Ex - 3 **Feature Selection Techniques in Machine Learning**

Aim

To implement feature subset selection techniques in machine learning.

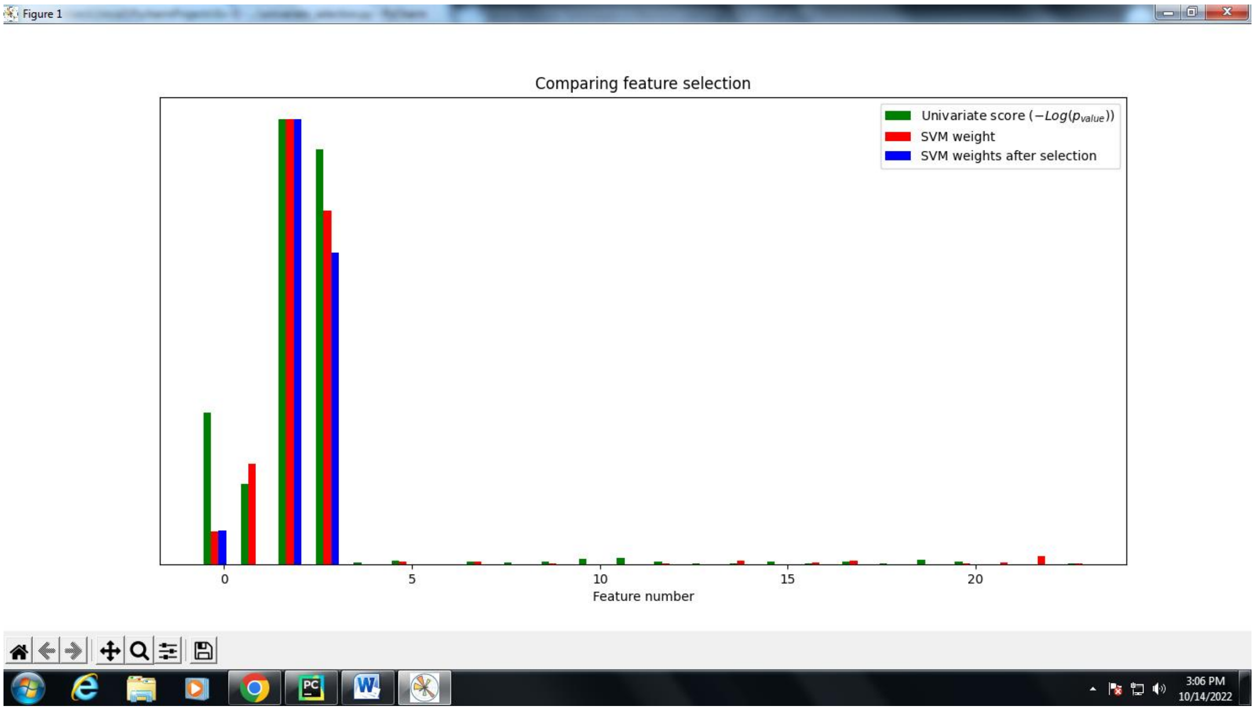
1. Univariate Feature Selection:

univariate_selection.py

```
print(__doc__)
import numpy as np
import matplotlib.pyplot as plt

from sklearn import datasets, svm
from sklearn.feature_selection import SelectPercentile, f_classif
iris = datasets.load_iris()
E = np.random.uniform(0, 0.1, size=(len(iris.data), 20))
X = np.hstack((iris.data, E))
y = iris.target
plt.figure(1)
plt.clf()
X_indices = np.arange(X.shape[-1])
selector = SelectPercentile(f_classif, percentile=10)
selector.fit(X, y)
scores = -np.log10(selector.pvalues_)
scores /= scores.max()
plt.bar(X_indices - .45, scores, width=.2,
label=r'Univariate score ($-Log(p_{value})$)', color='g')
clf = svm.SVC(kernel='linear')
```

```
clf.fit(X, y)


svm_weights = (clf.coef_ ** 2).sum(axis=0)

svm_weights /= svm_weights.max()


plt.bar(X_indices - .25, svm_weights, width=.2, label='SVM weight', color='r')


clf_selected = svm.SVC(kernel='linear')

clf_selected.fit(selector.transform(X), y)


svm_weights_selected = (clf_selected.coef_ ** 2).sum(axis=0)

svm_weights_selected /= svm_weights_selected.max()


plt.bar(X_indices[selector.get_support()] - .05, svm_weights_selected, width=.2, label='SVM weights after selection', color='b')



plt.title("Comparing feature selection")

plt.xlabel('Feature number')

plt.yticks(())

plt.axis('tight')

plt.legend(loc='upper right')

plt.show()
```

Output



2. Feature Importance:

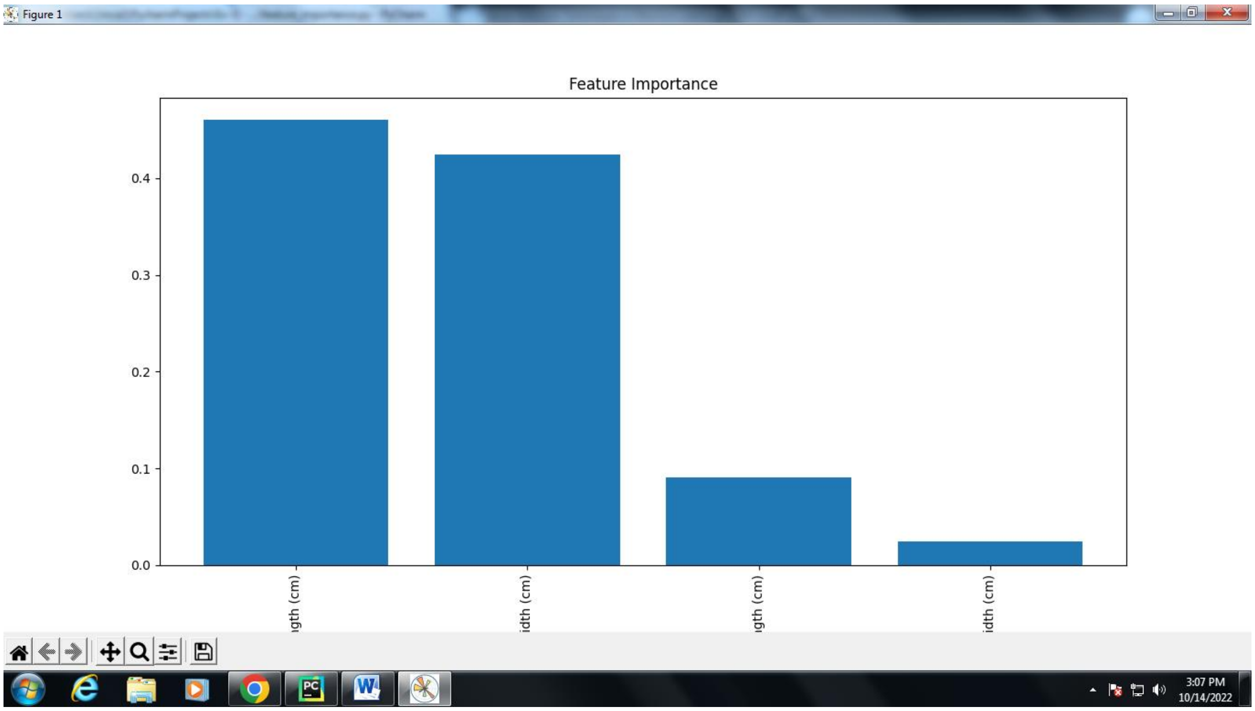
feature_importance.py

```
# Load libraries

from sklearn.ensemble import RandomForestClassifier

from sklearn import datasets

import numpy as np

import matplotlib.pyplot as plt

# Load data

iris = datasets.load_iris()
```

```
X = iris.data
y = iris.target
# Create decision tree classifer object
clf = RandomForestClassifier(random_state=0, n_jobs=-1)

# Train model
model = clf.fit(X, y)
# Calculate feature importances
importances = model.feature_importances_
# Sort feature importances in descending order
indices = np.argsort(importances)[::-1]

# Rearrange feature names so they match the sorted feature importances
names = [iris.feature_names[i] for i in indices]

# Create plot
plt.figure()

# Create plot title
plt.title("Feature Importance")

# Add bars
plt.bar(range(X.shape[1]), importances[indices])

# Add feature names as x-axis labels
```

```
plt.xticks(range(X.shape[1]), names, rotation=90)


# Show plot

plt.show()
```

Output



3. Correlation Matrix with Heatmap:

heatmap.py

```
# Load iris data
from sklearn.datasets import load_iris
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

iris = load_iris()

# Create features and target
X = iris.data
y = iris.target
# Convert feature matrix into DataFrame
df = pd.DataFrame(X)
```

```python
# View the data frame
print(df)
# Create correlation matrix
corr_matrix = df.corr()
print(corr_matrix)
# Create correlation heatmap
plt.figure(figsize=(8,6))
plt.title('Correlation Heatmap of Iris Dataset')
a = sns.heatmap(corr_matrix, square=True, annot=True, fmt='.2f', linecolor='black')
a.set_xticklabels(a.get_xticklabels(), rotation=30)
a.set_yticklabels(a.get_yticklabels(), rotation=30)
plt.show()
 # Select upper triangle of correlation matrix
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))
# Find index of feature columns with correlation greater than 0.9
to_drop = [column for column in upper.columns if any(upper[column] > 0.9)]
print(to_drop)
# Drop Marked Features
df1 = df.drop(df.columns[to_drop], axis=1)
print(df1)
```

Output

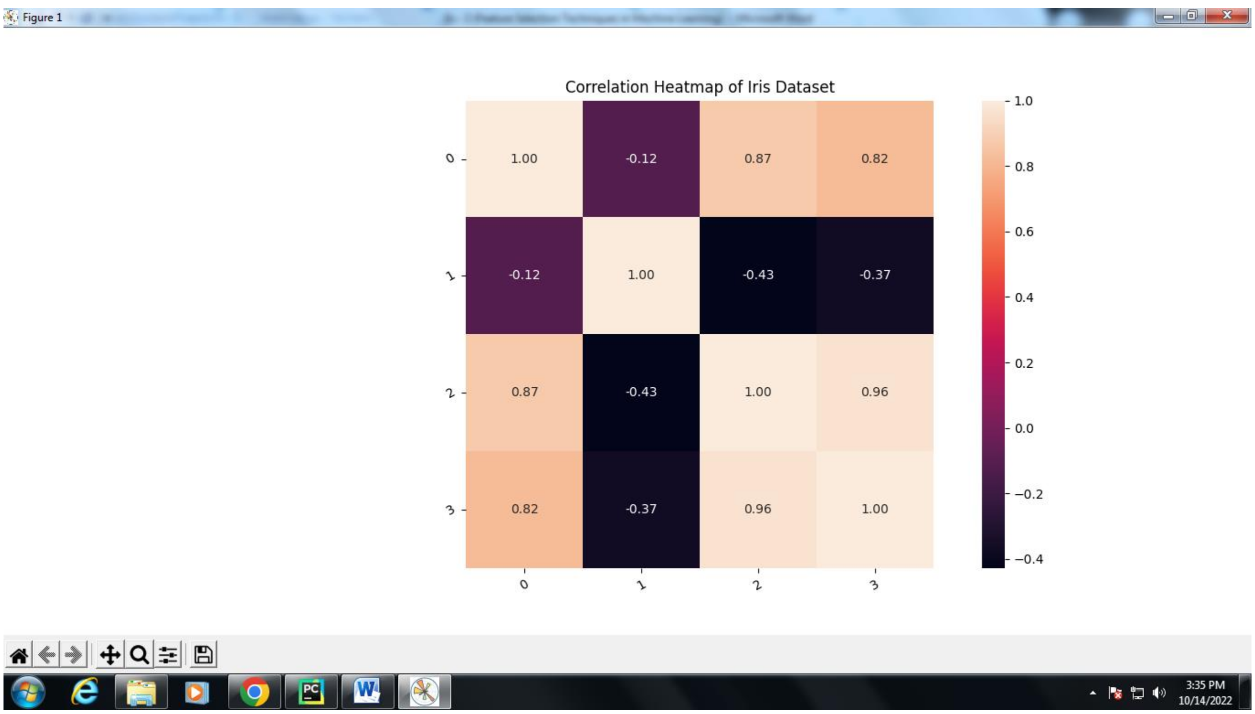
C:\Users\2mca1\PycharmProjects\Ex-3\venv\Scripts\python.exe C:/Users/2mca1/PycharmProjects/Ex-3/heatmap.py

```
      0    1    2    3
0    5.1  3.5  1.4  0.2
1    4.9  3.0  1.4  0.2
2    4.7  3.2  1.3  0.2
3    4.6  3.1  1.5  0.2
4    5.0  3.6  1.4  0.2
..   ...  ...  ...  ...
145  6.7  3.0  5.2  2.3
146  6.3  2.5  5.0  1.9
147  6.5  3.0  5.2  2.0
148  6.2  3.4  5.4  2.3
```

149 5.9 3.0 5.1 1.8

[150 rows x 4 columns]

	0	1	2	3
0	1.000000	-0.117570	0.871754	0.817941
1	-0.117570	1.000000	-0.428440	-0.366126
2	0.871754	-0.428440	1.000000	0.962865
3	0.817941	-0.366126	0.962865	1.000000



Result

Thus, feature subset selection techniques have been implemented successfully.