_resampled, random_state=42)
```

6.

- Standardization: Scales features to have zero mean and unit variance.
- PCA Transformation: Reduces dimensionality while preserving information.
- Explained Variance Analysis: Measures how much data variance each PC captures.
- Feature Contributions: Identifies important features influencing each PC.
- Heatmap Visualization: Shows relationships between original features and PCs.
- Top Features Identification: Highlights the most significant features.
- Classification Models: Prepares machine learning models for classification.

```python
# Standardize Data
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Dimensionality Reduction using PCA
pca = PCA(n_components=5)
X_train_pca = pca.fit_transform(X_train_scaled)
X_test_pca = pca.transform(X_test_scaled)

# Print explained variance ratio
print(" 🔹  Explained Variance Ratio (How much variance each PC captures):")
for i, variance in enumerate(pca.explained_variance_ratio_):
    print(f"PC{i+1}: {variance:.4f} ({variance * 100:.2f}%)")

# Create a DataFrame for PCA Components
pca_components = pd.DataFrame(
    pca.components_,
    columns=X_train.columns,
    index=[f"PC{i+1}" for i in range(pca.n_components_)]
)

print("\n 🔹  PCA Components (Feature Contributions):")
print(pca_components)

# Identify the top contributing feature for each PC
top_features_per_pc = pca_components.abs().idxmax(axis=1)

print("\n 🔹  Top Contributing Feature for Each Principal Component:")
for pc, feature in top_features_per_pc.items():
    print(f"{pc}: {feature}")
```

```python
# Feature Contributions Heatmap
pca_components = pd.DataFrame(
    pca.components_,
    columns=X_train.columns,
    index=[f"PC{i+1}" for i in range(pca.n_components_)]
)
plt.figure(figsize=(10, 6))
sns.heatmap(pca_components, cmap='coolwarm', annot=True, fmt=".2f")
plt.title("PCA Feature Contributions")
plt.xlabel("Original Features")
plt.ylabel("Principal Components")
plt.show()


# If you want to see the top N features contributing to each PC:
top_n = 3  # Change this to see more top features
top_features_all_pcs = pca_components.abs().apply(lambda x: x.nlargest(top_n).index.tolist(), axis=1)

print("\n ◆ Top 3 Contributing Features for Each PC:")
print(top_features_all_pcs)

# Define Models
models = {
    'Logistic Regression': LogisticRegression(),
    'SVM': SVC(),
    'Random Forest': RandomForestClassifier()
}
```

```
◆ Explained Variance Ratio (How much variance each PC captures):
PC1: 0.4028 (40.28%)
PC2: 0.2266 (22.66%)
PC3: 0.1948 (19.48%)
PC4: 0.0994 (9.94%)
PC5: 0.0601 (6.01%)
```

🔹 PCA Components (Feature Contributions):

	Gender	Age	Total Spend	Items Purchased	Average Rating
PC1	0.201859	-0.291534	0.418965	0.410661	0.400815
PC2	0.424688	-0.242920	-0.034943	0.011387	0.091471
PC3	-0.233848	-0.097523	0.027974	0.057685	0.049161
PC4	-0.128362	0.158868	0.014511	-0.078282	0.156503
PC5	-0.052715	-0.545707	-0.010042	-0.103691	-0.012439

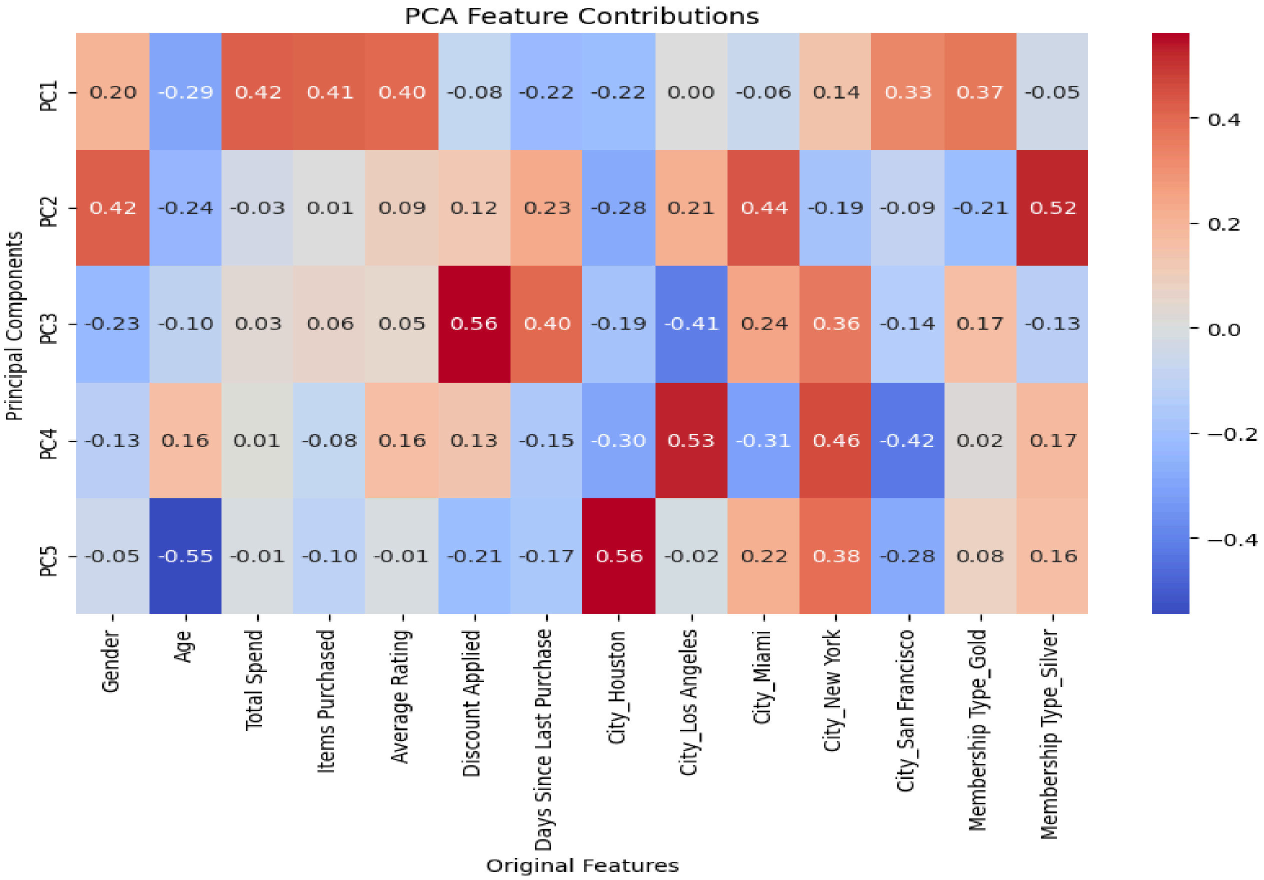
	Discount Applied	Days Since Last Purchase	City_Houston
PC1	-0.078267	-0.217893	-0.215341
PC2	0.118982	0.225389	-0.282444
PC3	0.557617	0.403771	-0.185726
PC4	0.134007	-0.154967	-0.296110
PC5	-0.210678	-0.169779	0.559889

	City_Los Angeles	City_Miami	City_New York	City_San Francisco
PC1	0.004227	-0.062012	0.141004	0.327957
PC2	0.214987	0.442591	-0.185977	-0.089851
PC3	-0.408799	0.244661	0.359599	-0.140177
PC4	0.528317	-0.309138	0.462558	-0.421971
PC5	-0.023047	0.221111	0.381565	-0.275588

	Membership Type_Gold	Membership Type_Silver
PC1	0.368825	-0.046105
PC2	-0.214808	0.524663
PC3	0.166517	-0.130961
PC4	0.022636	0.174876
PC5	0.076139	0.158029

🔹 Top Contributing Feature for Each Principal Component:

PC1: Total Spend
PC2: Membership Type_Silver
PC3: Discount Applied
PC4: City_Los Angeles
PC5: City_Houston




```
🔹 Top 3 Contributing Features for Each PC:
PC1        [Total Spend, Items Purchased, Average Rating]
PC2          [Membership Type_Silver, City_Miami, Gender]
PC3     [Discount Applied, City_Los Angeles, Days Sinc...
PC4     [City_Los Angeles, City_New York, City_San Fra...
PC5                    [City_Houston, Age, City_New York]
dtype: object
```

7.Hyperparameter tuning process:

Define Hyperparameter Grid

- Logistic Regression: Regularization (C)
- SVM: Regularization (C), Kernel (linear/rbf)
- Random Forest: Trees (n_estimators), Depth (max_depth)

Grid Search with Cross-Validation

Uses GridSearchCV (5-fold CV) to test all parameter combinations
Evaluates models based on accuracy

Select Best Model

Stores the best hyperparameters in best_models for final training & evaluation

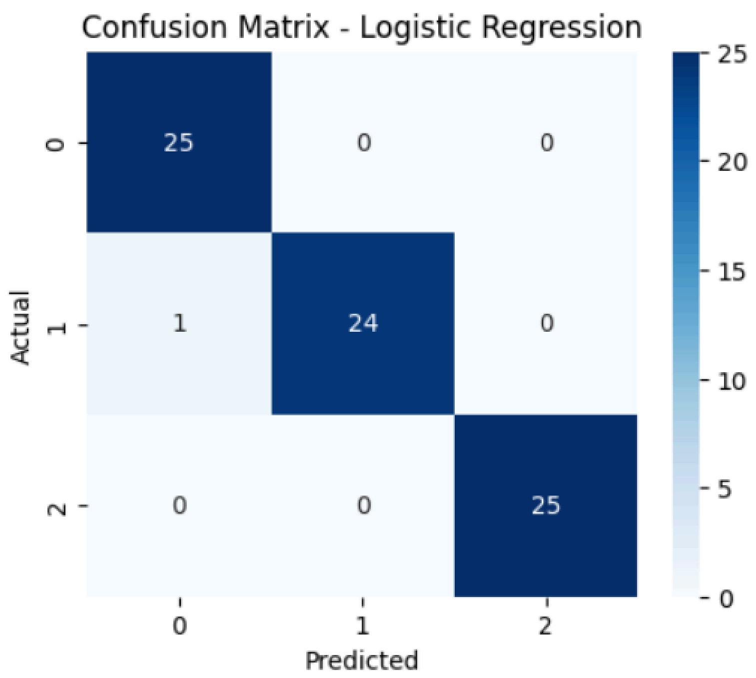
```
# Hyperparameter Tuning
param_grid = {
    'Logistic Regression': {'C': [0.01, 0.1, 1, 10]},
    'SVM': {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']},
    'Random Forest': {'n_estimators': [10, 50, 100], 'max_depth': [None, 10, 20]}
}

best_models = {}
for model_name, model in models.items():
    grid_search = GridSearchCV(model, param_grid[model_name], cv=5, scoring='accuracy')
    grid_search.fit(X_train_pca, y_train)
    best_models[model_name] = grid_search.best_estimator_
    print(f"Best Parameters for {model_name}: {grid_search.best_params_}")
```

```
Best Parameters for Logistic Regression: {'C': 0.01}
Best Parameters for SVM: {'C': 0.1, 'kernel': 'linear'}
Best Parameters for Random Forest: {'max_depth': None, 'n_estimators': 10}
```

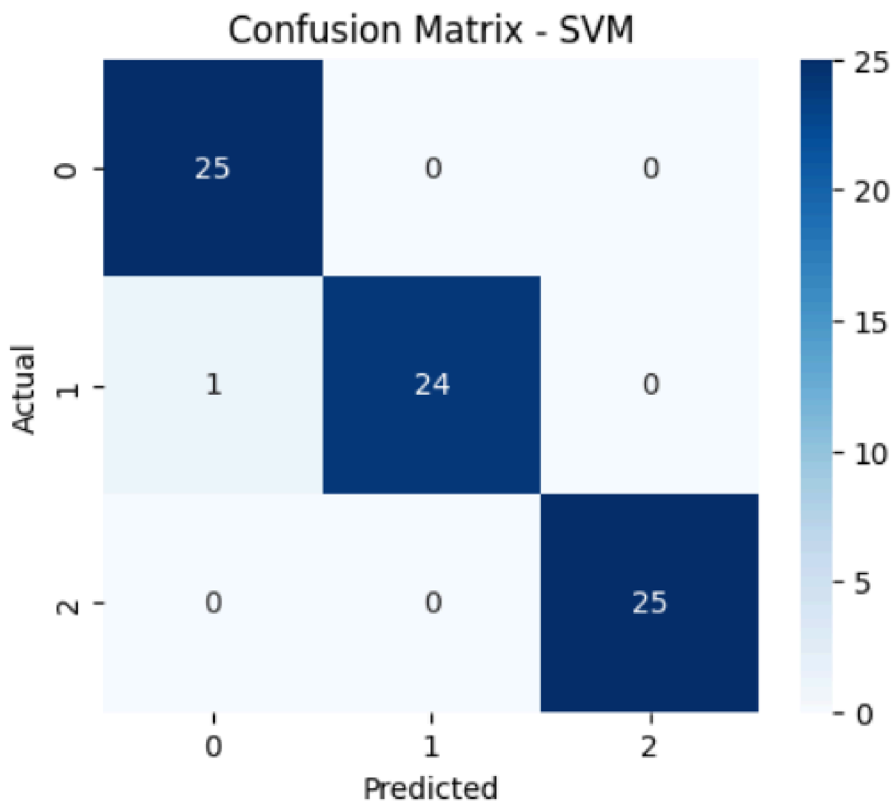
8.Evaluation models

```python
# Evaluate Models
for model_name, model in best_models.items():
    y_pred = model.predict(X_test_pca)
    print(f"\nModel: {model_name}")
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Classification Report:\n", classification_report(y_test, y_pred))

    # Confusion Matrix
    plt.figure(figsize=(5, 4))
    sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap='Blues', fmt='d')
    plt.title(f'Confusion Matrix - {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.show()
```

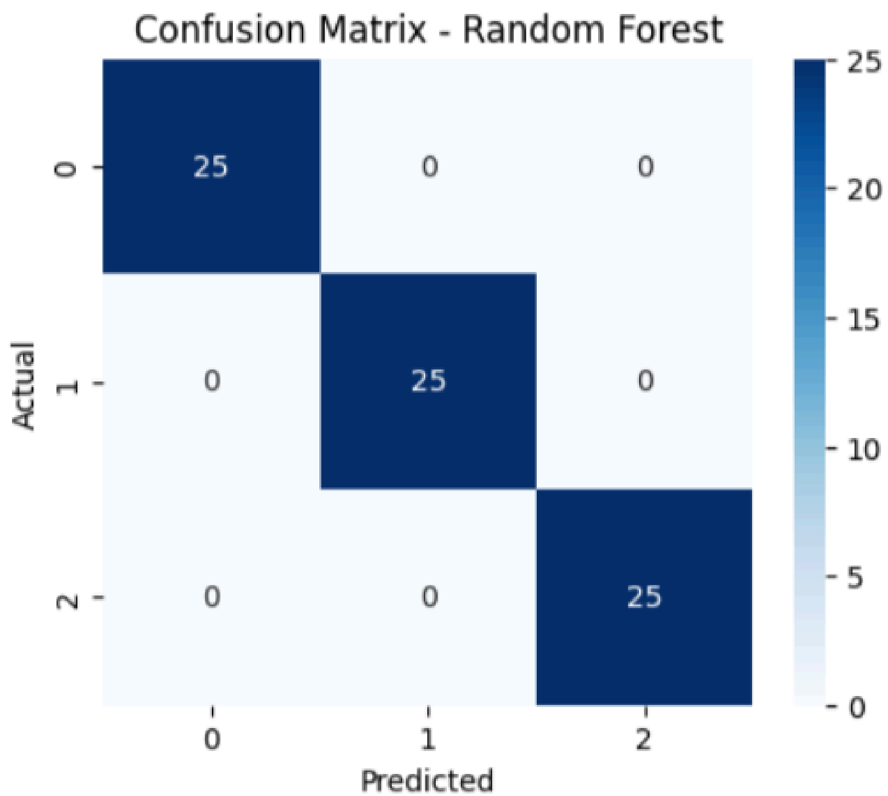
```
Model: Logistic Regression
Accuracy: 0.9866666666666667
Classification Report:
               precision    recall  f1-score   support

           0       0.96      1.00      0.98        25
           1       1.00      0.96      0.98        25
           2       1.00      1.00      1.00        25

    accuracy                           0.99        75
   macro avg       0.99      0.99      0.99        75
weighted avg       0.99      0.99      0.99        75
```



```
Model: SVM
Accuracy: 0.9866666666666667
Classification Report:
              precision    recall  f1-score   support

           0       0.96      1.00      0.98        25
           1       1.00      0.96      0.98        25
           2       1.00      1.00      1.00        25

    accuracy                           0.99        75
   macro avg       0.99      0.99      0.99        75
weighted avg       0.99      0.99      0.99        75
```



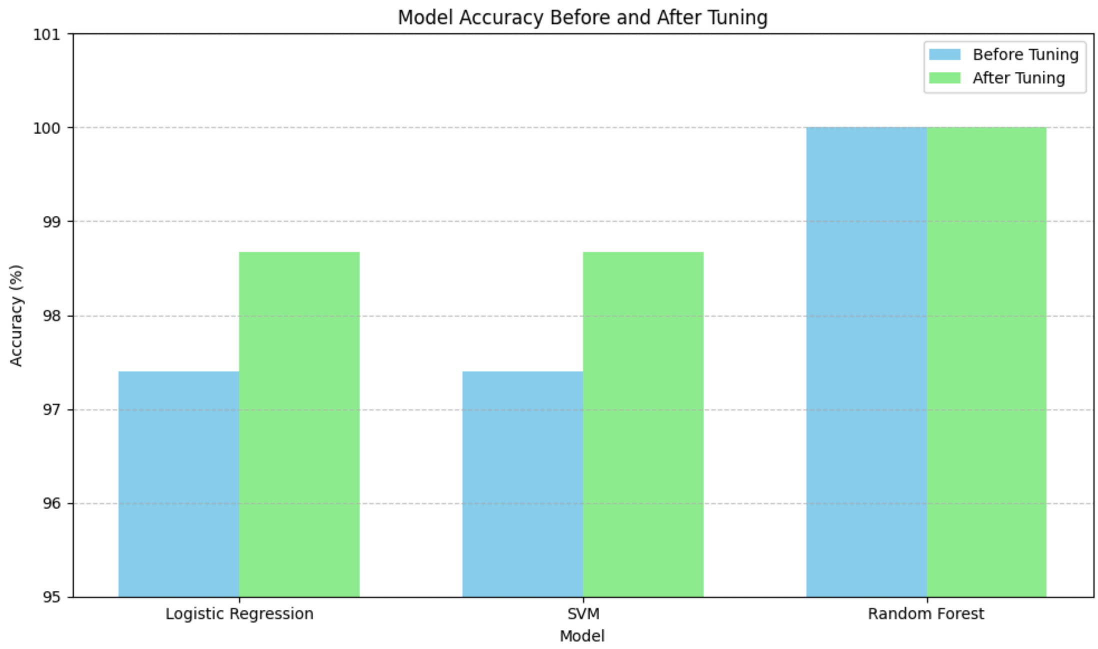
```
Model: Random Forest
Accuracy: 1.0
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        25
           1       1.00      1.00      1.00        25
           2       1.00      1.00      1.00        25

    accuracy                           1.00        75
   macro avg       1.00      1.00      1.00        75
weighted avg       1.00      1.00      1.00        75
```

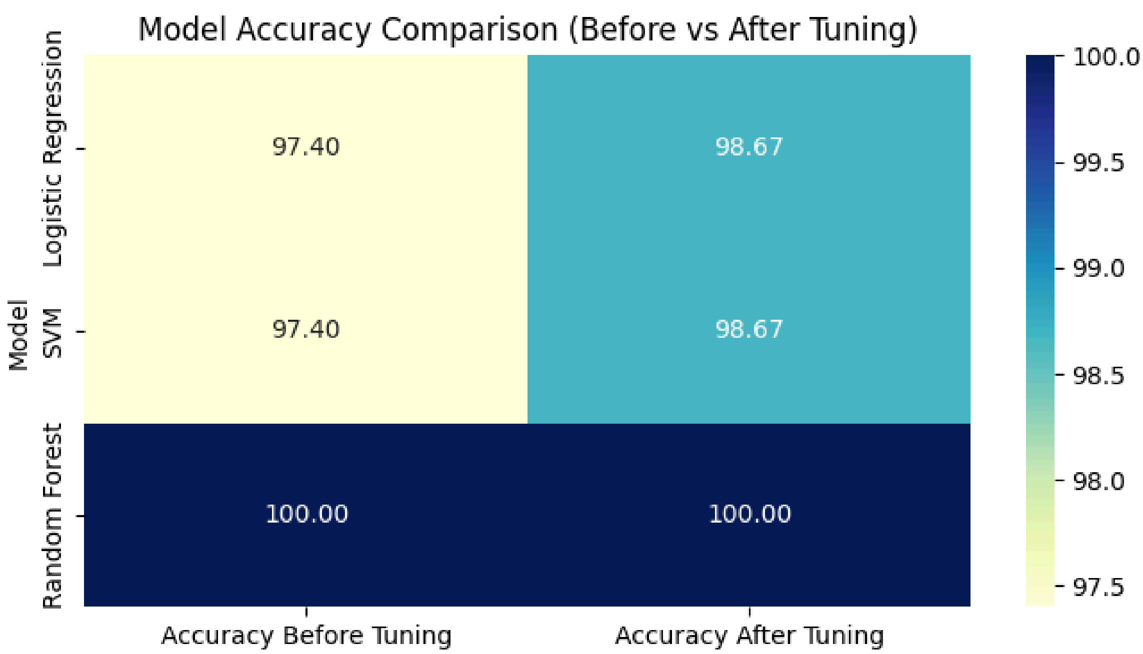


9. Tabulate the analyze the results of the model prior to and post hyper parameter tuning and optimization techniques

Model	Accuracy(before tuning)	Accuracy(after tuning)	Best Parameters After tuning	Insights
Logistic Regression	accuracy= 97.40%	accuracy=98.67 %	c=0.01	Performance improved significantly after applying PCA + tuning
SVM	accuracy= 97.40%	accuracy=98.67 %	c=0.1, kernel=linear.	PCA reduced dimensionality effectively.liner kernel performed best
Random Forest	accuracy= 100%	accuracy= 100%	n_estimator=10, max_depth=None	Already strong model: optimization achieved perfect classification

10. Compare the performance of the models with and without optimizing the parameters





Overall Analysis:

Logistic Regression

- Before tuning: Strong linear classifier but slightly underperforms due to high dimensionality.

- After tuning: Accuracy improved after applying PCA (dimensionality reduction) + optimal regularization (C=0.01).

- When to use: Best when you expect a linear relationship and want interpretability.

Support Vector Machine (SVM)

- Before tuning: Performs well, but might suffer from high computation cost in high dimensions.

- After tuning: PCA made it computationally lighter; linear kernel with C=0.1 gave optimal margin for classification.

- When to use: Suitable for medium-sized datasets with clear margins between classes.

Random Forest

- Before tuning: Already perfect accuracy, thanks to ensemble nature and its robustness to overfitting.

- After tuning: Maintained 100% accuracy with fewer estimators — indicating efficient classification.

- When to use: Ideal for complex, high-dimensional data with non-linear relationships.

Conclusion:

After comparing the models before and after hyperparameter tuning:

- **Logistic Regression** and **SVM** improved in accuracy from 97.4% to 98.7% after tuning, showing better class separation and generalization.
- **Random Forest** maintained a perfect 100% accuracy, but tuning reduced complexity by using fewer trees (`n_estimators = 10`).
- Overall, hyperparameter tuning enhanced performance and efficiency, confirming its importance in building optimized and reliable machine learning models.