PREDICTIVE ANALYSIS WITH DECISION TREES

Submitted by:

Name : Priyadharshini R

Register Number : 727723EUCS175

Class : CSE – ‘C’

Year : III

Department : Computer Science and Engineering

1. Introduction

Predictive analytics focuses on analyzing historical data to predict future outcomes. Decision Trees are one of the most intuitive and powerful supervised learning algorithms used for both classification and regression tasks. They work by recursively splitting data based on feature values to maximize prediction accuracy.

2. Objectives

- Implement Decision Tree for classification
- Understand entropy and Gini index
- Apply pruning techniques to avoid overfitting
- Visualize the decision tree
- Evaluate feature importance

3. Dataset Description

The Heart Disease dataset consists of patient medical records used to predict the presence of heart disease. The dataset contains numerical and categorical attributes related to heart health.

4. Decision Tree Theory

4.1 Entropy

Entropy measures impurity or randomness.

$$Entropy(S) = -\sum p_i \log_2(p_i)$$

Where p_i is the probability of class i.

4.2 Information Gain

Used to decide the best feature to split.

$$IG(S,A) = Entropy(S) - \sum \frac{|S_v|}{|S|} Entropy(S_v)$$

4.3 Gini Index

Measures impurity (used by CART algorithm).

$$Gini = 1 - \sum p_i^2$$

Lower Gini → better split.

5. Overfitting in Decision Trees

Decision trees tend to memorize training data leading to overfitting.

Solutions:

- **Pre-Pruning:** Stop tree growth early
- **Post-Pruning:** Remove unnecessary branches

6. Methodology

1. Load dataset
2. Preprocess data

3. Compute entropy and Gini manually
4. Train Decision Tree
5. Apply pruning
6. Evaluate performance
7. Visualize tree
8. Interpret feature importance

7. Tools & Technologies

- Python
- NumPy
- Pandas
- Scikit-learn
- Matplotlib
- Graphviz

8. Results

- Accuracy before pruning
- Accuracy after pruning
- Improved generalization
- Key features identified

9. Conclusion

Decision Trees provide interpretability and strong predictive performance. Pruning techniques significantly reduce overfitting and improve generalization.

10. Future Enhancements

- Use Random Forests
- Apply Gradient Boosting
- Hyperparameter tuning

Source Code:

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt


# 1. IMPORT LIBRARIES

from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier, plot_tree

from sklearn.metrics import accuracy_score, classification_report

from sklearn.preprocessing import LabelEncoder


# 2. LOAD DATASET

df = pd.read_csv("heart.csv")
```

```
print("\nDataset Preview:")
display(df.head())
print("\nDataset Shape:", df.shape)

#  FIX: HANDLE CATEGORICAL DATA

label_encoder = LabelEncoder()

for col in df.columns:
    if df[col].dtype == 'object':
        df[col] = label_encoder.fit_transform(df[col])

print("\nDataset After Encoding:")
display(df.head())

# 3. MATHEMATICAL CALCULATIONS

def entropy(y):
    values, counts = np.unique(y, return_counts=True)
    probabilities = counts / counts.sum()
    return -np.sum(probabilities * np.log2(probabilities))

def gini_index(y):
    values, counts = np.unique(y, return_counts=True)
    probabilities = counts / counts.sum()
    return 1 - np.sum(probabilities ** 2)

print("\nEntropy of Target:", entropy(df['target']))
```

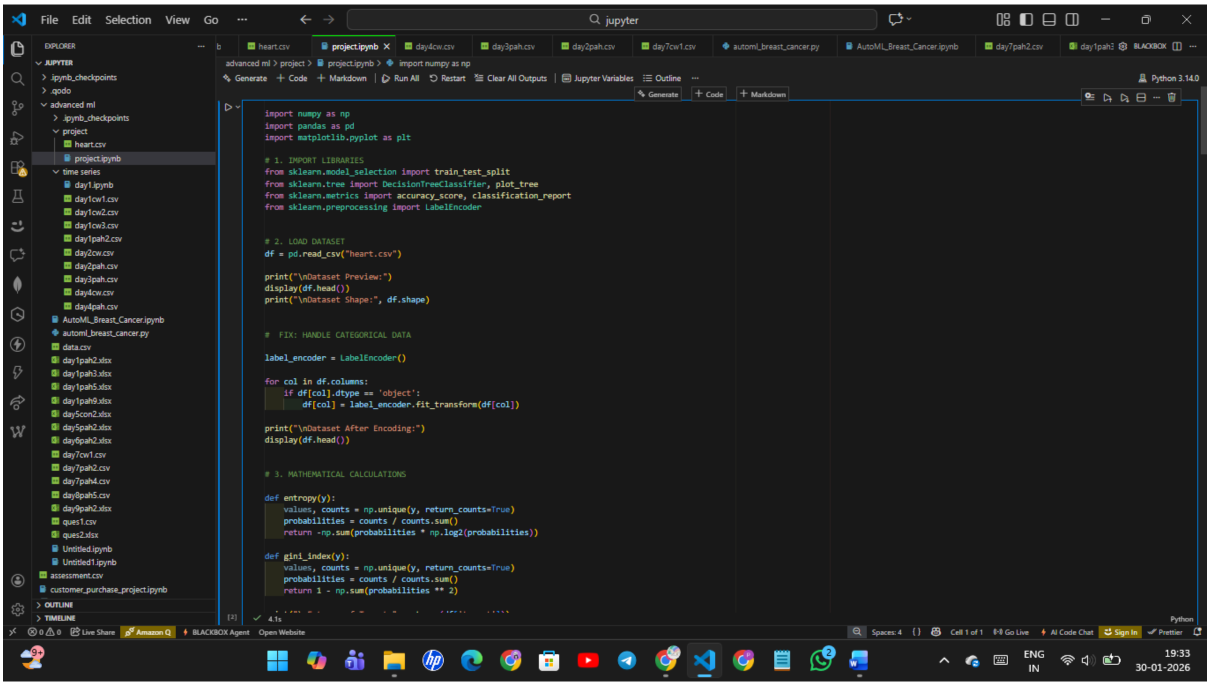
```
print("Gini Index of Target:", gini_index(df['target']))

# 4. FEATURE & TARGET SPLIT
X = df.drop('target', axis=1)
y = df['target']

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

# 5. DECISION TREE (NO PRUNING)
dt_full = DecisionTreeClassifier(
    criterion='gini',
    random_state=42
)

dt_full.fit(X_train, y_train)
y_pred_full = dt_full.predict(X_test)

acc_full = accuracy_score(y_test, y_pred_full)
print("\nAccuracy (No Pruning):", acc_full)

# 6. PRE-PRUNING
dt_pre_pruned = DecisionTreeClassifier(
    criterion='gini',
    max_depth=4,
    min_samples_split=10,
    random_state=42
)
```

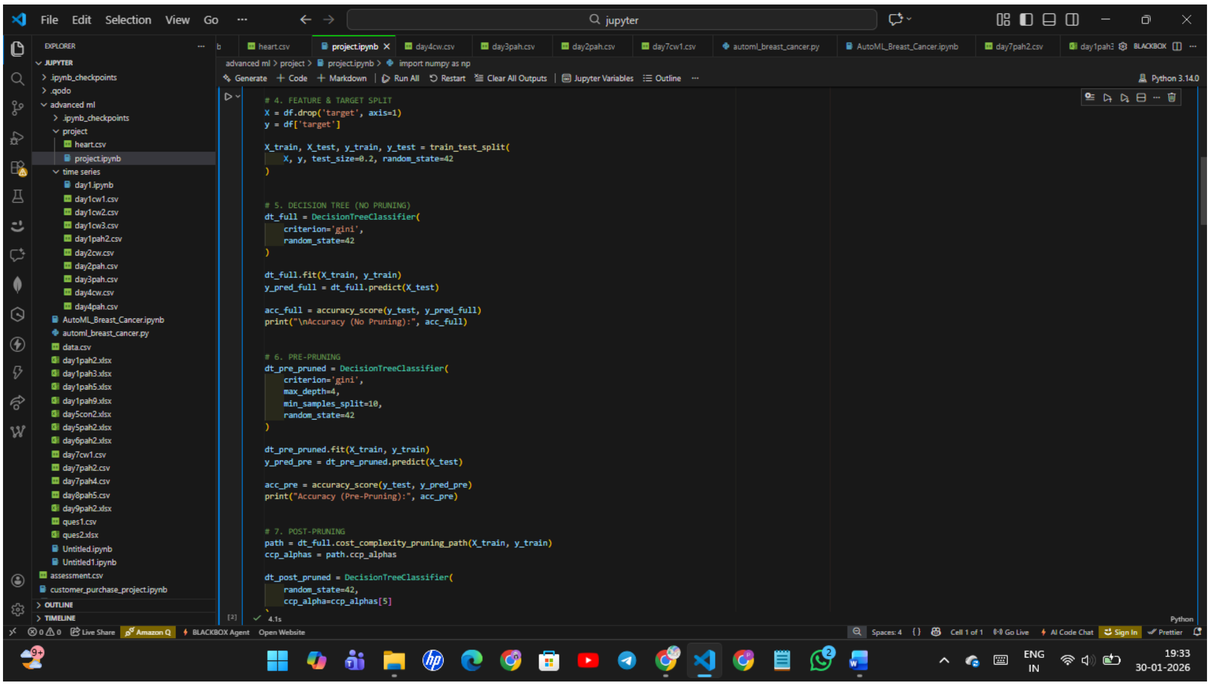
```
dt_pre_pruned.fit(X_train, y_train)
y_pred_pre = dt_pre_pruned.predict(X_test)

acc_pre = accuracy_score(y_test, y_pred_pre)
print("Accuracy (Pre-Pruning):", acc_pre)

# 7. POST-PRUNING
path = dt_full.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas = path.ccp_alphas

dt_post_pruned = DecisionTreeClassifier(
    random_state=42,
    ccp_alpha=ccp_alphas[5]
)

dt_post_pruned.fit(X_train, y_train)
y_pred_post = dt_post_pruned.predict(X_test)

acc_post = accuracy_score(y_test, y_pred_post)
print("Accuracy (Post-Pruning):", acc_post)

# 8. CLASSIFICATION REPORT
print("\nClassification Report (Pre-Pruned Model):")
print(classification_report(y_test, y_pred_pre))

# 9. DECISION TREE VISUALIZATION
plt.figure(figsize=(20, 10))
plot_tree(
```

```
    dt_pre_pruned,
    feature_names=X.columns,
    class_names=['No Disease', 'Disease'],
    filled=True
)
plt.title("Decision Tree Visualization (Pre-Pruned)")
plt.show()

# 10. FEATURE IMPORTANCE
feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Importance': dt_pre_pruned.feature_importances_
}).sort_values(by='Importance', ascending=False)

print("\nFeature Importance:")
display(feature_importance)

# 11. FEATURE IMPORTANCE VISUALIZATION
plt.figure(figsize=(10, 5))
plt.bar(feature_importance['Feature'], feature_importance['Importance'])
plt.xticks(rotation=90)
plt.title("Feature Importance Based on Decision Tree")
plt.tight_layout()
plt.show()

# 12. ACCURACY COMPARISON
models = ['No Pruning', 'Pre-Pruning', 'Post-Pruning']
accuracies = [acc_full, acc_pre, acc_post]
```

```
plt.figure(figsize=(6, 4))

plt.bar(models, accuracies)

plt.ylabel("Accuracy")

plt.title("Decision Tree Model Accuracy Comparison")

plt.show()


print("\nPROJECT EXECUTED SUCCESSFULLY")
```

Screenshots:





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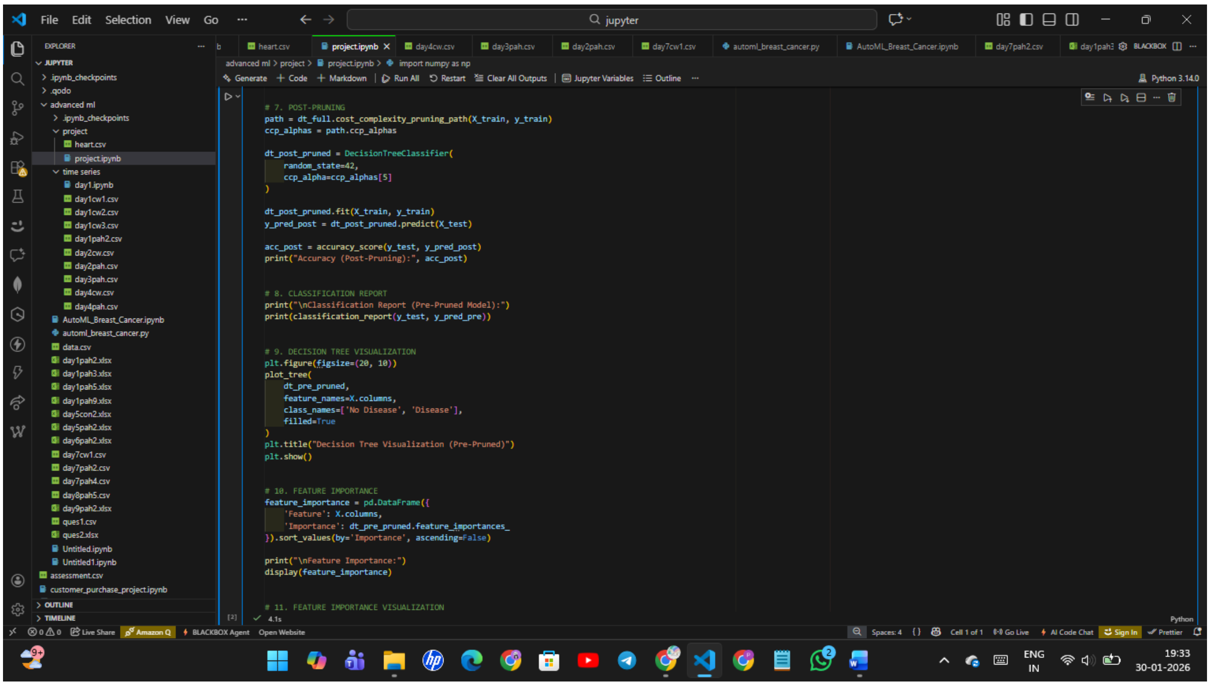

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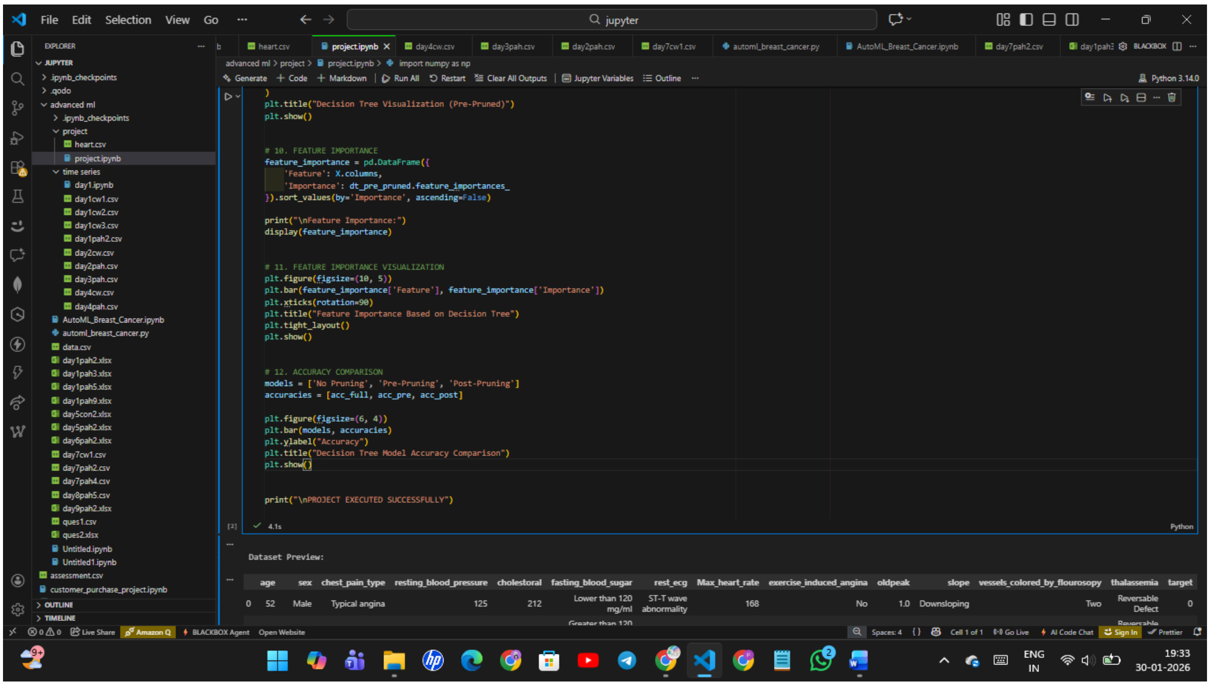
project.ipynb
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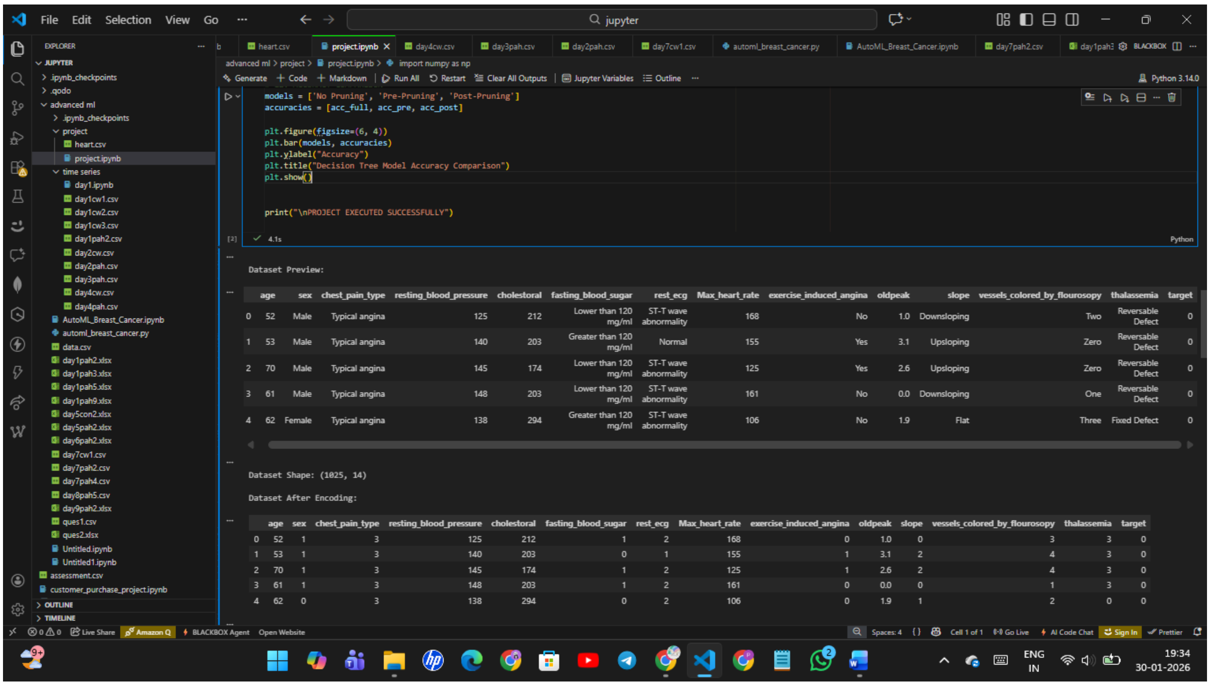
Dataset Preview:
age sex chest_pain_type resting_blood_pressure cholestoral fasting_blood_sugar rest_ecg Max_heart_rate exercise_induced_angina oldpeak slope vessels_colored_by_flourosopy thalassemia target
0 52 Male Typical angina 125 212 Lower than 120 mg/ml ST-T wave abnormality 168 No 1.0 Downsloping Two Reversable Defect 0
19:33
30-01-2026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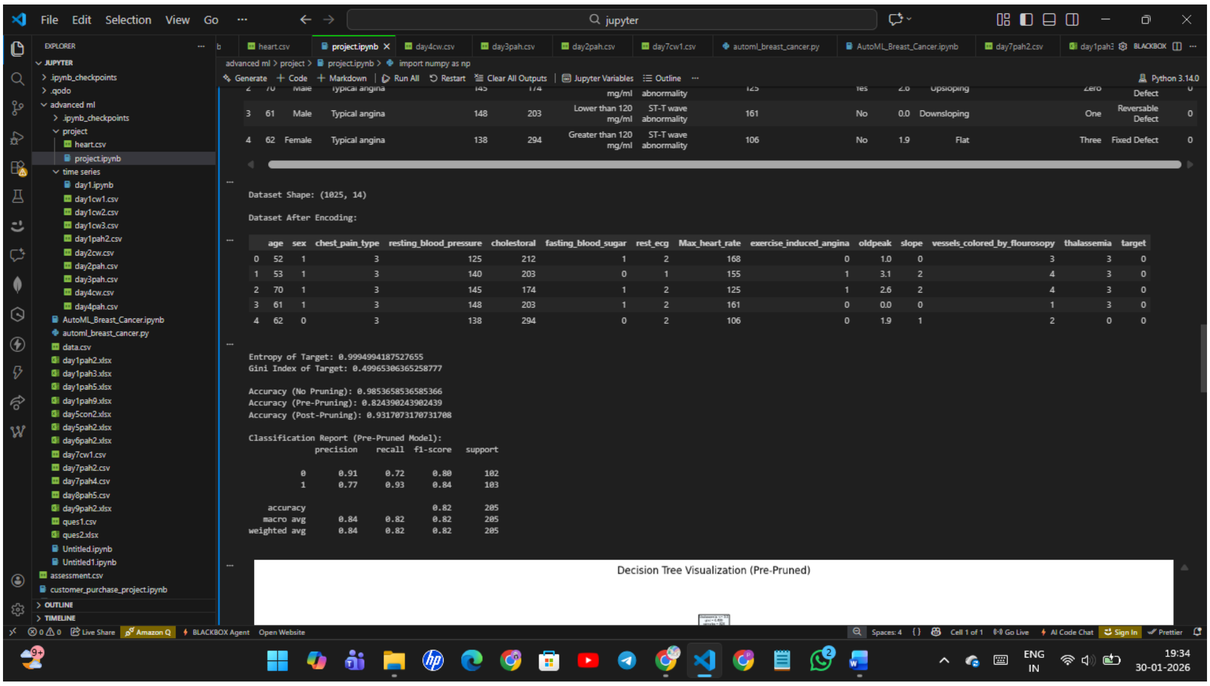
0 52 Male Typical angina 125 212 Lower than 120 mg/ml ST-T wave abnormality 168 No 1.0 Downsloping Two Reversable Defect 0
1 53 Male Typical angina 140 203 Greater than 120 mg/ml Normal 155 Yes 3.1 Upsloping Zero Reversable Defect 0
2 70 Male Typical angina 145 174 Lower than 120 mg/ml ST-T wave abnormality 125 Yes 2.6 Upsloping Zero Reversable Defect 0
3 61 Male Typical angina 148 203 Lower than 120 mg/ml ST-T wave abnormality 161 No 0.0 Downsloping One Reversable Defect 0
4 62 Female Typical angina 138 294 Greater than 120 mg/ml ST-T wave abnormality 106 No 1.9 Flat Three Fixed Defect 0
Dataset Shape: (1025, 14)
Dataset After Encoding:
age sex chest_pain_type resting_blood_pressure cholestoral fasting_blood_sugar rest_ecg Max_heart_rate exercise_induced_angina oldpeak slope vessels_colored_by_flourosopy thalassemia target
0 52 1 3 125 212 1 2 168 0 1.0 0 3 3 0
1 53 1 3 140 203 0 1 155 1 3.1 2 4 3 0
2 70 1 3 145 174 1 2 125 1 2.6 2 4 3 0
3 61 1 3 148 203 1 2 161 0 0.0 0 1 3 0
4 62 0 3 138 294 0 2 106 0 1.9 1 2 0 0
19:34
30-01-2026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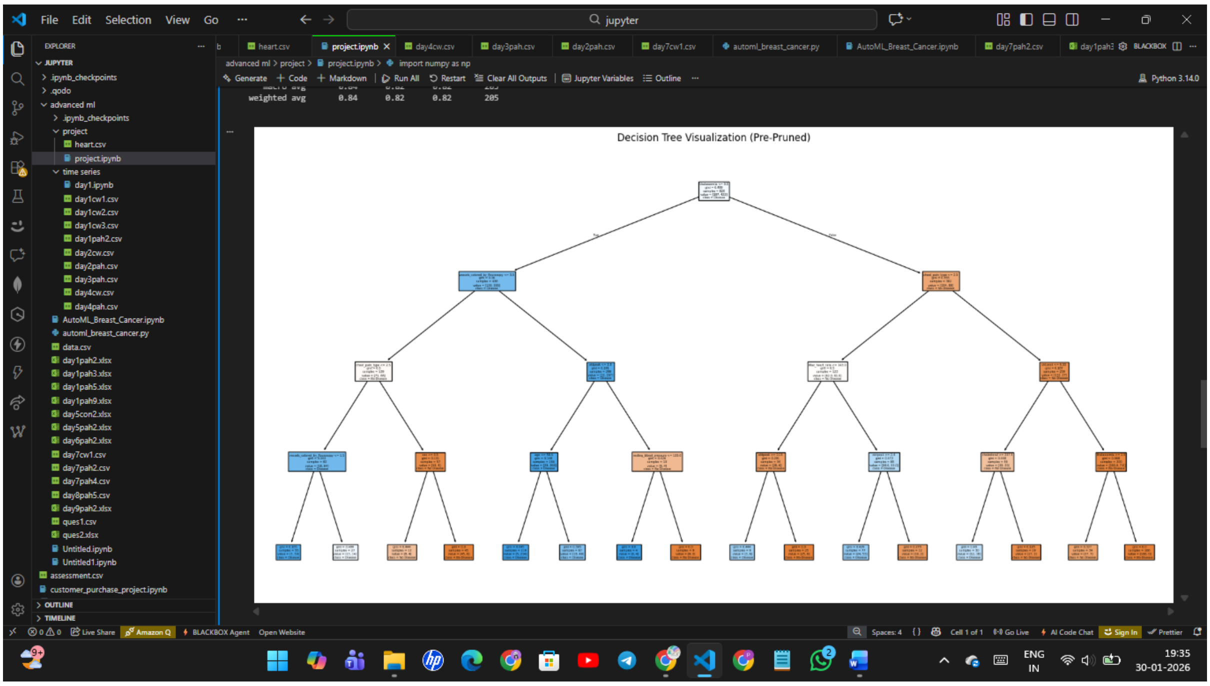
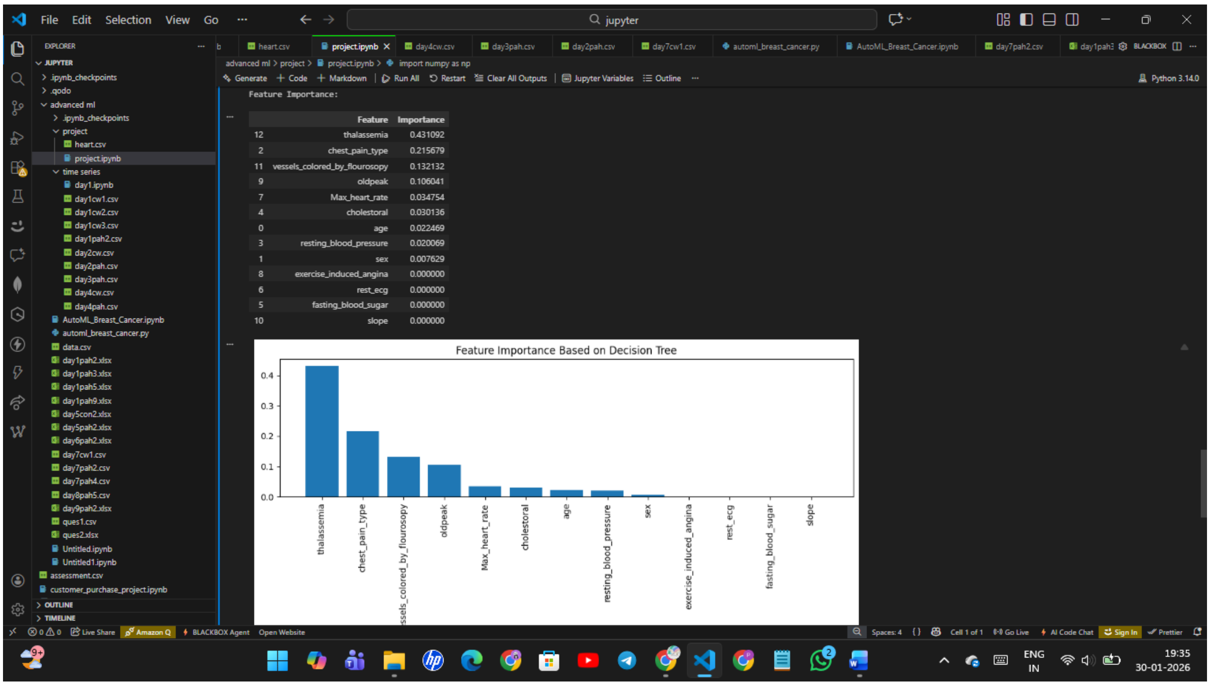
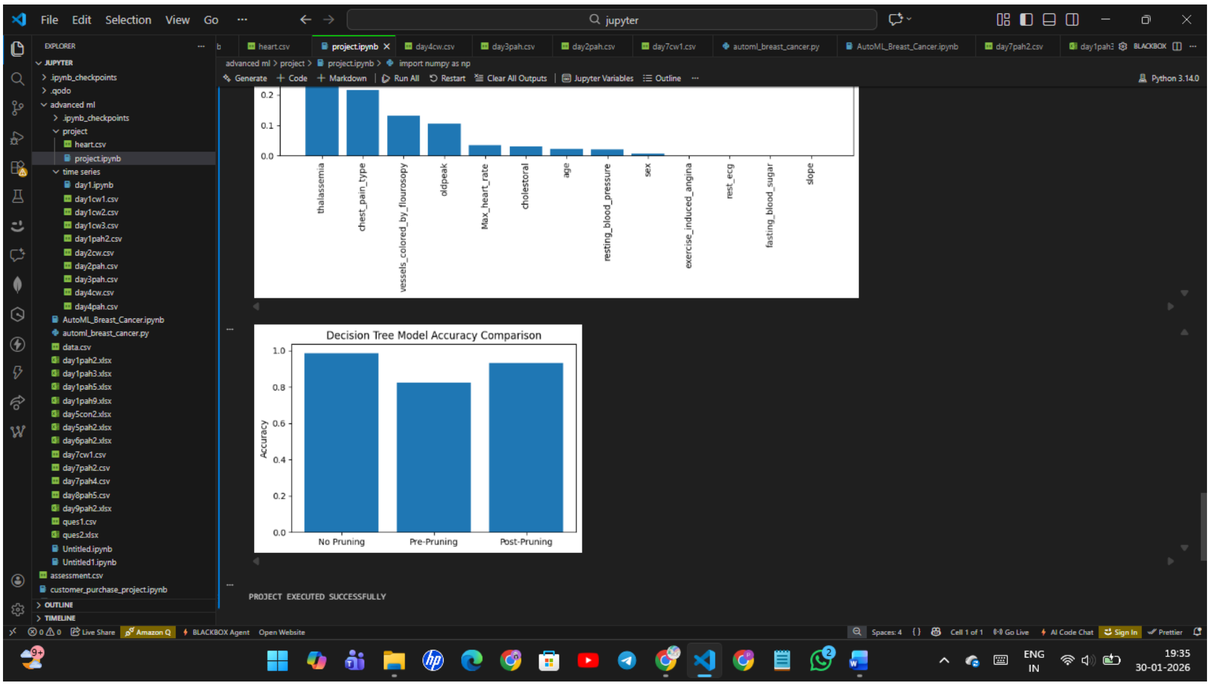
Dataset After Encoding:
age sex chest_pain_type resting_blood_pressure cholestoral fasting_blood_sugar rest_ecg Max_heart_rate exercise_induced_angina oldpeak slope vessels_colored_by_flourosopy thalassemia target
0 52 1 3 125 212 1 2 168 0 1.0 0 3 3 0
1 53 1 3 140 203 0 1 155 1 3.1 2 4 3 0
2 70 1 3 145 174 1 2 125 1 2.6 2 4 3 0
3 61 1 3 148 203 1 2 161 0 0.0 0 1 3 0
4 62 0 3 138 294 0 2 106 0 1.9 1 2 0 0
Entropy of Target: 0.9994994187527655
Gini Index of Target: 0.499653063652587777
Accuracy (No Pruning): 0.9853658536585366
Accuracy (Pre-Pruning): 0.824390243902439
Accuracy (Post-Pruning): 0.9317073170731708
Classification Report (Pre-Pruned Model):
precision recall f1-score support
0 0.91 0.72 0.80 102
1 0.77 0.93 0.84 103
accuracy 0.82 205
macro avg 0.84 0.82 0.82 205
weighted avg 0.84 0.82 0.82 205
Decision Tree Visualization (Pre-Pruned)


weighted avg 0.84 0.82 0.82 205
Decision Tree Visualization (Pre-Pruned)


Feature Importance:
Feature Importance
12 thalassemia 0.431092
2 chest_pain_type 0.215679
11 vessels_colored_by_flourosopy 0.132132
9 oldpeak 0.106041
7 Max_heart_rate 0.034754
4 cholestoral 0.030136
0 age 0.022469
3 resting_blood_pressure 0.020069
1 sex 0.007629
8 exercise_induced_angina 0.000000
6 rest_ecg 0.000000
5 fasting_blood_sugar 0.000000
10 slope 0.000000
Feature Importance Based on Decision Tree
thalassemia
chest_pain_type
vessels_colored_by_flourosopy
oldpeak
Max_heart_rate
cholestoral
age
resting_blood_pressure
sex
exercise_induced_angina
rest_ecg
fasting_blood_sugar
slope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