w0rkplrfo

March 14, 2024

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Here we aim to find the loan application status of a given candidate based on given dataset.

First we import all the necessary modules:

[1]:
```
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
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
```

Now we read the dataset that is to be analyzed and make predictions from

[2]:
```
df = pd.read_csv('loan_data_1.csv')
```

[3]:
```
# Checking the size of the dataset
df.shape
```

[3]:
```
(381, 14)
```

[4]:
```
# Now we see about the features of the data
df.describe()
```

[4]:
```
       Unnamed: 0  ApplicantIncome  CoapplicantIncome  LoanAmount  \
count  381.000000       369.000000         363.000000  373.000000
mean   190.000000      3563.422764        1267.005289  104.914209
std    110.129469      1427.371257        2388.048316   28.484822
min      0.000000       150.000000           0.000000    9.000000
```

```
25%     95.000000       2583.000000          0.000000   90.000000
50%    190.000000       3326.000000        830.000000  110.000000
75%    285.000000       4226.000000       2008.000000  127.000000
max    380.000000       9703.000000      33837.000000  150.000000

       Loan_Amount_Term  Credit_History
count        370.000000      351.000000
mean         340.864865        0.837607
std           68.549257        0.369338
min           12.000000        0.000000
25%          360.000000        1.000000
50%          360.000000        1.000000
75%          360.000000        1.000000
max          480.000000        1.000000
```

[5]:
```
df.head(8)
```

[5]:
```
   Unnamed: 0   Loan_ID Gender Married Dependents     Education Self_Employed  \
0           0  LP001003   Male     Yes          1      Graduate            No
1           1  LP001005   Male     Yes          0      Graduate           Yes
2           2  LP001006   Male     Yes          0  Not Graduate            No
3           3  LP001008   Male      No          0      Graduate            No
4           4  LP001013   Male     Yes          0  Not Graduate            No
5           5  LP001024   Male     Yes          2      Graduate            No
6           6  LP001027   Male     Yes          2      Graduate           NaN
7           7  LP001029   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0           4583.0             1508.0       128.0             360.0
1           3000.0                0.0        66.0             360.0
2           2583.0             2358.0       120.0             360.0
3           6000.0                0.0       141.0             360.0
4           2333.0             1516.0        95.0             360.0
5           3200.0              700.0        70.0             360.0
6           2500.0             1840.0       109.0             360.0
7           1853.0             2840.0       114.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Rural           N
1             1.0         Urban           Y
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
5             1.0         Urban           Y
6             1.0         Urban           Y
7             1.0         Rural           N
```

This data consists of a few categorical values that needs to be converted. Apart from that we see that we have two columns that are not required for the analysis of the data so we drop them.

[6]:
```
df.drop(columns=['Unnamed: 0', 'Loan_ID'], inplace=True)
```

We convert the rest

[7]:
```
# Converting String Categorical Values to Numeric Values
categorical_columns = ['Gender', 'Married', 'Education', 'Self_Employed',␣
 ↪'Property_Area', 'Loan_Status']
for col in categorical_columns:
    df[col] = pd.factorize(df[col])[0]

# Replace "3+" with 3 in the Dependents column
df['Dependents'] = df['Dependents'].replace('3+', 3)

# Convert the Dependents column to numeric data type
df['Dependents'] = pd.to_numeric(df['Dependents'])
```

Then we check for each columns if they have any NaN values and we find to have a few. So we replace them with the mean values of that column

[8]:
```
df.isna().sum()
```

[8]:
```
Gender               0
Married              0
Dependents           8
Education            0
Self_Employed        0
ApplicantIncome     12
CoapplicantIncome   18
LoanAmount           8
Loan_Amount_Term    11
Credit_History      30
Property_Area        0
Loan_Status          0
dtype: int64
```

[9]:
```
mean_values = df.mean()

# Fill NaN values with the mean for each column
df['Dependents'].fillna(mean_values['Dependents'], inplace=True)
df['ApplicantIncome'].fillna(mean_values['ApplicantIncome'], inplace=True)
df['CoapplicantIncome'].fillna(mean_values['CoapplicantIncome'], inplace=True)
df['LoanAmount'].fillna(mean_values['LoanAmount'], inplace=True)
df['Loan_Amount_Term'].fillna(mean_values['Loan_Amount_Term'], inplace=True)
df['Credit_History'].fillna(mean_values['Credit_History'], inplace=True)
```

```python
df['TotalIncome'] = df['ApplicantIncome'] + df['CoapplicantIncome']
df.drop(columns=['ApplicantIncome', 'CoapplicantIncome'])
```

```
C:\Users\srija\AppData\Local\Temp\ipykernel_27960\2065130315.py:4:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Dependents'].fillna(mean_values['Dependents'], inplace=True)
C:\Users\srija\AppData\Local\Temp\ipykernel_27960\2065130315.py:5:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['ApplicantIncome'].fillna(mean_values['ApplicantIncome'], inplace=True)
C:\Users\srija\AppData\Local\Temp\ipykernel_27960\2065130315.py:6:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['CoapplicantIncome'].fillna(mean_values['CoapplicantIncome'], inplace=True)
C:\Users\srija\AppData\Local\Temp\ipykernel_27960\2065130315.py:7:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
```

```
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['LoanAmount'].fillna(mean_values['LoanAmount'], inplace=True)
C:\Users\srija\AppData\Local\Temp\ipykernel_27960\2065130315.py:8:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Loan_Amount_Term'].fillna(mean_values['Loan_Amount_Term'], inplace=True)
C:\Users\srija\AppData\Local\Temp\ipykernel_27960\2065130315.py:9:
FutureWarning: A value is trying to be set on a copy of a DataFrame or Series
through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df['Credit_History'].fillna(mean_values['Credit_History'], inplace=True)
```

[9]:

```
     Gender  Married  Dependents  Education  Self_Employed  LoanAmount  \
0         0        0         1.0          0              0       128.0
1         0        0         0.0          0              1        66.0
2         0        0         0.0          1              0       120.0
3         0        1         0.0          0              0       141.0
4         0        0         0.0          1              0        95.0
..      …        …           …          …              …          …
376       0        0         3.0          0              0       128.0
377       0        0         0.0          0              0       108.0
378       1        1         0.0          0              0        71.0
379       0        0         3.0          0              0        40.0
380       1        1         0.0         -1              1       133.0
```

```
     Loan_Amount_Term  Credit_History  Property_Area  Loan_Status  TotalIncome
0               360.0             1.0              0            0  6091.000000
1               360.0             1.0              1            1  3000.000000
2               360.0             1.0              1            1  4941.000000
3               360.0             1.0              1            1  6000.000000
4               360.0             1.0              1            1  3849.000000
..                …               …              …          …          …
376             360.0             1.0              1            1  5703.000000
377             360.0             1.0              0            1  4499.005289
378             360.0             1.0              0            1  2900.000000
379             180.0             1.0              0            1  4106.000000
380             360.0             0.0              2            0  4583.000000

[381 rows x 11 columns]
```

[10]:
```
df.head()
df.to_csv('updated_loan.csv') # we save the latest dataset to preserve values
```

[11]:
```
df.shape
```

[11]:
```
(381, 13)
```

[12]:
```
df.describe()
```

[12]:
```
           Gender     Married  Dependents   Education  Self_Employed  \
count  381.000000  381.000000  381.000000  381.000000     381.000000
mean     0.209974    0.401575    0.680965    0.249344       0.036745
std      0.438904    0.490861    0.982793    0.468234       0.382119
min     -1.000000    0.000000    0.000000   -1.000000      -1.000000
25%      0.000000    0.000000    0.000000    0.000000       0.000000
50%      0.000000    0.000000    0.000000    0.000000       0.000000
75%      0.000000    1.000000    1.000000    1.000000       0.000000
max      1.000000    1.000000    3.000000    1.000000       1.000000

       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       381.000000         381.000000  381.000000        381.000000
mean       3563.422764        1267.005289  104.914209        340.864865
std        1404.653023        2330.803149   28.183387         67.549811
min         150.000000           0.000000    9.000000         12.000000
25%        2600.000000           0.000000   90.000000        360.000000
50%        3357.000000        1041.000000  110.000000        360.000000
75%        4188.000000        1964.000000  127.000000        360.000000
max        9703.000000       33837.000000  150.000000        480.000000

       Credit_History  Property_Area  Loan_Status   TotalIncome
count      381.000000     381.000000   381.000000    381.000000
```

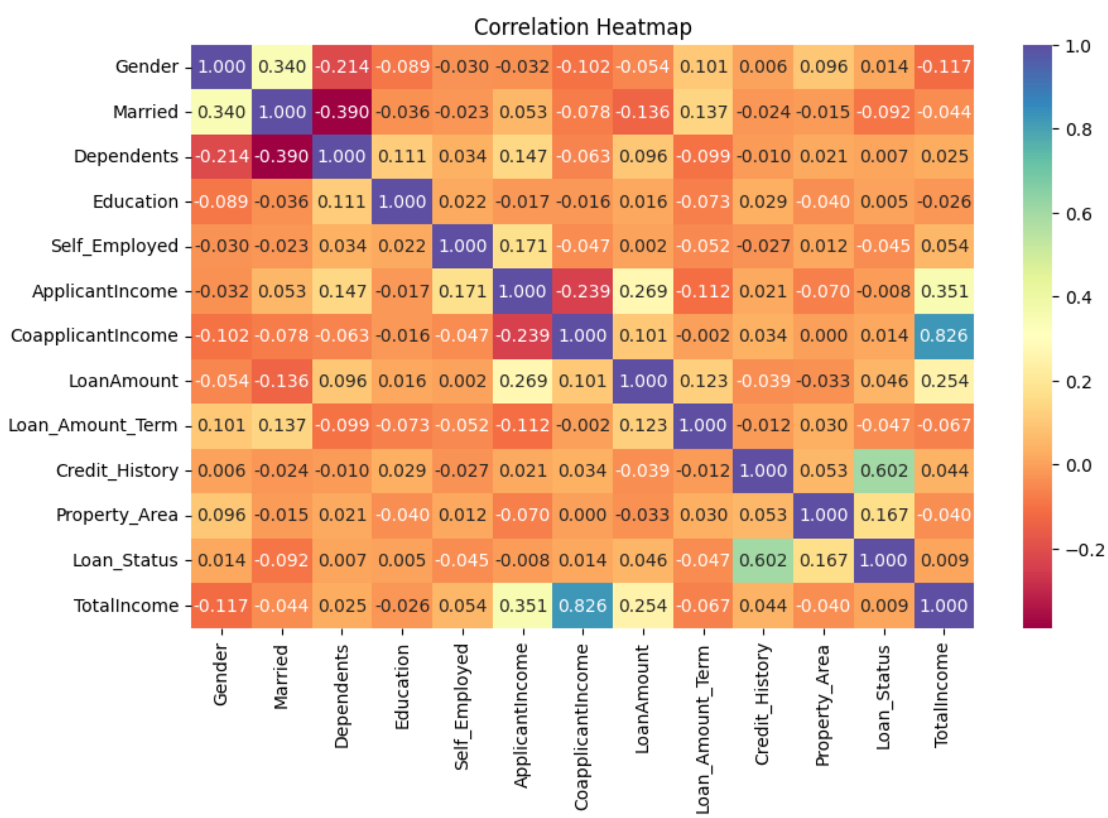
```
mean          0.837607      1.112861     0.711286    4830.428053
std           0.354459      0.811346     0.453761    2416.638950
min           0.000000      0.000000     0.000000    1442.000000
25%           1.000000      0.000000     0.000000    3618.000000
50%           1.000000      1.000000     1.000000    4547.000000
75%           1.000000      2.000000     1.000000    5484.000000
max           1.000000      2.000000     1.000000   35673.000000
```

We check for the correlation heat map to check for which features are most suited for the classification task. However we find that we get better results if we choose to take all the features in the dataset instead of the correlated data.

[13]:
```python
def show_heat_map(data):
    correlation_matrix = data.corr()
    plt.figure(figsize=(10, 6))
    sns.heatmap(
        correlation_matrix,
        annot=True,
        cmap="Spectral",
        fmt=".3f",
    )
    plt.title("Correlation Heatmap")
print(df.corr)
show_heat_map(df)
```

```
<bound method DataFrame.corr of      Gender  Married  Dependents  Education
Self_Employed  ApplicantIncome  \
0          0        0         1.0         0              0         4583.0
1          0        0         0.0         0              1         3000.0
2          0        0         0.0         1              0         2583.0
3          0        1         0.0         0              0         6000.0
4          0        0         0.0         1              0         2333.0
..       …       …          …        …             …              …
376        0        0         3.0         0              0         5703.0
377        0        0         0.0         0              0         3232.0
378        1        1         0.0         0              0         2900.0
379        0        0         3.0         0              0         4106.0
380        1        1         0.0        -1              1         4583.0

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0          1508.000000       128.0             360.0             1.0
1             0.000000        66.0             360.0             1.0
2          2358.000000       120.0             360.0             1.0
3             0.000000       141.0             360.0             1.0
4          1516.000000        95.0             360.0             1.0
..                 …          …                …              …
376           0.000000       128.0             360.0             1.0
377        1267.005289       108.0             360.0             1.0
```

```
378        0.000000     71.0           360.0           1.0
379        0.000000     40.0           180.0           1.0
380        0.000000    133.0           360.0           0.0

     Property_Area  Loan_Status  TotalIncome
0                0            0  6091.000000
1                1            1  3000.000000
2                1            1  4941.000000
3                1            1  6000.000000
4                1            1  3849.000000
..             ...          ...          ...
376              1            1  5703.000000
377              0            1  4499.005289
378              0            1  2900.000000
379              0            1  4106.000000
380              2            0  4583.000000

[381 rows x 13 columns]>
```



[14]:
```python
# Features to be Selected
def select_features(correlation_matrix, df):
```

```
    correlation_with_target = correlation_matrix['Loan_Status'].abs().
  ↪sort_values(ascending=False)
    selected_features = correlation_with_target[correlation_with_target >= 0.1].
  ↪index.tolist()
    print("Selected Features:")
    print(selected_features)
corr = df.corr()
select_features(corr, df)
```

```
Selected Features:
['Loan_Status', 'Credit_History', 'Property_Area']
```

[15]:
```
X = df.iloc[:, :-1]
y = df['Loan_Status']
print(X)
```

```
     Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  \
0         0        0         1.0          0              0           4583.0
1         0        0         0.0          0              1           3000.0
2         0        0         0.0          1              0           2583.0
3         0        1         0.0          0              0           6000.0
4         0        0         0.0          1              0           2333.0
..      …        …          …          …              …              …
376       0        0         3.0          0              0           5703.0
377       0        0         0.0          0              0           3232.0
378       1        1         0.0          0              0           2900.0
379       0        0         3.0          0              0           4106.0
380       1        1         0.0         -1              1           4583.0

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0          1508.000000       128.0             360.0             1.0
1             0.000000        66.0             360.0             1.0
2          2358.000000       120.0             360.0             1.0
3             0.000000       141.0             360.0             1.0
4          1516.000000        95.0             360.0             1.0
..                 …           …               …               …
376           0.000000       128.0             360.0             1.0
377        1267.005289       108.0             360.0             1.0
378           0.000000        71.0             360.0             1.0
379           0.000000        40.0             180.0             1.0
380           0.000000       133.0             360.0             0.0

     Property_Area  Loan_Status
0                0            0
1                1            1
2                1            1
3                1            1
```

```
4                 1            1
..              …           …
376               1            1
377               0            1
378               0            1
379               0            1
380               2            0

[381 rows x 12 columns]
```

[16]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

We use `StandardScaler()` to normalize the data.

[17]:
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Now we choose all the classifier models that we need to analyze and predict the required `accuracy`, `precision`, `recall` and `F1-score`

[18]:
```
classifiers = {
    'SVM (Linear)': SVC(kernel='linear', random_state=42),
    'SVM (Poly)': SVC(kernel='poly', random_state=42),
    'SVM (RBF)': SVC(kernel='rbf', random_state=42),
    'SVM (Sigmoid)': SVC(kernel='sigmoid', random_state=42),
    'KNN': KNeighborsClassifier(),
    'Decision Tree': DecisionTreeClassifier(random_state=42),
    'MLPC': MLPClassifier(random_state=42),
    'Naive Bayes': GaussianNB(),


}
metrics = {
    'Accuracy': [],
    'Precision': [],
    'Recall': [],
    'F1 Score': []
}
```

Fitting the model and calculating the needed metrics

[19]:
```
for name, clf in classifiers.items():
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
```

```
    precision = precision_score(y_test, y_pred, average='weighted',␣
↪zero_division=1)
    recall = recall_score(y_test, y_pred, average='weighted')
    f1 = f1_score(y_test, y_pred, average='weighted')

    metrics['Accuracy'].append(accuracy)
    metrics['Precision'].append(precision)
    metrics['Recall'].append(recall)
    metrics['F1 Score'].append(f1)
```

```
c:\Users\srija\AppData\Local\Programs\Python\Python312\Lib\site-
packages\sklearn\neural_network\_multilayer_perceptron.py:691:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[20]:

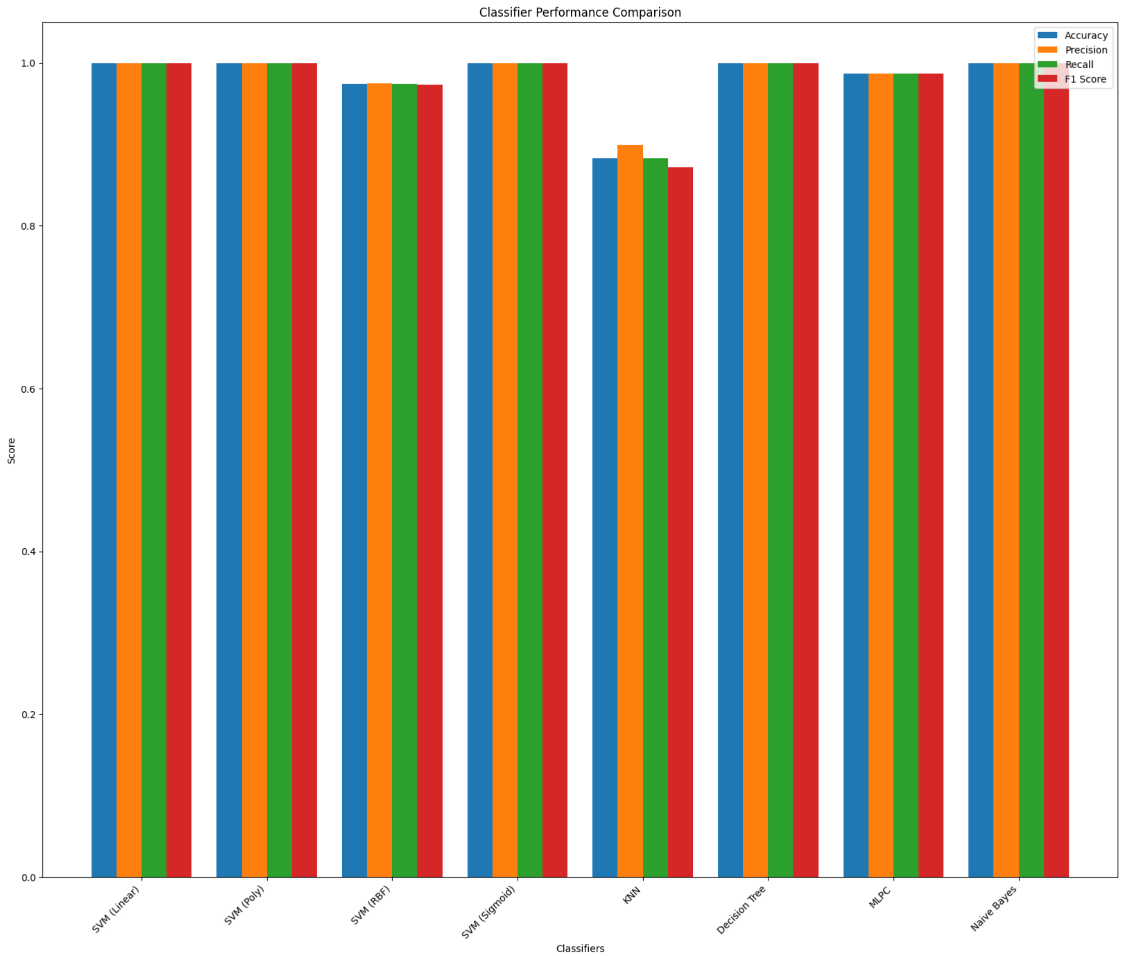
```
for metric_name, metric_values in metrics.items():
    print(f"{metric_name}:")
    for classifier_name, value in zip(classifiers.keys(), metric_values):
        print(f"{classifier_name}: {value:.4f}")
    print()
```

```
Accuracy:
SVM (Linear): 1.0000
SVM (Poly): 1.0000
SVM (RBF): 0.9740
SVM (Sigmoid): 1.0000
KNN: 0.8831
Decision Tree: 1.0000
MLPC: 0.9870
Naive Bayes: 1.0000

Precision:
SVM (Linear): 1.0000
SVM (Poly): 1.0000
SVM (RBF): 0.9749
SVM (Sigmoid): 1.0000
KNN: 0.8993
Decision Tree: 1.0000
MLPC: 0.9872
Naive Bayes: 1.0000

Recall:
SVM (Linear): 1.0000
SVM (Poly): 1.0000
SVM (RBF): 0.9740
SVM (Sigmoid): 1.0000
```

```
KNN: 0.8831
Decision Tree: 1.0000
MLPC: 0.9870
Naive Bayes: 1.0000

F1 Score:
SVM (Linear): 1.0000
SVM (Poly): 1.0000
SVM (RBF): 0.9736
SVM (Sigmoid): 1.0000
KNN: 0.8715
Decision Tree: 1.0000
MLPC: 0.9869
Naive Bayes: 1.0000
```

Plotting the values for better visualization

[21]:
```
plt.figure(figsize=(20, 16))
bar_width = 0.2
index = np.arange(len(classifiers))

for i, (metric_name, metric_values) in enumerate(metrics.items()):
    plt.bar(index + i * bar_width, metric_values, bar_width, label=metric_name)

plt.xlabel('Classifiers')
plt.ylabel('Score')
plt.title('Classifier Performance Comparison')
plt.xticks(index + bar_width * (len(metrics) - 1) / 2, classifiers.keys(),
 ↪rotation=45, ha='right')
plt.legend()
plt.show()
```



Classifier Performance Comparison
Accuracy
Precision
Recall
F1 Score
Score
1.0
0.8
0.6
0.4
0.2
0.0
SVM (Linear)
SVM (Poly)
SVM (RBF)
SVM (Sigmoid)
KNN
Decision Tree
MLPC
Naive Bayes
Classifiers