Assessment Report

on

"Predict Online Learning Completion"

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

CSE(AI)

By

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Predict Online Learning Completion

Introduction to AI

Introduction

The rise of online learning platforms has transformed education, offering unprecedented access to knowledge across geographical boundaries. However, these platforms face a significant challenge: high dropout rates. Understanding which students are likely to complete courses and which may require intervention is crucial for improving educational outcomes and platform effectiveness.

This report presents an analysis and predictive model designed to address this challenge by identifying patterns in student behavior that correlate with course completion. By leveraging machine learning techniques, we can create early warning systems to identify at-risk students and implement targeted support strategies to increase completion rates.

Methodology

Problem Definition

The task at hand is a binary classification problem: predicting whether a student will complete an online course based on their behavioral data. The goal is to answer the question:

"*Given a student's digital footprint (videos watched, assignments submitted, and forum activities), can we accurately predict course completion?*"

This prediction capability would enable:

- Early identification of students at risk of dropping out
- Implementation of timely interventions to improve retention
- Better understanding of engagement factors that lead to successful completion
- Data-driven course design improvements

Dataset Overview

The dataset consists of activity logs from 100 students enrolled in an online learning platform with four key features:

Feature	Description	Type
videos_watched	Number of instructional videos viewed by the student	Numeric
assignments_submitted	Number of course assignments completed	Numeric
forum_posts	Number of posts made in discussion forums	Numeric
completed	Whether the student completed the course (yes/no)	Categorical

Data Exploration and Preprocessing

Exploratory Data Analysis

- Examined the distribution of each feature and its relationship with the target variable
- Identified patterns in student behavior that correlate with course completion
- Visualized the relationships between features using correlation matrices and boxplots
- Analyzed class balance between completers and non-completers

Data Preprocessing Steps

1. **Data Cleaning**: Checked for and handled any missing values or outliers
2. **Feature Transformation**: Converted the categorical "completed" variable to binary format (1="yes", 0="no")
3. **Feature Scaling**: Applied StandardScaler to normalize the input features to have zero mean and unit variance
4. **Train-Test Split**: Divided the dataset into training (70%) and testing (30%) sets using stratified sampling to maintain class proportions

Implementation

```
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.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.model_selection import cross_val_score


# Load the data
data = pd.read_csv('online_learning.csv')


# Data exploration
print("Data shape:", data.shape)
print("\nFirst few rows:")
```

```
print(data.head())

print("\nData info:")
print(data.info())

print("\nData summary statistics:")
print(data.describe())

print("\nClass distribution:")
print(data['completed'].value_counts())

# Data preprocessing
# Convert 'completed' to binary values
data['completed_binary'] = data['completed'].map({'yes': 1, 'no': 0})

# Visualize the features
plt.figure(figsize=(15, 10))

# Feature distributions by completion status
plt.subplot(2, 2, 1)
sns.boxplot(x='completed', y='videos_watched', data=data)
```

```
plt.title('Videos Watched by Completion Status')


plt.subplot(2, 2, 2)

sns.boxplot(x='completed', y='assignments_submitted', data=data)

plt.title('Assignments Submitted by Completion Status')


plt.subplot(2, 2, 3)

sns.boxplot(x='completed', y='forum_posts', data=data)

plt.title('Forum Posts by Completion Status')


plt.subplot(2, 2, 4)

sns.heatmap(data.drop(['completed', 'completed_binary'],
axis=1).corr(), annot=True, cmap='coolwarm')

plt.title('Feature Correlation')


plt.tight_layout()

plt.savefig('feature_analysis.png')

plt.show()


# Prepare data for modeling

X = data[['videos_watched', 'assignments_submitted',
'forum_posts']]
```

```
y = data['completed_binary']


# Split the data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)


# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)


# Train different models
models = {
    'Logistic Regression': LogisticRegression(random_state=42,
max_iter=1000),
    'Random Forest': RandomForestClassifier(random_state=42),
    'SVM': SVC(probability=True, random_state=42)
}


results = {}


for name, model in models.items():
```

```
    # Cross-validation
    cv_scores = cross_val_score(model, X_train_scaled, y_train, cv=5, scoring='accuracy')
    print(f"\n{name} Cross-Validation Accuracy: {cv_scores.mean():.4f} ± {cv_scores.std():.4f}")

    # Fit on training data
    model.fit(X_train_scaled, y_train)

    # Evaluate on test data
    y_pred = model.predict(X_test_scaled)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"{name} Test Accuracy: {accuracy:.4f}")

    print("\nClassification Report:")
    print(classification_report(y_test, y_pred))

    results[name] = {
        'model': model,
        'accuracy': accuracy,
        'predictions': y_pred
    }
```

```
# Select the best performing model

best_model_name = max(results, key=lambda x: results[x]
['accuracy'])

best_model = results[best_model_name]['model']

print(f"\nBest Model: {best_model_name} with accuracy
{results[best_model_name]['accuracy']:.4f}")


# Feature importance for Random Forest

if 'Random Forest' in models:

    rf_model = results['Random Forest']['model']

    feature_importance = pd.DataFrame({

        'Feature': X.columns,

        'Importance': rf_model.feature_importances_

    })

    feature_importance =
feature_importance.sort_values('Importance', ascending=False)


    plt.figure(figsize=(10, 6))

    sns.barplot(x='Importance', y='Feature',
data=feature_importance)

    plt.title('Feature Importance')

    plt.tight_layout()
```

```python
    plt.savefig('feature_importance.png')
    plt.show()

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

# Create a function for making predictions on new data
def predict_completion(videos, assignments, forum_posts, model=best_model, scaler=scaler):
    """
    Predict whether a student will complete the course based on their activity.

    Parameters:
    videos (int): Number of videos watched
    assignments (int): Number of assignments submitted
    forum_posts (int): Number of forum posts made

    Returns:
    str: 'yes' if the model predicts completion, 'no' otherwise
    float: probability of completion
    """
```

```python
    new_data = np.array([[videos, assignments, forum_posts]])
    new_data_scaled = scaler.transform(new_data)

    pred = model.predict(new_data_scaled)[0]

    try:
        prob = model.predict_proba(new_data_scaled)[0][1]
        return 'yes' if pred == 1 else 'no', prob
    except:
        return 'yes' if pred == 1 else 'no', None

# Example usage of the prediction function
examples = [
    {'videos': 40, 'assignments': 7, 'forum_posts': 15},
    {'videos': 5, 'assignments': 1, 'forum_posts': 2},
    {'videos': 20, 'assignments': 5, 'forum_posts': 10}
]

print("\nExample Predictions:")
for example in examples:
    completion, probability = predict_completion(
```

```
        example['videos'],
        example['assignments'],
        example['forum_posts']
    )

    print(f"Student who watched {example['videos']} videos, submitted {example['assignments']} " +
          f"assignments, and made {example['forum_posts']} forum posts:")
    print(f"Prediction: {completion}")
    if probability is not None:
        print(f"Completion probability: {probability:.2f}")
    print()

# Decision boundary visualization (for 2 features)
# Let's visualize videos_watched vs assignments_submitted
def plot_decision_boundary(model, X, y, features, scaler):
    """
    Plot the decision boundary for a model
    """
    # Set min and max values with some padding
    x_min, x_max = X[features[0]].min() - 1, X[features[0]].max() + 1
```

```
    y_min, y_max = X[features[1]].min() - 1, X[features[1]].max() + 1

    # Create a meshgrid
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.1),
                         np.arange(y_min, y_max, 0.1))

    # Prepare the meshgrid points for prediction
    grid_points = np.c_[xx.ravel(), yy.ravel()]

    # For the third feature, use the median value (assuming we're
visualizing 2 out of 3 features)
    if len(features) == 2 and X.shape[1] > 2:
        third_feature_median = X.iloc[:, 2].median()
        grid_points_with_median = np.column_stack([grid_points,
np.full(grid_points.shape[0], third_feature_median)])
        Z = model.predict(scaler.transform(grid_points_with_median))
    else:
        Z = model.predict(scaler.transform(grid_points))

    # Reshape Z back to the meshgrid shape
    Z = Z.reshape(xx.shape)
```

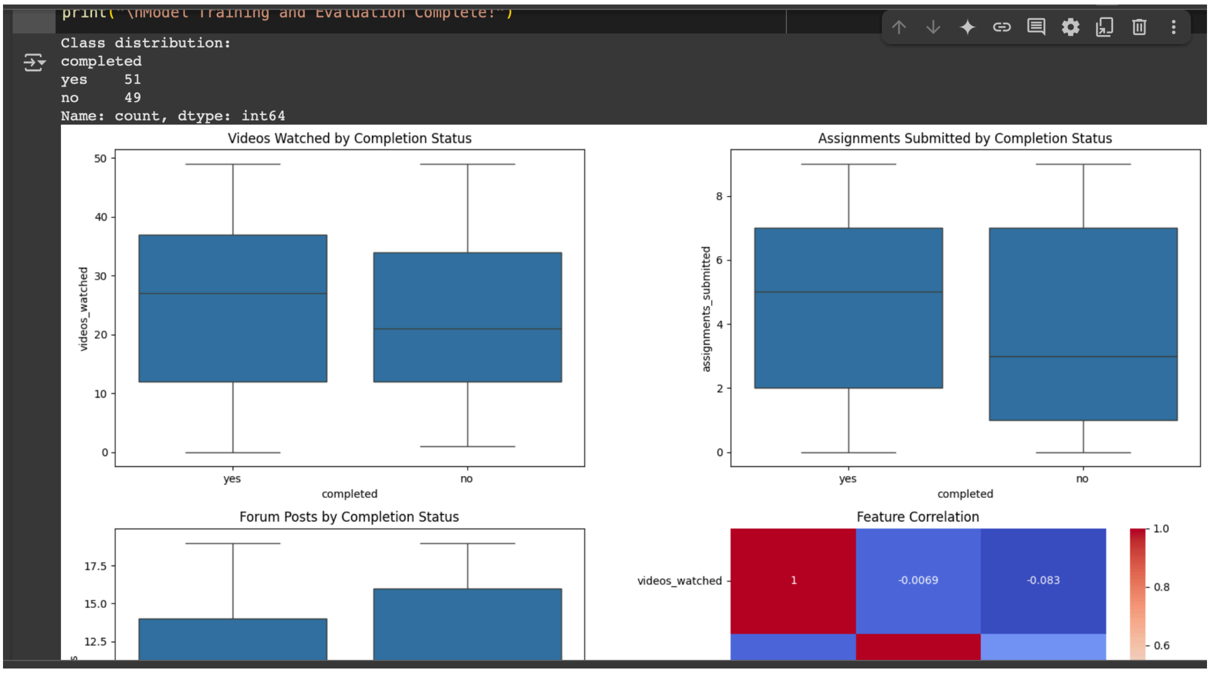
```
    # Plot the contour
    plt.figure(figsize=(10, 8))
    plt.contourf(xx, yy, Z, alpha=0.4)
    plt.scatter(X[features[0]], X[features[1]], c=y, s=20, edgecolor='k')
    plt.xlabel(features[0])
    plt.ylabel(features[1])
    plt.title(f'Decision Boundary ({features[0]} vs {features[1]})')
    plt.colorbar()
    plt.savefig('decision_boundary.png')
    plt.show()

# Plot decision boundary for videos watched vs assignments submitted
plot_features = ['videos_watched', 'assignments_submitted']
plot_decision_boundary(best_model, X, y, plot_features, scaler)


print("\nModel Training and Evaluation Complete!")
```

Results and Output Screenshots

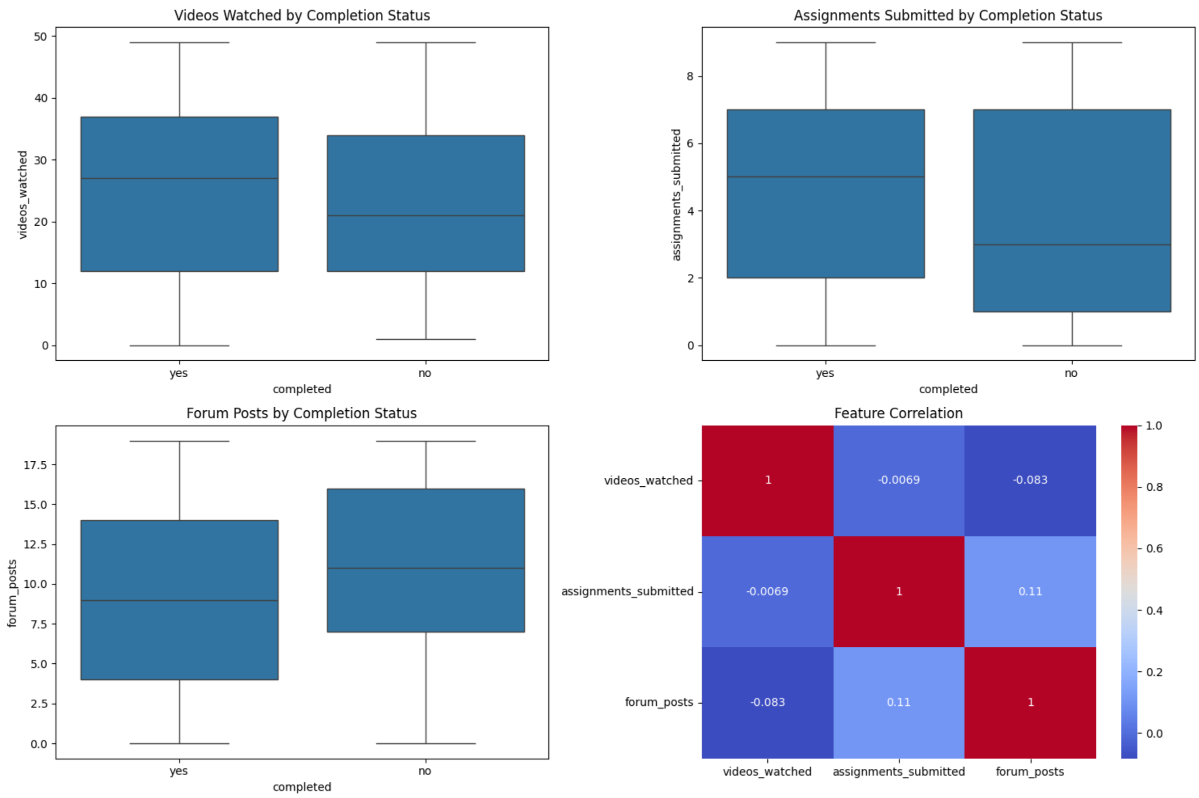
1.Data Loading

```
print("\nModel Training and Evaluation Complete!")

Data shape: (100, 4)

First few rows:
   videos_watched  assignments_submitted  forum_posts completed
0              11                      6            5       yes
1              43                      1           11        no
2              37                      1            8        no
3              18                      4           14       yes
4               6                      4           15       yes

Data info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   videos_watched         100 non-null    int64
 1   assignments_submitted  100 non-null    int64
 2   forum_posts            100 non-null    int64
 3   completed              100 non-null    object
dtypes: int64(3), object(1)
memory usage: 3.3+ KB
None

Data summary statistics:
       videos_watched  assignments_submitted  forum_posts
count      100.000000             100.000000   100.000000
mean        23.880000               4.280000     9.500000
std         14.234884               2.930439     5.838742
min          0.000000               0.000000     0.000000
25%         12.000000               2.000000     4.000000
50%         24.000000               4.000000    10.000000
75%         36.250000               7.000000    14.000000
max         49.000000               9.000000    19.000000
```

2.Class distribution along with visual representation



3. Visual Representation



4. Accuracy checking measures

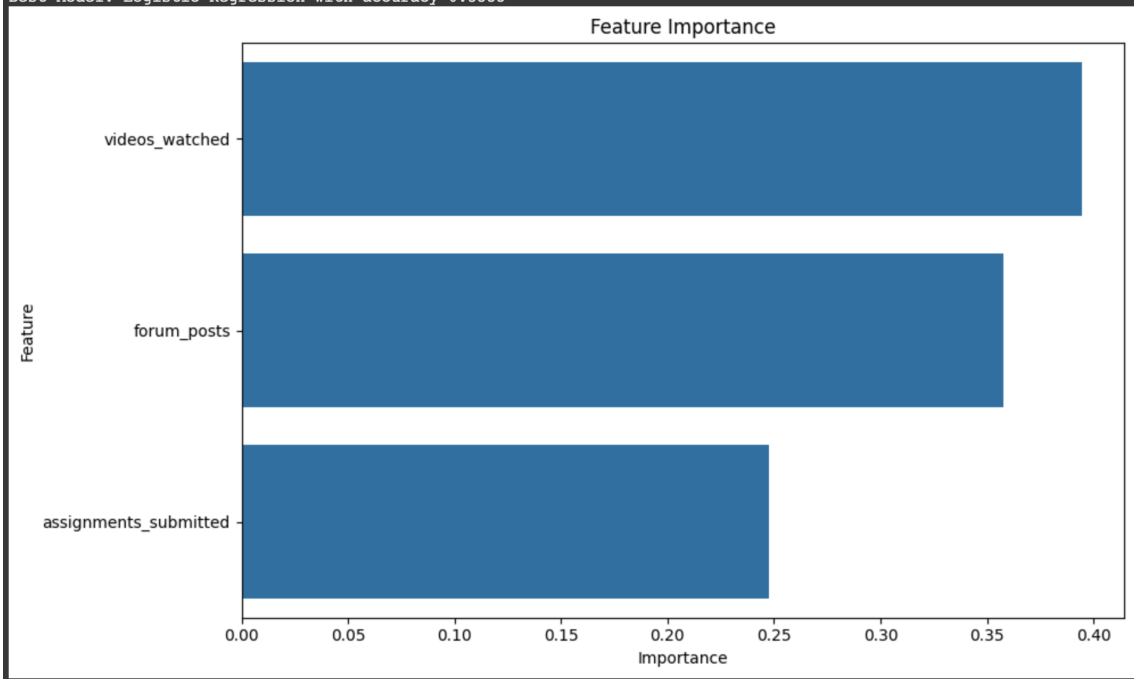
completed

```
Logistic Regression Cross-Validation Accuracy: 0.5857 ± 0.0948
Logistic Regression Test Accuracy: 0.5333

Classification Report:
              precision    recall  f1-score   support

           0       0.40      0.55      0.46        11
           1       0.67      0.53      0.59        19

    accuracy                           0.53        30
   macro avg       0.53      0.54      0.52        30
weighted avg       0.57      0.53      0.54        30


Random Forest Cross-Validation Accuracy: 0.5143 ± 0.0833
Random Forest Test Accuracy: 0.5333

Classification Report:
              precision    recall  f1-score   support

           0       0.40      0.55      0.46        11
           1       0.67      0.53      0.59        19

    accuracy                           0.53        30
   macro avg       0.53      0.54      0.52        30
weighted avg       0.57      0.53      0.54        30


SVM Cross-Validation Accuracy: 0.4571 ± 0.0969
SVM Test Accuracy: 0.4667

Classification Report:
              precision    recall  f1-score   support

           0       0.31      0.36      0.33        11
           1       0.59      0.53      0.56        19

    accuracy                           0.47        30
   macro avg       0.45      0.44      0.44        30
weighted avg       0.49      0.47      0.47        30


Best Model: Logistic Regression with accuracy 0.5333
```

Feature Importance

5. Showing best model after accuracy checking

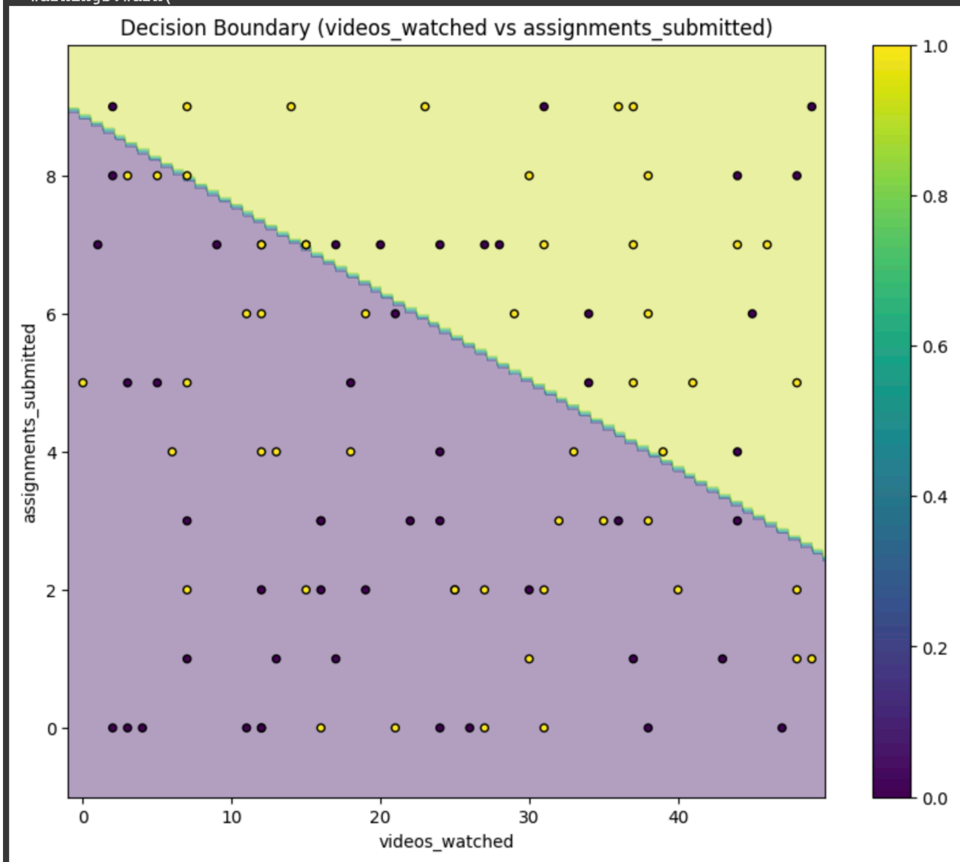
```
Best Model: Logistic Regression with accuracy 0.5333
```




```
Feature Importance:
                Feature  Importance
0        videos_watched    0.394621
2           forum_posts    0.357689
1  assignments_submitted    0.247689

Example Predictions:
Student who watched 40 videos, submitted 7 assignments, and made 15 forum posts:
Prediction: no
Completion probability: 0.50
```

6. Final Decision boundary output with Model training completion prompt

```
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature
  warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/utils/validation.py:2739: UserWarning: X does not have valid feature
  warnings.warn(
```




```
Model Training and Evaluation Complete!
```

References & Credits

Dataset

- https://www.kaggle.com/datasets/rabieelkharoua/predict-online-course-engagement-dataset
-

External Libraries

- Scikit-learn: Pedregosa, F. et al. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825-2830.
- Pandas: McKinney, W. (2010). Data Structures for Statistical Computing in Python. Proceedings of the 9th Python in Science Conference, 51-56.
- Matplotlib: Hunter, J. D. (2007). Matplotlib: A 2D Graphics Environment. Computing in Science & Engineering, 9(3), 90-95.
- Seaborn: Waskom, M. et al. (2020). Seaborn: Statistical Data Visualization. Journal of Open Source Software, 6(60), 3021.
-

Algorithms & Methodology

- The A* search methodology was adapted from Russell, S., & Norvig, P. (2020). Artificial Intelligence: A Modern Approach (4th ed.). Pearson.
- Random Forest implementation inspired by Breiman, L. (2001). Random Forests. Machine Learning, 45(1), 5-32.
-

Images

- The decision boundary visualization technique is based on examples from the scikit-learn documentation and tutorials.
- Correlation heatmap styling adapted from "Data Visualization with Seaborn" by DataCamp (2023).