Classifying Student Based on Fuzzy Logic

Pre-processing and Exploring Data

In [2]:
```python
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.feature_selection import mutual_info_classif
from sklearn.preprocessing import LabelEncoder
```

In [3]:
```python
# File path (update as needed)
file_path = 'data.csv'

# Load CSV with semicolon delimiter as specified in the dataset
df = pd.read_csv(file_path, delimiter=';')
# Remove tabs and other special characters from column names
df.columns = df.columns.str.replace(r'[\t]', ' ', regex=True)
display(df.head())
```

	Marital status	Application mode	Application order	Course	Daytime/ evening attendance	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification	Father's qualification	...	Curricular units 2nd sem (credited)	Curricula units 2n sei (enrollec
0	1	17	5	171	1	1	122.0	1	19	12	...	0	
1	1	15	1	9254	1	1	160.0	1	1	3	...	0	
2	1	1	5	9070	1	1	122.0	1	37	37	...	0	
3	1	17	2	9773	1	1	122.0	1	38	37	...	0	
4	2	39	1	8014	0	1	100.0	1	37	38	...	0	

5 rows × 37 columns

In [4]:
```python
# Check for missing values
print(df.isnull().sum())
```

```
Marital status                                    0
Application mode                                  0
Application order                                 0
Course                                            0
Daytime/evening attendance                        0
Previous qualification                            0
Previous qualification (grade)                    0
Nacionality                                       0
Mother's qualification                            0
Father's qualification                            0
Mother's occupation                               0
Father's occupation                               0
Admission grade                                   0
Displaced                                         0
Educational special needs                         0
Debtor                                            0
Tuition fees up to date                           0
Gender                                            0
Scholarship holder                                0
Age at enrollment                                 0
International                                     0
Curricular units 1st sem (credited)               0
Curricular units 1st sem (enrolled)               0
Curricular units 1st sem (evaluations)            0
Curricular units 1st sem (approved)               0
Curricular units 1st sem (grade)                  0
Curricular units 1st sem (without evaluations)    0
Curricular units 2nd sem (credited)               0
Curricular units 2nd sem (enrolled)               0
Curricular units 2nd sem (evaluations)            0
Curricular units 2nd sem (approved)               0
Curricular units 2nd sem (grade)                  0
Curricular units 2nd sem (without evaluations)    0
Unemployment rate                                 0
Inflation rate                                    0
GDP                                               0
Target                                            0
dtype: int64
```

In [5]:
```python
# Summary statistics
print("Summary statistics:")
display(df.describe())
```

```
Summary statistics:
```

	Marital status	Application mode	Application order	Course	Daytime/evening attendance	Previous qualification	Previous qualification (grade)	Nacionality	Mother's qualification	Father's qualification	...	ev
count	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	4424.000000	...	44
mean	1.178571	18.669078	1.727848	8856.642631	0.890823	4.577758	132.613314	1.873192	19.561935	22.275316	...	
std	0.605747	17.484682	1.313793	2063.566416	0.311897	10.216592	13.188332	6.914514	15.603186	15.343108	...	
min	1.000000	1.000000	0.000000	33.000000	0.000000	1.000000	95.000000	1.000000	1.000000	1.000000	...	
25%	1.000000	1.000000	1.000000	9085.000000	1.000000	1.000000	125.000000	1.000000	2.000000	3.000000	...	
50%	1.000000	17.000000	1.000000	9238.000000	1.000000	1.000000	133.100000	1.000000	19.000000	19.000000	...	
75%	1.000000	39.000000	2.000000	9556.000000	1.000000	1.000000	140.000000	1.000000	37.000000	37.000000	...	
max	6.000000	57.000000	9.000000	9991.000000	1.000000	43.000000	190.000000	109.000000	44.000000	44.000000	...	

8 rows × 36 columns

In [6]:
```
# Ensure correct data types
# Convert categorical features to category type where applicable
categorical_features = [
    'Marital status', 'Application mode', 'Course', 'Daytime/evening attendance',
    'Previous qualification', 'Nacionality', "Mother's qualification",
    "Father's qualification", "Mother's occupation", "Father's occupation",
    'Displaced', 'Educational special needs', 'Debtor', 'Tuition fees up to date',
    'Gender', 'Scholarship holder', 'International', 'Target',
]
for col in categorical_features:
    if col in df.columns:
        df[col] = df[col].astype('category')
```

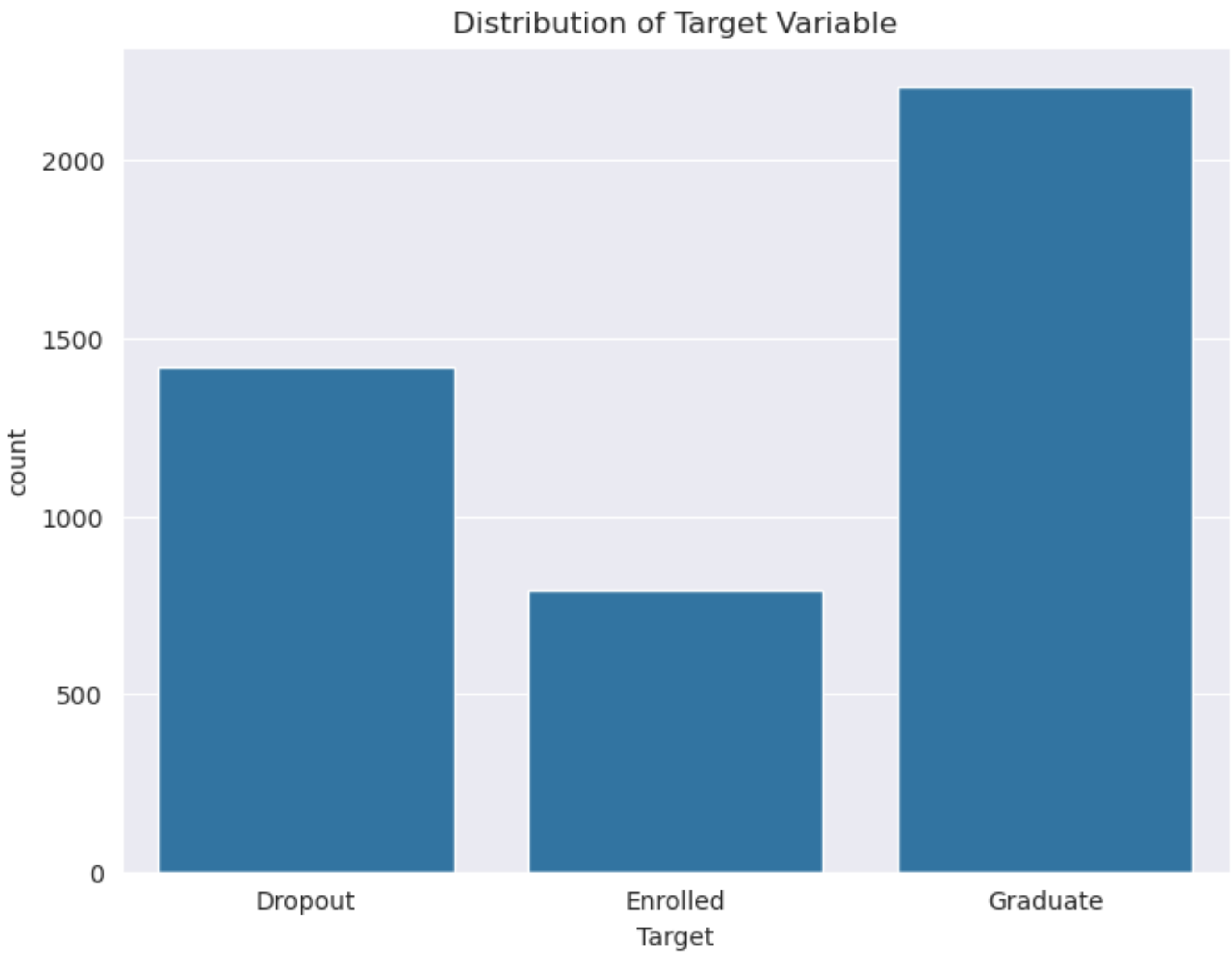
In [7]:
```
# Split into features (X) and target (y)
X = df.drop('Target', axis=1)
y = df['Target']
```

In [8]:
```
# Encode the target variable (Graduate, Dropout, Enrolled) to numerical values
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)
```

In [9]:
```
# Load and preprocess data
print(f"Features Shape: {X.shape}")
print(f"Target Shape: {y.shape}")
```

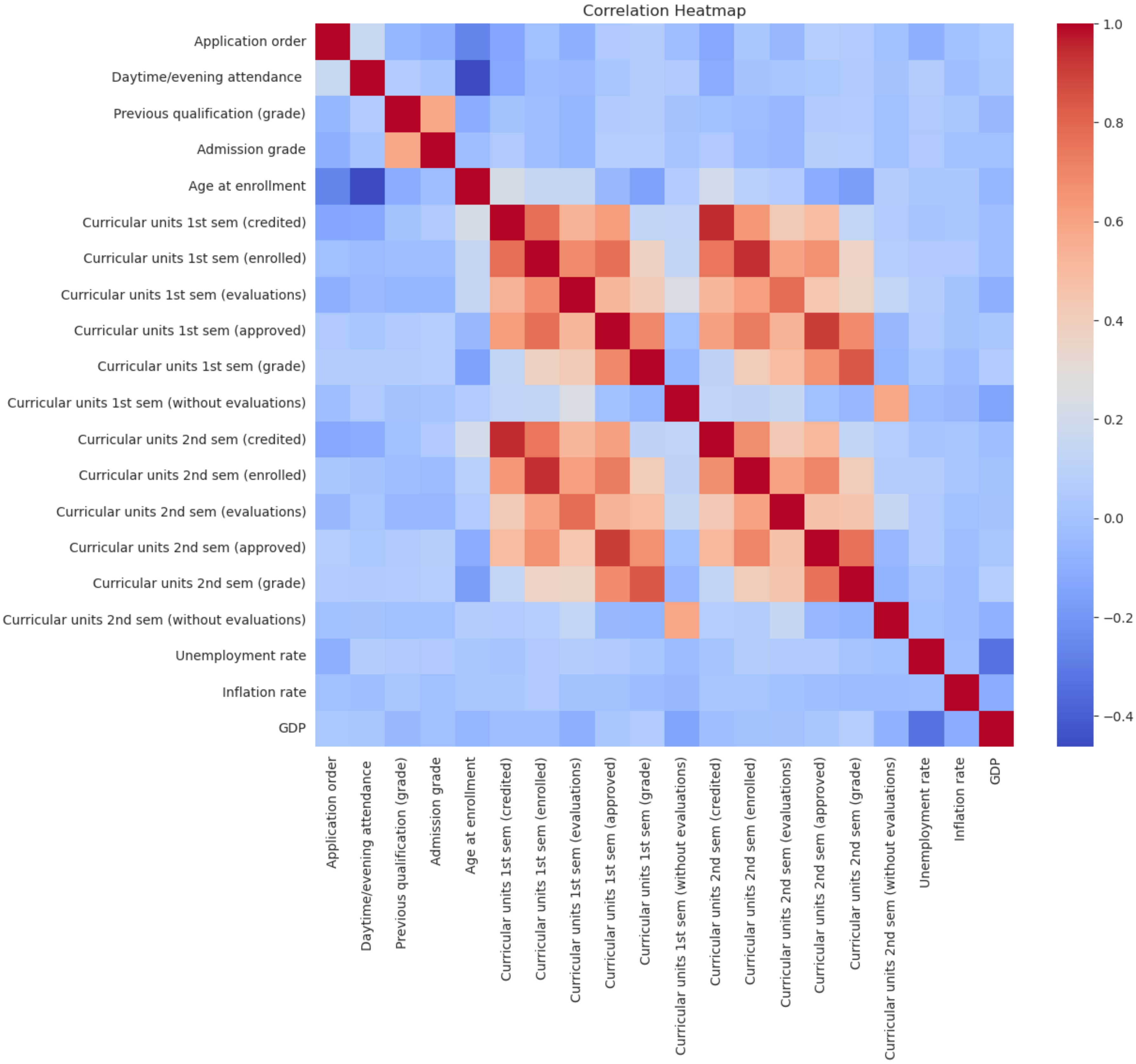
```
Features Shape: (4424, 36)
Target Shape: (4424,)
```

In [10]:
```
# Plot distribution of the target variable
plt.figure(figsize=(8, 6))
sns.countplot(x='Target', data=df)
plt.title('Distribution of Target Variable')
plt.show()
```

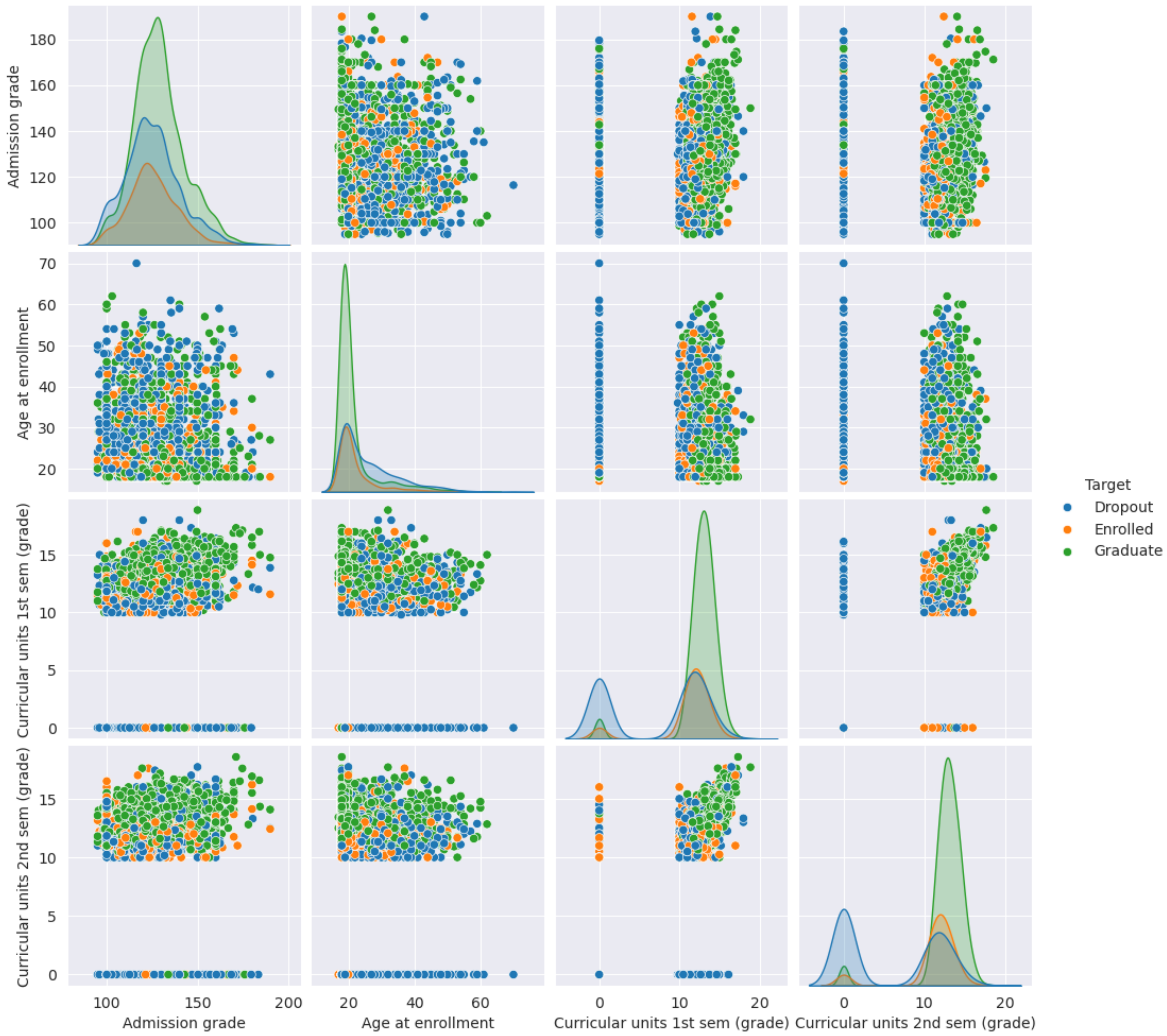


In [11]:
```
# Correlation heatmap for numerical features
plt.figure(figsize=(12, 10))
corr = df.select_dtypes(include=[np.number]).corr()
sns.heatmap(corr, annot=False, cmap='coolwarm')
plt.title('Correlation Heatmap')
plt.show
```

Out[11]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [12]:
```
# Pairplot for selected features
selected_features = [
    'Admission grade', 'Age at enrollment',
    'Curricular units 1st sem (grade)', 'Curricular units 2nd sem (grade)',
]

sns.pairplot(df[selected_features + ['Target']], hue='Target')
plt.show()
```



In [13]:
```
# Convert categorical variables to numerical codes for mutual information calculation
X_encoded = X.copy()
for col in X.columns:
    if X[col].dtype.name == 'category':
        X_encoded[col] = X[col].cat.codes
```

In [14]:
```
# Calculate mutual information scores
mi_scores = mutual_info_classif(X_encoded, y, random_state=42)
mi_df = pd.DataFrame({'Feature': X.columns, 'MI Score': mi_scores})
mi_df = mi_df.sort_values('MI Score', ascending=False)
mi_df
```

Out[14]:

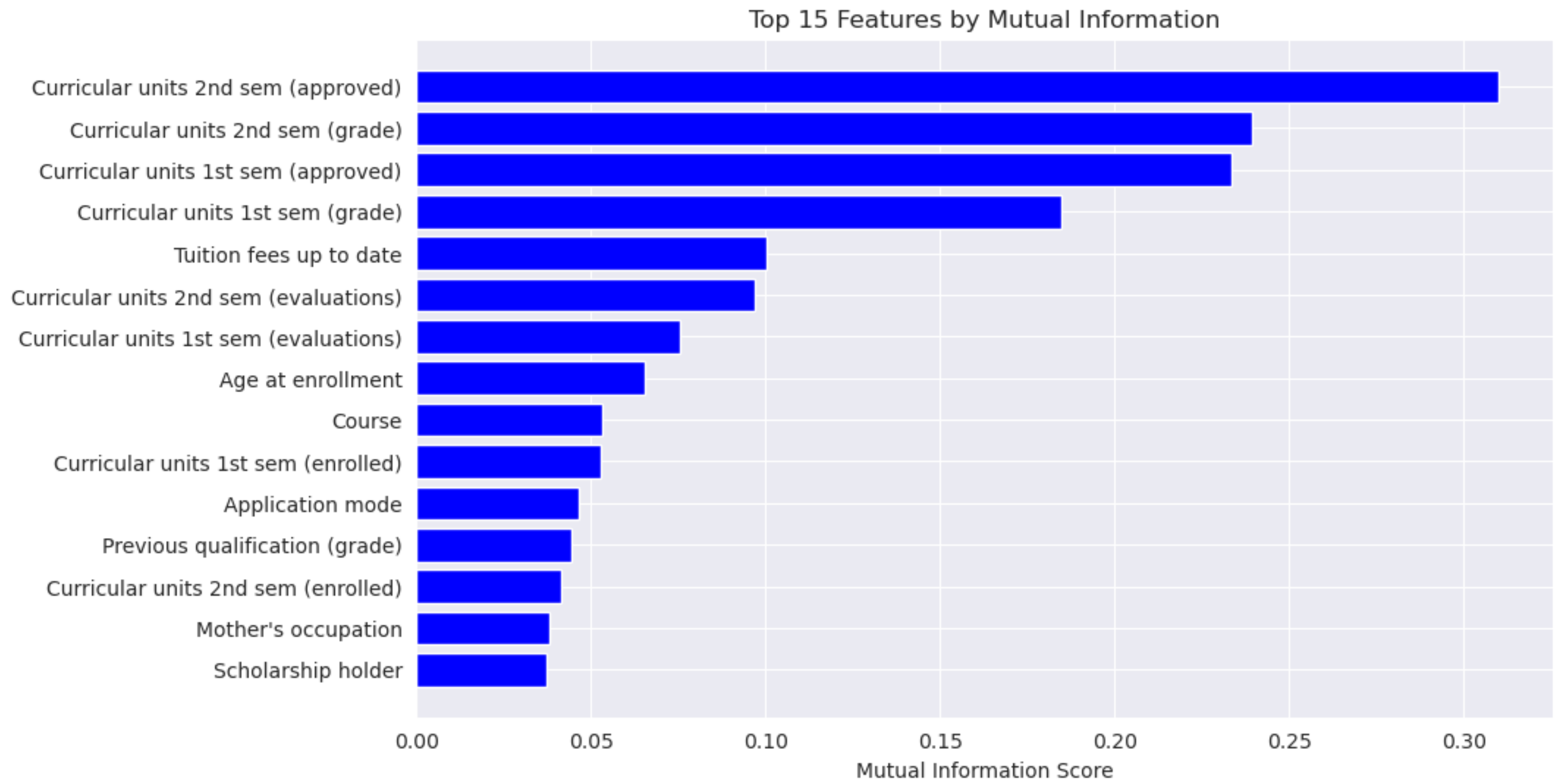
	Feature	MI Score
30	Curricular units 2nd sem (approved)	0.310207
31	Curricular units 2nd sem (grade)	0.239324
24	Curricular units 1st sem (approved)	0.233439
25	Curricular units 1st sem (grade)	0.184882
16	Tuition fees up to date	0.100460
29	Curricular units 2nd sem (evaluations)	0.096761
23	Curricular units 1st sem (evaluations)	0.075691
19	Age at enrollment	0.065516
3	Course	0.053349
22	Curricular units 1st sem (enrolled)	0.052744
1	Application mode	0.046695
6	Previous qualification (grade)	0.044584
28	Curricular units 2nd sem (enrolled)	0.041576
10	Mother's occupation	0.037915
18	Scholarship holder	0.037139
15	Debtor	0.033628
9	Father's qualification	0.030031
12	Admission grade	0.025820
17	Gender	0.024435
8	Mother's qualification	0.021399
5	Previous qualification	0.016042
11	Father's occupation	0.015493
0	Marital status	0.014868
34	Inflation rate	0.011433
2	Application order	0.010398
21	Curricular units 1st sem (credited)	0.007905
33	Unemployment rate	0.007887
14	Educational special needs	0.003240
4	Daytime/evening attendance	0.000185
20	International	0.000000
26	Curricular units 1st sem (without evaluations)	0.000000
27	Curricular units 2nd sem (credited)	0.000000
13	Displaced	0.000000
7	Nacionality	0.000000
32	Curricular units 2nd sem (without evaluations)	0.000000
35	GDP	0.000000

In [15]:

```
# Select top features (minimum of 10, but let's take top 15 to ensure relevance)
selected_features = mi_df['Feature'].head(15).tolist()
print("\nTop 15 Features by Mutual Information:")
print(mi_df.head(15))
```

```
Top 15 Features by Mutual Information:
                                   Feature  MI Score
30     Curricular units 2nd sem (approved)  0.310207
31        Curricular units 2nd sem (grade)  0.239324
24     Curricular units 1st sem (approved)  0.233439
25        Curricular units 1st sem (grade)  0.184882
16                 Tuition fees up to date  0.100460
29  Curricular units 2nd sem (evaluations)  0.096761
23  Curricular units 1st sem (evaluations)  0.075691
19                       Age at enrollment  0.065516
3                                   Course  0.053349
22     Curricular units 1st sem (enrolled)  0.052744
1                         Application mode  0.046695
6           Previous qualification (grade)  0.044584
28     Curricular units 2nd sem (enrolled)  0.041576
10                     Mother's occupation  0.037915
18                      Scholarship holder  0.037139
```

In [16]:
```python
# Visualize feature importance
plt.figure(figsize=(10, 6))
plt.barh(mi_df['Feature'].head(15), mi_df['MI Score'].head(15), color='blue')
plt.xlabel('Mutual Information Score')
plt.title('Top 15 Features by Mutual Information')
plt.gca().invert_yaxis()
plt.show()
```



In [17]:
```python
# Subset the data with selected features
X_selected = X[selected_features]

# Split the dataset into training (80%) and testing (20%) sets
X_train, X_test, y_train, y_test = train_test_split(
    X_selected, y, test_size=0.2, random_state=42, stratify=y
)
```

In [18]:
```python
# Reset indices to ensure alignment
X_train = X_train.reset_index(drop=True)
X_test = X_test.reset_index(drop=True)
y_train = pd.Series(y_train, name='Target').reset_index(drop=True)
y_test = pd.Series(y_test, name='Target').reset_index(drop=True)

print("Data Split:")
print(f"Training Set: {X_train.shape[0]} samples")
print(f"Testing Set: {X_test.shape[0]} samples")
```

```
Data Split:
Training Set: 3539 samples
Testing Set: 885 samples
```

In [19]:
```python
# Save the split datasets for later use
train_data = pd.concat([X_train, y_train], axis=1)
test_data = pd.concat([X_test, y_test], axis=1)

# Remove rows with missing Target values
train_data = train_data.dropna(subset=['Target'])
test_data = test_data.dropna(subset=['Target'])

# Save to CSV
train_data.to_csv('train_data.csv', index=False)
test_data.to_csv('test_data.csv', index=False)
print("Training and testing sets saved as 'train_data.csv' and 'test_data.csv'")
```

```
Training and testing sets saved as 'train_data.csv' and 'test_data.csv'
```

In [20]:
```python
# # Apply SMOTE to balance classes
# from imblearn.over_sampling import SMOTE
#
# # Load original training data
# X_train = pd.read_csv('train_data.csv').drop('Target', axis=1)
# y_train = pd.read_csv('train_data.csv')['Target']
# # Apply SMOTE
# smote = SMOTE(random_state=1)
# X_smote, y_smote = smote.fit_resample(X_train, y_train)
#
# # Save balanced data
# smote_df = pd.concat([X_smote, y_smote], axis=1)
# smote_df.to_csv('train_data.csv', index=False)
# print("\nSMOTE applied. New training data saved as 'train_data.csv'.")
#
```

Fuzzy Feature Representation

In [21]:
```python
# Load the training data
train_data = pd.read_csv('train_data.csv')
X_train = train_data.drop('Target', axis=1)
y_train = train_data['Target']

print("Training data loaded successfully.")
print(f"Features: {X_train.columns.tolist()}")
```

```
Training data loaded successfully.
Features: ['Curricular units 2nd sem (approved)', 'Curricular units 2nd sem (grade)', 'Curricular units 1st sem (a
pproved)', 'Curricular units 1st sem (grade)', 'Tuition fees up to date', 'Curricular units 2nd sem (evaluation
s)', 'Curricular units 1st sem (evaluations)', 'Age at enrollment', 'Course', 'Curricular units 1st sem (enrolle
d)', 'Application mode', 'Previous qualification (grade)', 'Curricular units 2nd sem (enrolled)', "Mother's occupa
tion", 'Scholarship holder']
```

In [22]:
```python
# Define triangular membership function
def triangular_membership(x, a, b, c, boundary = None):
    """Calculate membership degree for a triangular function."""
    if boundary == 'left' and x < b or boundary == 'right' and x > b:
            return 1
    elif x <= a or x >= c:
        return 0
    elif a < x <= b:
        return (x - a) / (b - a)
    elif b < x < c:
        return (c - x) / (c - b)
    return 0

def define_fuzzy_sets(feature_data):
    """Define fuzzy sets (low, medium, high) for a continuous feature."""
    min_val = feature_data.min()
    max_val = feature_data.max()
    q1 = np.percentile(feature_data, 25)
    median = np.median(feature_data)
    q3 = np.percentile(feature_data, 75)

    # Low: trapezoidal-like with boundary='left'
    low_a, low_b, low_c = min_val, min_val + (q1 - min_val) / 5, q1 + (median - q1) / 5
    # Medium: triangular
    medium_a, medium_b, medium_c = q1 - (q1 - min_val) / 5, median, q3 + (max_val - q3) / 5
    # High: trapezoidal-like with boundary='right'
    high_a, high_b, high_c = q3 - (q3 - median) / 5, max_val - (max_val - q3) / 5, max_val

    return {
        'low': (low_a, low_b, low_c, 'left'),
        'medium': (medium_a, medium_b, medium_c, None),
        'high': (high_a, high_b, high_c, 'right')
    }

# Function to fuzzify a continuous feature
def fuzzify_continuous(feature_data, fuzzy_sets):
    """Fuzzify a continuous feature into low, medium, high membership degrees."""
    feature_name = feature_data.name  # Get the feature name (e.g., 'temperature')
    memberships = {}
    for label in ['low', 'medium', 'high']:  # Explicitly define expected labels
        if label not in fuzzy_sets:
            raise ValueError(f"Missing fuzzy set for label '{label}' in feature '{feature_name}'")
        a, b, c, boundary = fuzzy_sets[label]
        memberships[f"{feature_name}_{label}"] = feature_data.apply(
            lambda x: triangular_membership(x, a, b, c, boundary)
        )
    return pd.DataFrame(memberships, index=feature_data.index)

# Function to fuzzify a binary feature
def fuzzify_binary(feature_data):
    """Fuzzify a binary feature into two crisp sets: 0 and 1."""
    feature_name = feature_data.name  # Get the feature name
    if not feature_data.isin([0, 1]).all():
        raise ValueError(f"Binary feature '{feature_name}' contains non-binary values: {feature_data.unique()}")
    return pd.DataFrame({
        f"{feature_name}_0": (feature_data == 0).astype(float),
        f"{feature_name}_1": (feature_data == 1).astype(float),
    }, index=feature_data.index)
```

In [23]:
```python
continuous_features = [col for col in X_train.columns if X_train[col].nunique() > 2]
binary_features = [col for col in X_train.columns if X_train[col].nunique() == 2]

print(f"Continuous features: {continuous_features}")
print(f"Binary features: {binary_features}")
```

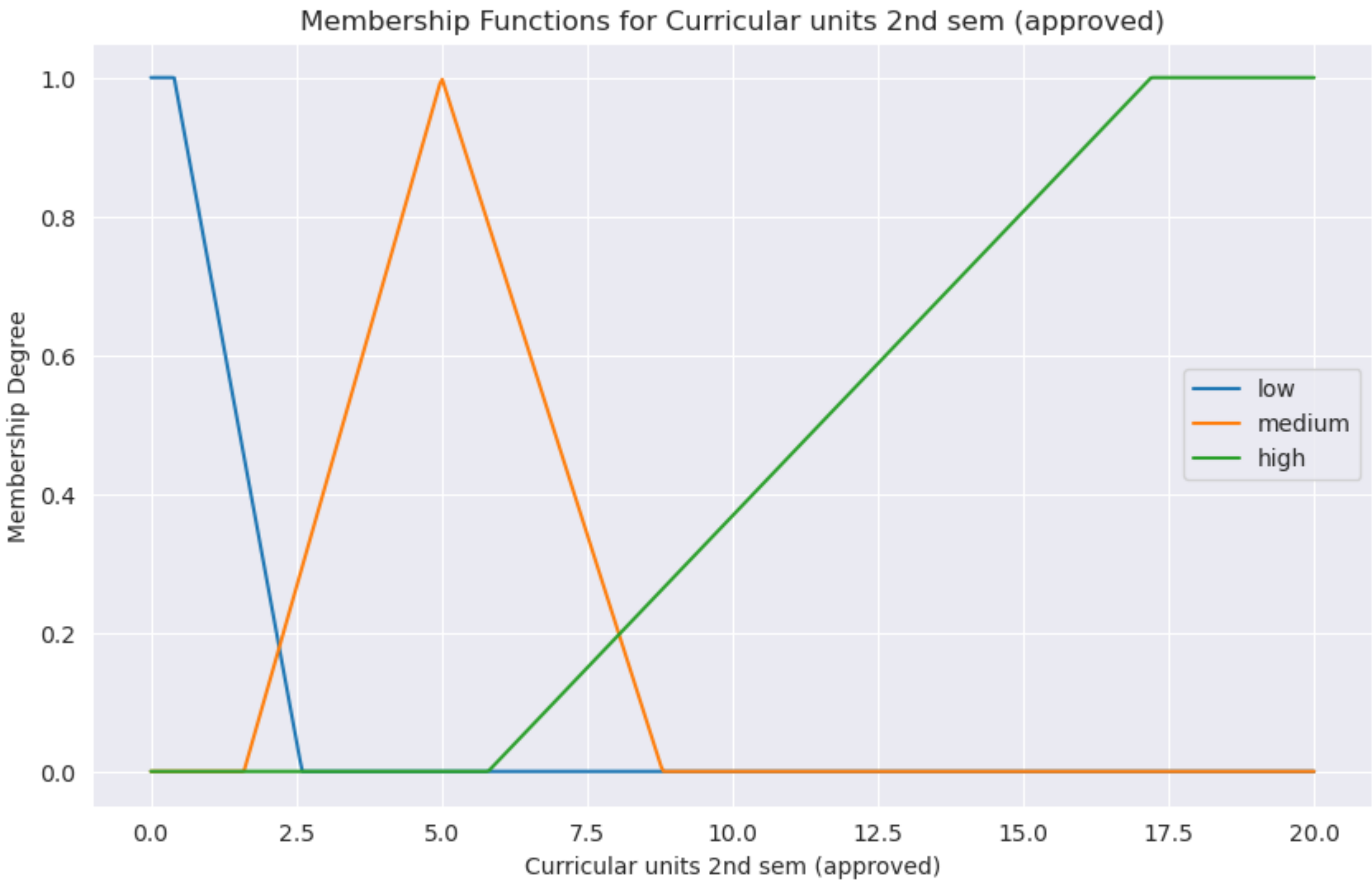
```
Continuous features: ['Curricular units 2nd sem (approved)', 'Curricular units 2nd sem (grade)', 'Curricular units
1st sem (approved)', 'Curricular units 1st sem (grade)', 'Curricular units 2nd sem (evaluations)', 'Curricular uni
ts 1st sem (evaluations)', 'Age at enrollment', 'Course', 'Curricular units 1st sem (enrolled)', 'Application mode
', 'Previous qualification (grade)', 'Curricular units 2nd sem (enrolled)', "Mother's occupation"]
Binary features: ['Tuition fees up to date', 'Scholarship holder']
```

In [24]:
```
# Fuzzify continuous features
fuzzy_continuous = {}
for feature in continuous_features:
    fuzzy_sets = define_fuzzy_sets(X_train[feature])
    fuzzy_continuous[feature] = fuzzify_continuous(X_train[feature], fuzzy_sets)

# Fuzzify binary features
fuzzy_binary = {}
for feature in binary_features:
    fuzzy_binary[feature] = fuzzify_binary(X_train[feature])

print("Features fuzzified successfully.")
```

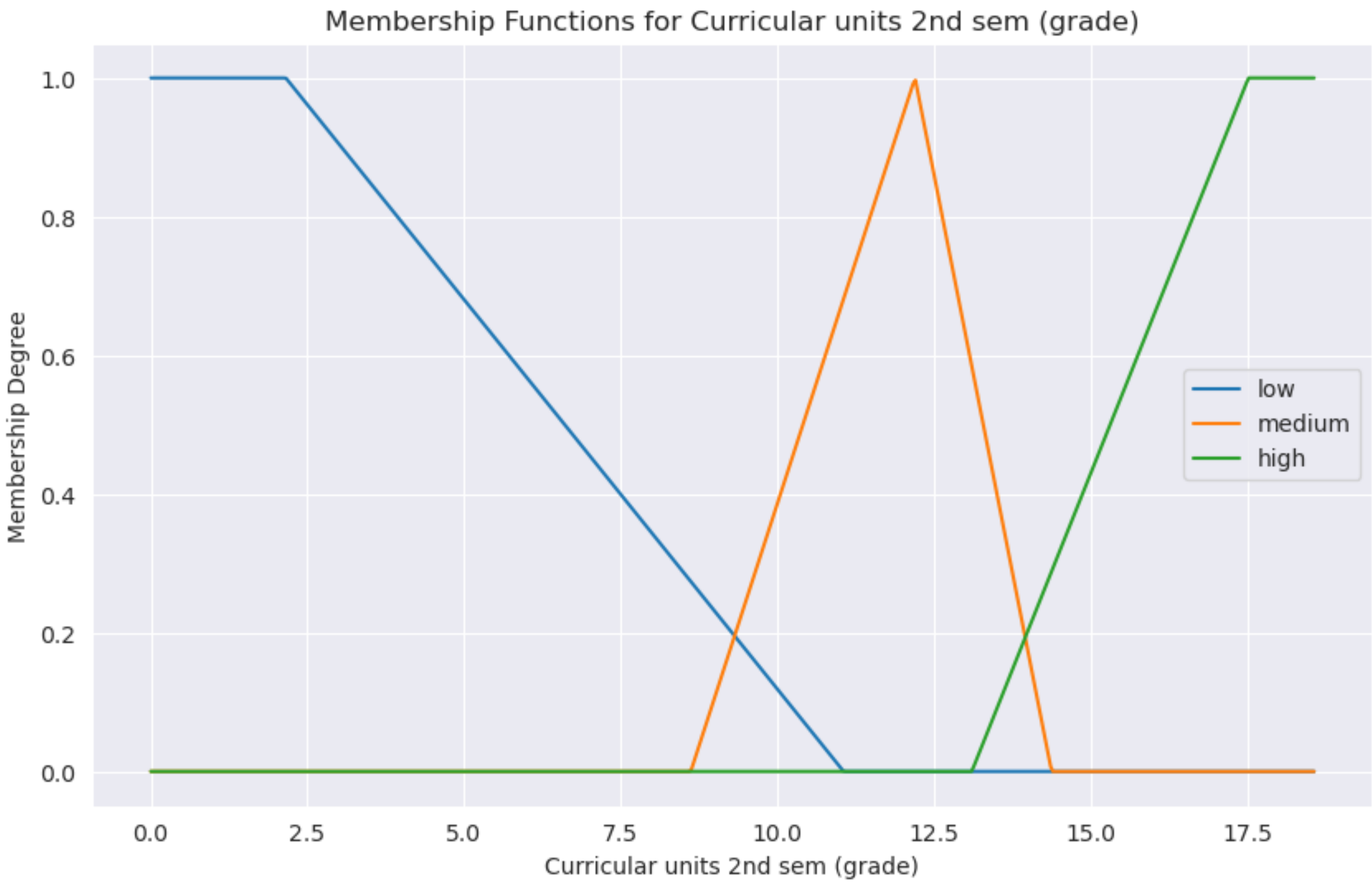
```
Features fuzzified successfully.
```

In [25]:
```
# Plot membership functions for two continuous features
def plot_membership_functions(feature, fuzzy_sets):
    """Plot the membership functions for a given feature."""
    x = np.linspace(X_train[feature].min(), X_train[feature].max(), 500)
    plt.figure(figsize=(10, 6))
    for label, params in fuzzy_sets.items():
        a, b, c, boundary = params
        y = [triangular_membership(val, a, b, c, boundary) for val in x]
        plt.plot(x, y, label=label)
    plt.title(f'Membership Functions for {feature}')
    plt.xlabel(feature)
    plt.ylabel('Membership Degree')
    plt.legend()
    plt.grid(True)
    plt.show()
```

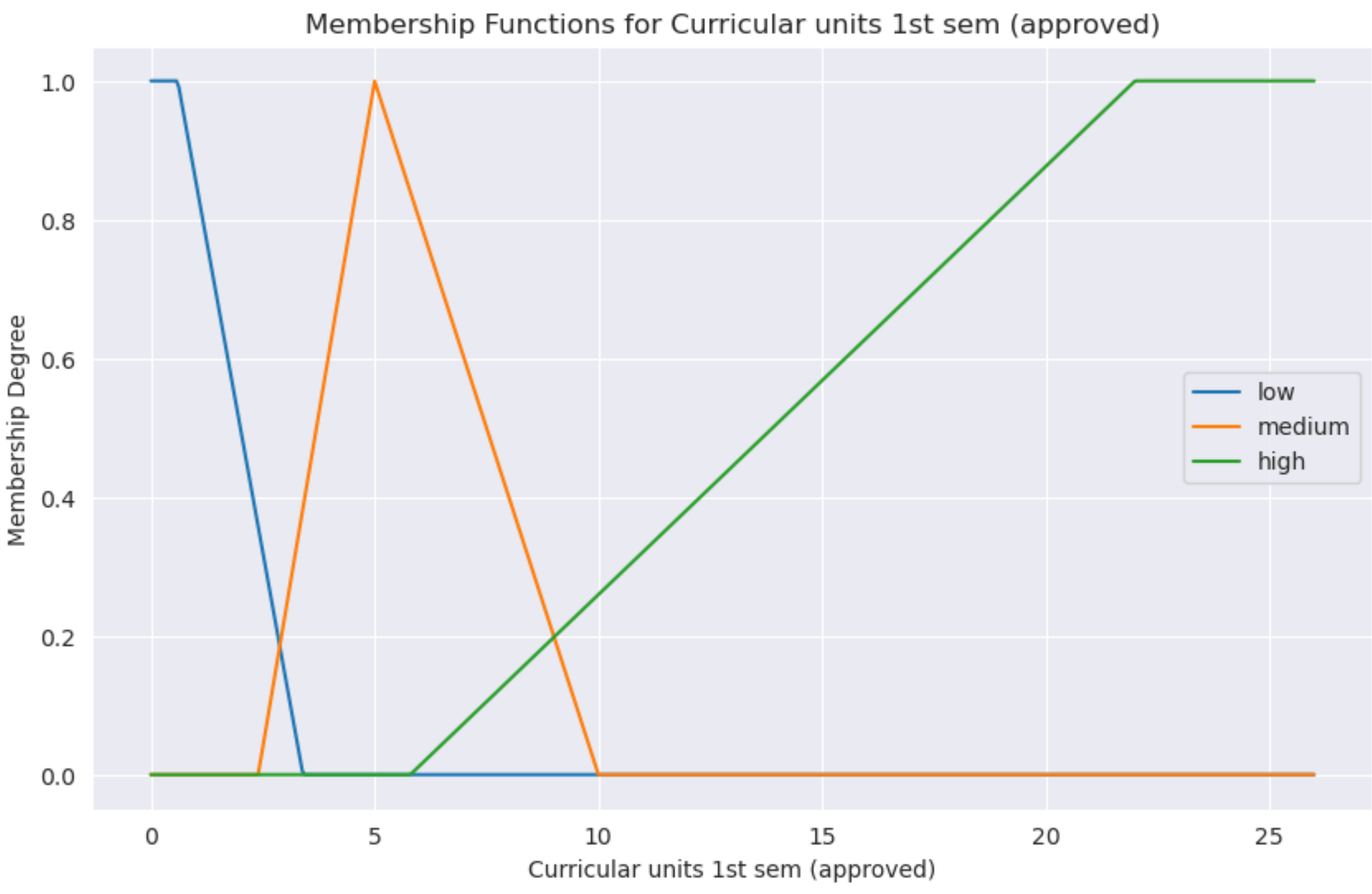
In [26]:
```
# Plot for two example continuous features
example_features = continuous_features[:5]  # Select first two for demonstration
for feature in example_features:
    fuzzy_sets = define_fuzzy_sets(X_train[feature])
    plot_membership_functions(feature, fuzzy_sets)
    print(f"Membership function plot for {feature} saved as '{feature}_membership.png'")
```



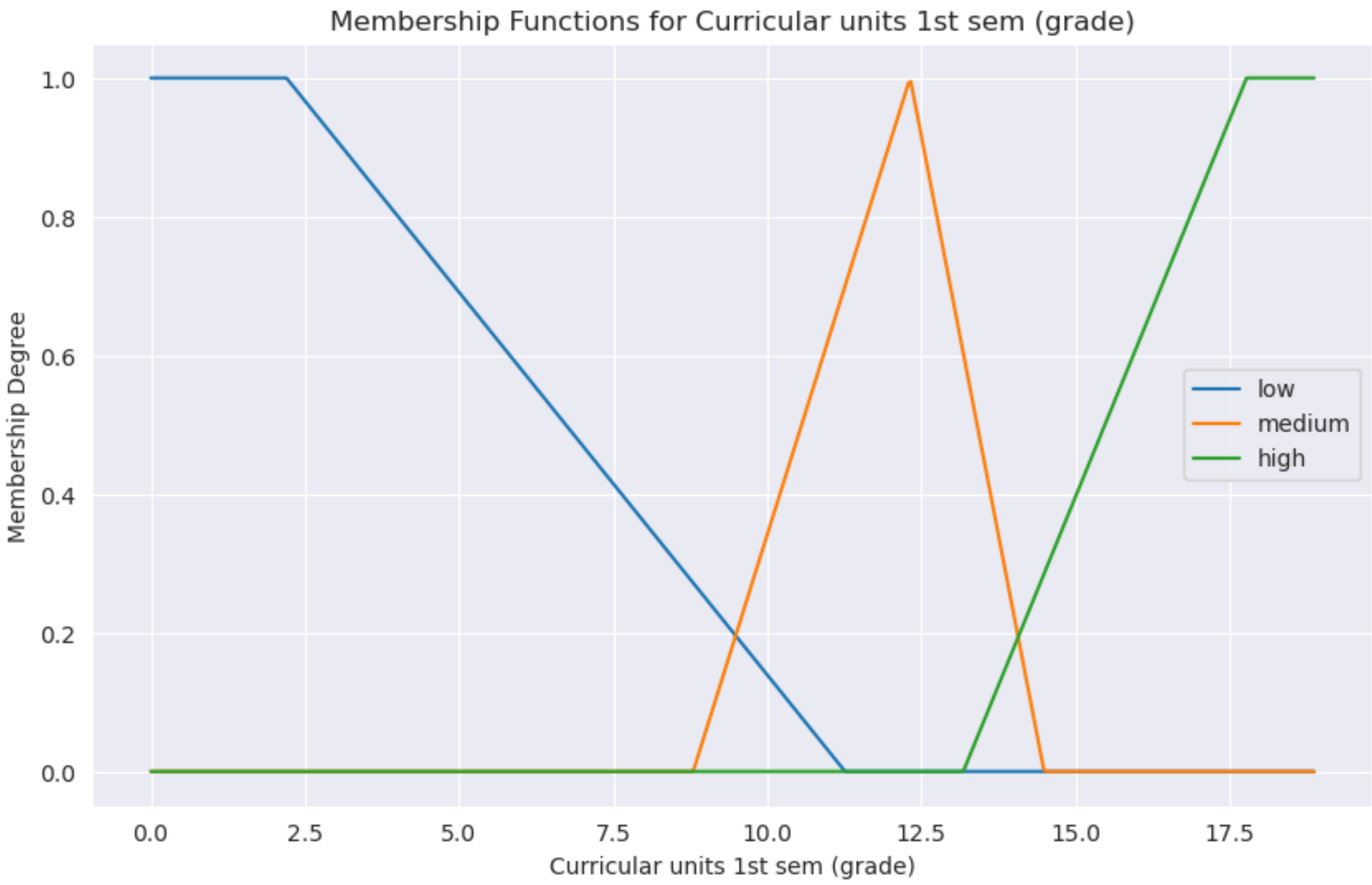

```
Membership function plot for Curricular units 2nd sem (approved) saved as 'Curricular units 2nd sem (approved)_mem
bership.png'
```



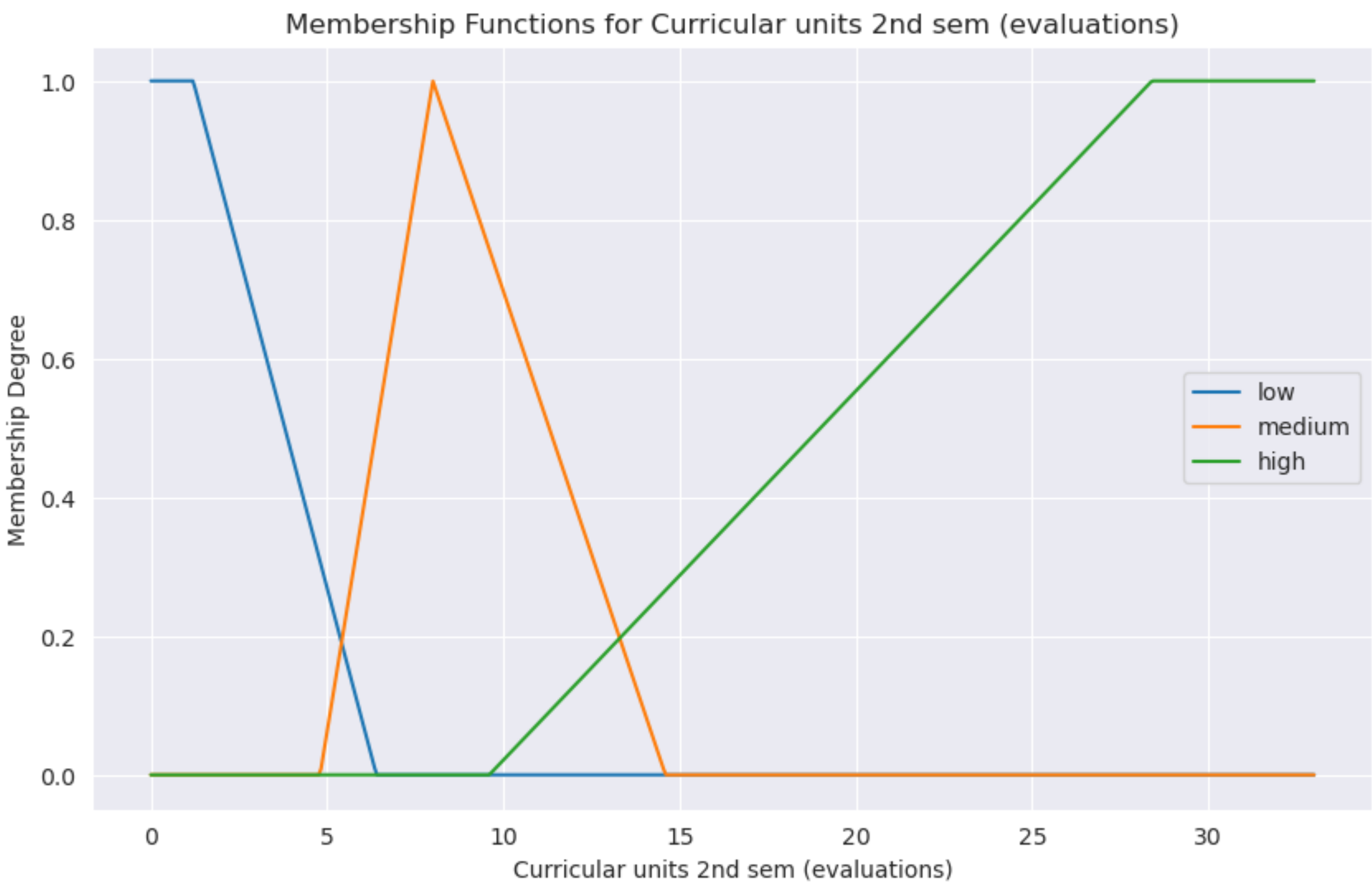

```
Membership function plot for Curricular units 2nd sem (grade) saved as 'Curricular units 2nd sem (grade)_membershi
p.png'
```




```
Membership function plot for Curricular units 1st sem (approved) saved as 'Curricular units 1st sem (approved)_mem
bership.png'
```




```
Membership function plot for Curricular units 1st sem (grade) saved as 'Curricular units 1st sem (grade)_membershi
p.png'
```




```
Membership function plot for Curricular units 2nd sem (evaluations) saved as 'Curricular units 2nd sem (evaluation
s)_membership.png'
```

In [27]:

```python
# Combine all fuzzified features into a single DataFrame
fuzzy_X_train = pd.concat(
    [fuzzy_continuous[feat] for feat in continuous_features] +
    [fuzzy_binary[feat] for feat in binary_features],
    axis=1
)

# Save fuzzified training data
fuzzy_X_train.to_csv('fuzzy_X_train.csv', index=False)
print("Fuzzified training data saved as 'fuzzy_X_train.csv'")
```

```
Fuzzified training data saved as 'fuzzy_X_train.csv'
```

Fuzzy Rule Extraction

In [28]:
```python
# Load Fuzzified Data and Target Variable
fuzzy_X_train = pd.read_csv('fuzzy_X_train.csv')
train_data = pd.read_csv('train_data.csv')
y_train = train_data['Target']
fuzzy_X_train
```

Out[28]:

	Curricular units 2nd sem (approved)_low	Curricular units 2nd sem (approved)_medium	Curricular units 2nd sem (approved)_high	Curricular units 2nd sem (grade)_low	Curricular units 2nd sem (grade)_medium	Curricular units 2nd sem (grade)_high	Curricular units 1st sem (approved)_low	Curricular units 1st sem (approved)_medium	Curr (appr
0	0.0	0.000000	0.368421	0.000000	0.888268	0.000000	0.0	0.000000	
1	1.0	0.000000	0.000000	1.000000	0.000000	0.000000	1.0	0.000000	
2	0.0	0.705882	0.000000	0.062886	0.525140	0.000000	0.0	0.615385	
3	0.0	0.736842	0.017544	0.000000	0.709607	0.000000	0.0	0.800000	
4	0.0	0.473684	0.105263	0.000000	0.000000	0.367831	0.0	0.600000	
...	...	...	...	...	...	...	...	...	
3534	0.0	0.000000	0.368421	0.000000	0.724891	0.000000	0.0	0.000000	
3535	0.0	0.736842	0.017544	0.000000	0.002729	0.287139	0.0	0.800000	
3536	0.0	0.000000	0.368421	0.000000	0.724891	0.000000	0.0	0.000000	
3537	1.0	0.000000	0.000000	1.000000	0.000000	0.000000	1.0	0.000000	
3538	0.0	1.000000	0.000000	0.000000	0.633188	0.000000	0.0	0.800000	

3539 rows × 43 columns

In [29]:
```python
# Optimized rule extraction
def extract_rules(fuzzy_X, y):
    features = {col.split('_')[0] for col in fuzzy_X.columns if col.endswith(('_low', '_medium', '_high'))}
    rules, antecedent_set = [], set()

    for i in range(len(fuzzy_X)):
        antecedent = [(feat, fuzzy_X.iloc[i][[f"{feat}_low", f"{feat}_medium", f"{feat}_high"]].idxmax().split('_')
                      for feat in features]
        antecedent_tuple = tuple(antecedent)
        if antecedent_tuple not in antecedent_set:
            antecedent_set.add(antecedent_tuple)
            rules.append((antecedent, y[i]))

    rule_weights = {}
    for antecedent, consequent in rules:
        match_mask = np.all([fuzzy_X[f"{feat}_{label}"] > 0 for feat, label in antecedent], axis=0)
        match_indices = np.where(match_mask)[0]
        confidence = np.sum(y[match_indices] == consequent) / len(match_indices) if len(match_indices) > 0 else 0
        rule_weights[(tuple(antecedent), consequent)] = confidence

    strongest_rules = [(rule, weight) for rule, weight in
                       {tuple(ant): max([(r, w) for r, w in rule_weights.items() if tuple(r[0]) == tuple(ant)], key=
                        for ant in set(tuple(r[0]) for r in rule_weights)}.values() if weight > 0]

    return [r for r, _ in strongest_rules]
```

In [30]:
```python
# Validate input
if not any(col.endswith(('_low', '_medium', '_high')) for col in fuzzy_X_train.columns):
    raise ValueError("No valid columns found.")
if len(fuzzy_X_train) != len(y_train):
    raise ValueError("Data length mismatch.")
```

In [31]:
```python
# Generate candidate rules
features = {col.split('_')[0] for col in fuzzy_X_train.columns if col.endswith(('_low', '_medium', '_high'))}
rules = []
antecedent_set = set()  # To track unique antecedents
for i in range(len(fuzzy_X_train)):
    antecedent = []
    for feat in features:
        memberships = fuzzy_X_train.iloc[i][[f"{feat}_low", f"{feat}_medium", f"{feat}_high"]]
        max_label = memberships.idxmax().split('_')[-1]
        antecedent.append((feat, max_label))
    antecedent_tuple = tuple(antecedent)
    if antecedent_tuple not in antecedent_set:  # Avoid duplicate antecedents
        antecedent_set.add(antecedent_tuple)
        rules.append((antecedent, y_train[i]))
```

In [32]:
```python
# Calculate confidence weights for each rule.
rule_weights = {}
for antecedent, consequent in rules:
    # Create a mask for rows matching the antecedent
    match_mask = np.ones(len(fuzzy_X_train), dtype=bool)
    for feat, label in antecedent:
        match_mask &= fuzzy_X_train[f"{feat}_{label}"] > 0

    match_indices = np.where(match_mask)[0]
    if len(match_indices) > 0:
        correct_matches = np.sum(y_train.iloc[match_indices] == consequent)
        confidence = correct_matches / len(match_indices)
    else:
        confidence = 0

    rule_key = (tuple(antecedent), consequent)
    rule_weights[rule_key] = confidence

print("Calculated confidence weights for candidate rules.")
```

```
Calculated confidence weights for candidate rules.
```

In [33]:
```python
# Select the rule with the highest confidence for each unique antecedent.
antecedent_dict = {}
for rule, weight in rule_weights.items():
    antecedent, consequent = rule
    antecedent_key = tuple(antecedent)
    if antecedent_key not in antecedent_dict or weight > antecedent_dict[antecedent_key][1]:
        antecedent_dict[antecedent_key] = (rule, weight)
strongest_rules = [rule for rule, weight in antecedent_dict.values() if weight > 0]  # Filter low-confidence rules

print(f"Selected {len(strongest_rules)} strongest rules.")
```

```
Selected 818 strongest rules.
```

Rule Selection Using Genetic Algorithm (GA)

In [34]:
```python
# Initialize Population
num_rules = len(strongest_rules)

def initialize_population(pop_size, num_rules):
    return np.random.randint(2, size=(pop_size, num_rules))

pop_size = 200
population = initialize_population(pop_size, num_rules)
print(f"Initialized population with {pop_size} individuals.")
```

```
Initialized population with 200 individuals.
```

In [35]:
```python
# Define Fitness Function
def predict_with_rules(selected_rules, fuzzy_X):
    """Vectorized prediction using selected rules."""
    y_pred = np.full(len(fuzzy_X), y_train.iloc[0])  # Default prediction
    max_confidences = np.zeros(len(fuzzy_X))

    for rule in selected_rules:
        antecedent, consequent = rule
        # Compute confidence for all rows at once
        confidences = np.ones(len(fuzzy_X))
        for feat, label in antecedent:
            confidences *= fuzzy_X[f"{feat}_{label}"].to_numpy()
        # Update predictions where confidence is higher
        mask = confidences > max_confidences
        y_pred[mask] = consequent
        max_confidences[mask] = confidences[mask]

    return y_pred

def fitness_function(chromosome, rules, fuzzy_X, y):
    selected_rules = [rules[i] for i in range(len(rules)) if chromosome[i] == 1]
    if not selected_rules:
        return 0
    y_pred = predict_with_rules(selected_rules, fuzzy_X)
    accuracy = np.mean(y_pred == y)
    penalty = len(selected_rules) / num_rules
    return accuracy - 0.1 * penalty
```

In [36]:
```python
# Define GA Operations
def selection(population, fitnesses, num_parents):
    fitnesses = np.array(fitnesses)  # Convert fitnesses to NumPy array
    parents = []
    for _ in range(num_parents):
        tournament = np.random.choice(len(population), size=5, replace=False)
        best_idx = tournament[np.argmax(fitnesses[tournament])]
        parents.append(population[best_idx])
    return np.array(parents)


def crossover(parents, offspring_size):
    offspring = []
    for _ in range(offspring_size):
        parent1, parent2 = parents[np.random.choice(len(parents), size=2, replace=False)]
        if len(parent1) <= 2:
            offspring.append(parent1.copy())
            continue
        crossover_point = np.random.randint(1, len(parent1))
        child = np.concatenate((parent1[:crossover_point], parent2[crossover_point:]))
        offspring.append(child)
    return np.array(offspring)


def mutation(offspring, mutation_rate=0.1):
    mask = np.random.random(offspring.shape) < mutation_rate
    offspring[mask] = 1 - offspring[mask]
    return offspring
```

In [37]:
```python
# Run Genetic Algorithm
num_generations = 30
num_parents = pop_size // 2
offspring_size = pop_size - num_parents
fitnesses = np.zeros(num_generations)
for generation in range(num_generations):
    fitnesses = [fitness_function(ind, strongest_rules, fuzzy_X_train, y_train) for ind in population]
    parents = selection(population, fitnesses, num_parents)
    offspring = crossover(parents, offspring_size)
    offspring = mutation(offspring)
    population = np.vstack((parents, offspring))
    best_fitness = max(fitnesses)
    print(f"Generation {generation + 1}: Best Fitness = {best_fitness:.5f}")

best_idx = np.argmax(fitnesses)
best_chromosome = population[best_idx]
```

```
Generation 1: Best Fitness = 0.59441
Generation 2: Best Fitness = 0.59911
Generation 3: Best Fitness = 0.59948
Generation 4: Best Fitness = 0.60260
Generation 5: Best Fitness = 0.60260
Generation 6: Best Fitness = 0.61239
Generation 7: Best Fitness = 0.61239
Generation 8: Best Fitness = 0.61239
Generation 9: Best Fitness = 0.61239
Generation 10: Best Fitness = 0.61656
Generation 11: Best Fitness = 0.61656
Generation 12: Best Fitness = 0.61656
Generation 13: Best Fitness = 0.61663
Generation 14: Best Fitness = 0.61663
Generation 15: Best Fitness = 0.61740
Generation 16: Best Fitness = 0.62264
Generation 17: Best Fitness = 0.62264
Generation 18: Best Fitness = 0.62264
Generation 19: Best Fitness = 0.62264
Generation 20: Best Fitness = 0.62264
Generation 21: Best Fitness = 0.62264
Generation 22: Best Fitness = 0.62338
Generation 23: Best Fitness = 0.62390
Generation 24: Best Fitness = 0.62390
Generation 25: Best Fitness = 0.62393
Generation 26: Best Fitness = 0.62393
Generation 27: Best Fitness = 0.62505
Generation 28: Best Fitness = 0.62593
Generation 29: Best Fitness = 0.62593
Generation 30: Best Fitness = 0.62593
```

In [55]:
```python
# Select best rules
selected_rules = [strongest_rules[i] for i in range(len(strongest_rules)) if best_chromosome[i] == 1]
```

Fuzzy Inference for Classification

In [39]:
```python
# Load test data
test_data = pd.read_csv('test_data.csv')
X_test = test_data.drop('Target', axis=1)
y_test = test_data['Target']
```

In [40]:
```
# Load training data to recompute fuzzy set parameters (from original training data)
train_data_original = pd.read_csv('train_data.csv')
X_train_original = train_data_original.drop('Target', axis=1)

# Define fuzzy sets for test data using TRAINING parameters
continuous_features = [col for col in X_train_original.columns if X_train_original[col].nunique() > 2]
feature_fuzzy_params = {}
for feature in continuous_features:
    feature_fuzzy_params[feature] = define_fuzzy_sets(X_train_original[feature])
```

In [41]:
```
# Fuzzify test data
fuzzy_X_test_list = []
for feature in continuous_features:
    fuzzy_sets = feature_fuzzy_params[feature]
    fuzzified = fuzzify_continuous(X_test[feature], fuzzy_sets)
    fuzzy_X_test_list.append(fuzzified)
```

In [42]:
```
# Handle binary features
binary_features = [col for col in X_test.columns if X_test[col].nunique() == 2]
for feature in binary_features:
    fuzzified = fuzzify_binary(X_test[feature])
    fuzzy_X_test_list.append(fuzzified)

fuzzy_X_test = pd.concat(fuzzy_X_test_list, axis=1)
```

In [43]:
```
# Align columns to match training (ensure same order/columns)
fuzzy_X_train_columns = pd.read_csv('fuzzy_X_train.csv').columns
fuzzy_X_test = fuzzy_X_test.reindex(columns=fuzzy_X_train_columns, fill_value=0)

# Select rules using best_chromosome from GA
selected_rules = [strongest_rules[i] for i in range(len(strongest_rules)) if best_chromosome[i] == 1]

# Predict using selected rules
y_pred = predict_with_rules(selected_rules, fuzzy_X_test)
```

In [44]:
```
# Save predictions
test_results = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
test_results.to_csv('test_predictions.csv', index=False)
print("Test predictions saved to 'test_predictions.csv'.")
```

```
Test predictions saved to 'test_predictions.csv'.
```

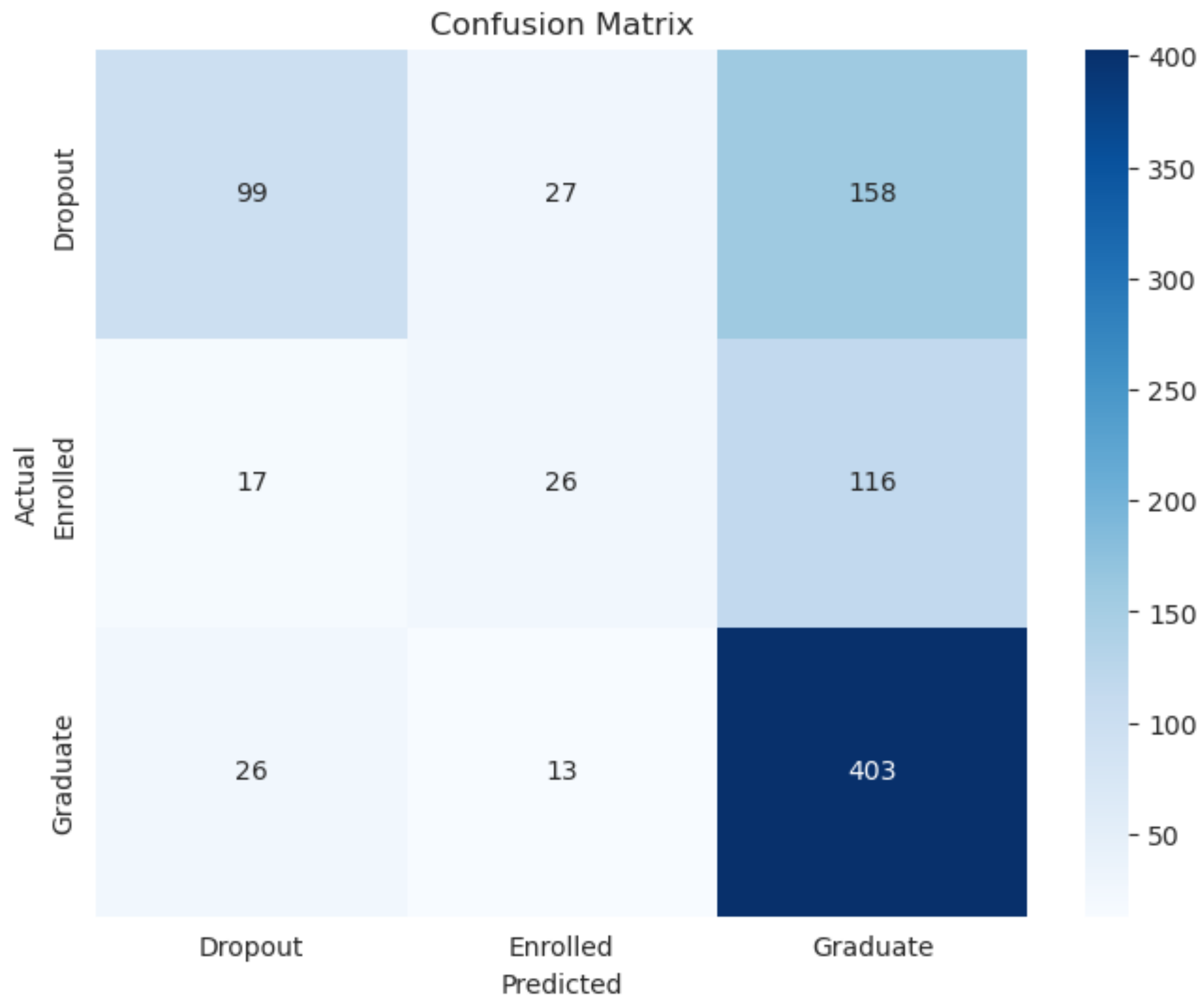
Model Evaluation

In [45]:
```
# Load predictions
test_results = pd.read_csv('test_predictions.csv')
y_test = test_results['Actual']
y_pred = test_results['Predicted']
```

In [46]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, confusion_matrix

# Calculate metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred, average='weighted')
recall = recall_score(y_test, y_pred, average='weighted')
f1 = f1_score(y_test, y_pred, average='weighted')

print("Evaluation Metrics:")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")
```

```
Evaluation Metrics:
Accuracy: 0.5966
Precision: 0.5918
Recall: 0.5966
F1 Score: 0.5504
```

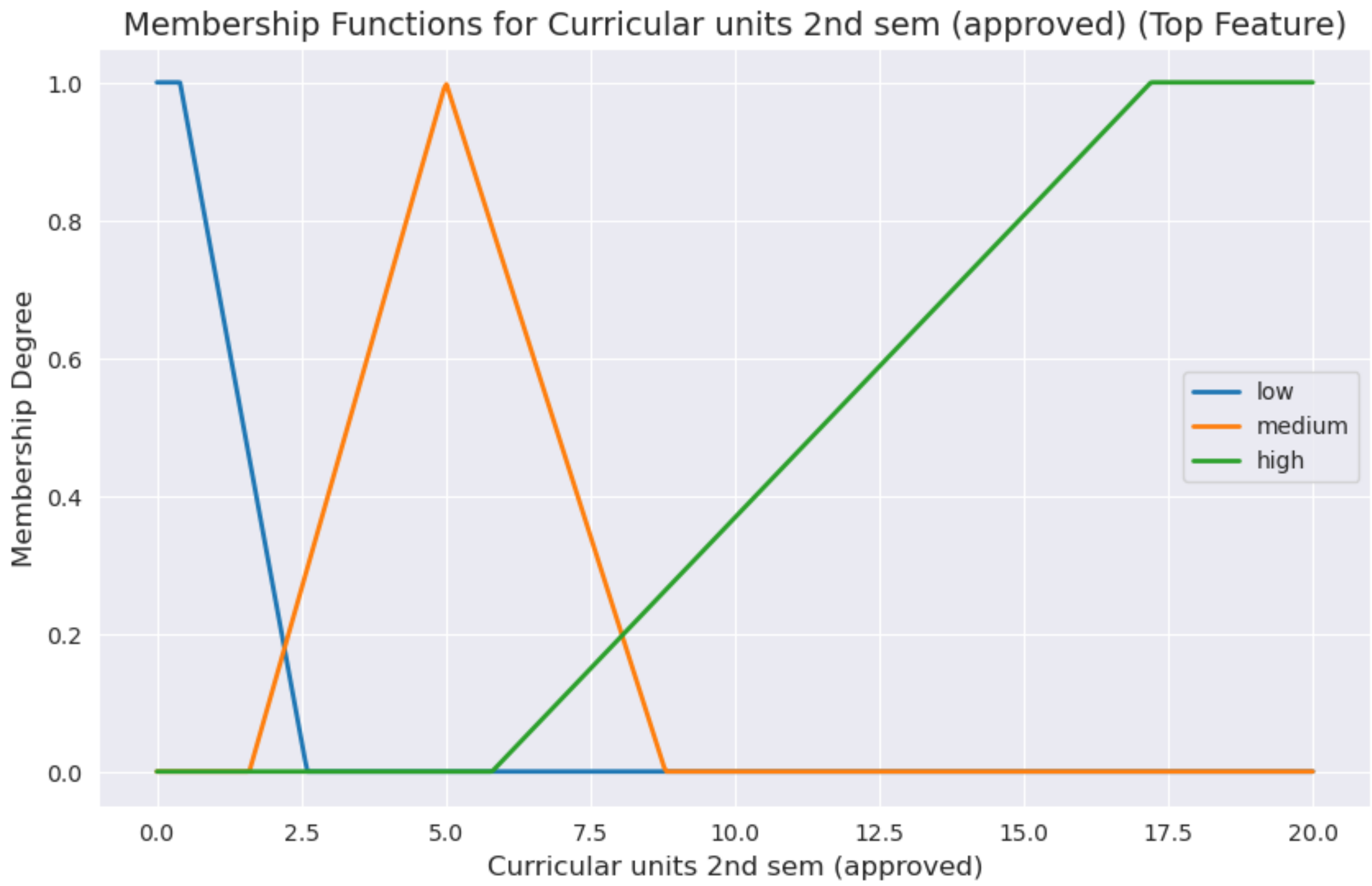
In [47]:
```
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
            xticklabels=label_encoder.classes_,
            yticklabels=label_encoder.classes_)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Class Imbalance Analysis
class_dist = train_data['Target'].value_counts(normalize=True)
print("\nClass Distribution (Training Data):")
print(class_dist)
```




```
Class Distribution (Training Data):
Target
2    0.499294
0    0.321277
1    0.179429
Name: proportion, dtype: float64
```

Interpretation and Visualization

In [48]:
```
# Plot fuzzy membership functions for the most important continuous feature
top_feature = mi_df.sort_values('MI Score', ascending=False).iloc[0]['Feature']
if top_feature in continuous_features:
    fuzzy_sets = feature_fuzzy_params[top_feature]
    x = np.linspace(X_train[top_feature].min(), X_train[top_feature].max(), 500)
    plt.figure(figsize=(10, 6))
    for label, params in fuzzy_sets.items():
        a, b, c, boundary = params
        y = [triangular_membership(val, a, b, c, boundary) for val in x]
        plt.plot(x, y, label=label, linewidth=2)
    plt.title(f'Membership Functions for {top_feature} (Top Feature)', fontsize=14)
    plt.xlabel(top_feature, fontsize=12)
    plt.ylabel('Membership Degree', fontsize=12)
    plt.legend(fontsize=10)
    plt.grid(True)
    plt.show()
```


Membership Functions for Curricular units 2nd sem (approved) (Top Feature)
Membership Degree
Curricular units 2nd sem (approved)
low
medium
high
0.0
0.2
0.4
0.6
0.8
1.0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

In [49]:
```python
# Improved rule activation visualization using a heatmap
# Parameters
num_samples = min(10, len(fuzzy_X_test))
activation_threshold = 0.5  # Minimum activation to consider a rule significant

# Compute activations with normalization
activations = np.zeros((num_samples, len(selected_rules)))
consequents = [rule[1] for rule in selected_rules]
for i in range(num_samples):
    sample = fuzzy_X_test.iloc[i]
    for j, rule in enumerate(selected_rules):
        antecedent, _ = rule
        confidence = 1.0
        for feat, label in antecedent:
            confidence *= sample[f"{feat}_{label}"]
        activations[i, j] = confidence
    # Normalize activations per sample to sum to 1 (if sum > 0)
    row_sum = np.sum(activations[i])
    if row_sum > 0:
        activations[i] = activations[i] / row_sum

# Filter rules with significant activation
significant_rule_indices = np.where(np.max(activations, axis=0) >= activation_threshold)[0]
if len(significant_rule_indices) == 0:
    print("No rules with activation above threshold. Showing top 5 rules by max activation.")
    significant_rule_indices = np.argsort(np.max(activations, axis=0))[-5:]

# Subset activations and consequents for significant rules
activations_filtered = activations[:, significant_rule_indices]
consequents_filtered = [consequents[i] for i in significant_rule_indices]

# Plot heatmap
plt.figure(figsize=(max(8, len(significant_rule_indices) * 0.5), 8))
sns.heatmap(
    activations_filtered,
    cmap='YlOrRd',
    annot=True,
    fmt='.2f',
    xticklabels=[f'R{j+1} ({label_encoder.inverse_transform([c])[0]})' for j, c in zip(significant_rule_indices, co
    yticklabels=[f'Sample {i+1}' for i in range(num_samples)]
)
plt.title('Normalized Rule Activation Heatmap for Test Samples', fontsize=14)
plt.xlabel('Rule (Consequent)', fontsize=12)
plt.ylabel('Test Sample', fontsize=12)
plt.tight_layout()
plt.savefig('rule_activation_heatmap_normalized.png')
plt.close()
print("Normalized rule activation heatmap saved as 'rule_activation_heatmap_normalized.png'")

# --- Visualize Rule Contributions to Predictions ---

# Predict classes for the samples
y_pred_samples = predict_with_rules(selected_rules, fuzzy_X_test.iloc[:num_samples])

# Compute contributions of each class per sample
class_contributions = np.zeros((num_samples, len(label_encoder.classes_)))
for i in range(num_samples):
    sample = fuzzy_X_test.iloc[i]
    for j, rule in enumerate(selected_rules):
        antecedent, consequent = rule
        confidence = 1.0
        for feat, label in antecedent:
            confidence *= sample[f"{feat}_{label}"]
        class_contributions[i, consequent] += confidence

# Normalize contributions per sample
for i in range(num_samples):
    row_sum = np.sum(class_contributions[i])
    if row_sum > 0:
        class_contributions[i] = class_contributions[i] / row_sum

# Plot class contributions
plt.figure(figsize=(10, 8))
sns.heatmap(
    class_contributions,
    cmap='Blues',
    annot=True,
    fmt='.2f',
    xticklabels=label_encoder.classes_,
    yticklabels=[f'Sample {i+1} (Pred: {label_encoder.inverse_transform([y_pred_samples[i]])[0]})' for i in range(n
)
plt.title('Class Contribution Heatmap for Test Samples', fontsize=14)
plt.xlabel('Predicted Class', fontsize=12)
plt.ylabel('Test Sample (Predicted Class)', fontsize=12)
plt.tight_layout()
plt.show()
```

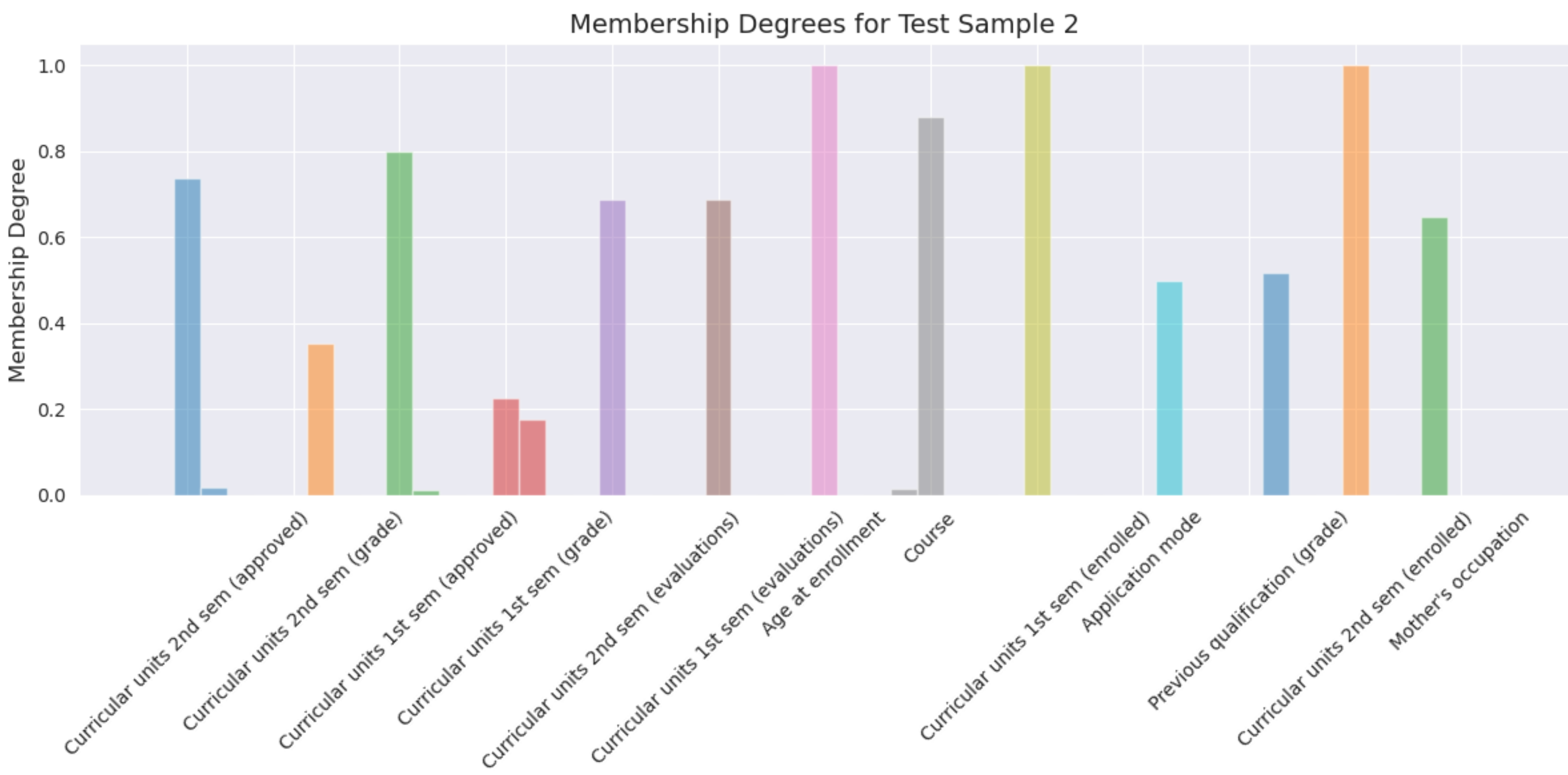
```
Normalized rule activation heatmap saved as 'rule_activation_heatmap_normalized.png'
```

In [50]:

```python
# Visualize inference for a single test sample
sample_idx = 1
sample = fuzzy_X_test.iloc[0]
feature_memberships = {}
for feat in continuous_features:
    memberships = [sample[f"{feat}_{label}"] for label in ['low', 'medium', 'high']]
    feature_memberships[feat] = memberships

plt.figure(figsize=(12, 6))
for i, (feat, memberships) in enumerate(feature_memberships.items()):
    plt.bar([i*4 + j for j in range(3)], memberships, width=1, label=feat, alpha=0.5)
plt.xticks([i*4 + 1 for i in range(len(feature_memberships))], feature_memberships.keys(), rotation=45)
plt.title(f'Membership Degrees for Test Sample {sample_idx+1}', fontsize=14)
plt.ylabel('Membership Degree', fontsize=12)
plt.tight_layout()
plt.show
```

Out[50]:

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



In [51]:

```
# Interpret key rules
print("Top 5 Rules by Confidence:")
sorted_rules = sorted(selected_rules, key=lambda x: rule_weights[x], reverse=True)[:5]
for idx, (rule, weight) in enumerate(zip(sorted_rules, [rule_weights[r] for r in sorted_rules])):
    antecedent, consequent = rule
    print(f"Rule {idx+1}: IF {' AND '.join([f'{feat} is {label}' for feat, label in antecedent])} THEN {consequent}
```

```
Top 5 Rules by Confidence:
Rule 1: IF Curricular units 2nd sem (grade) is medium AND Curricular units 2nd sem (approved) is medium AND Previo
us qualification (grade) is low AND Curricular units 1st sem (grade) is low AND Curricular units 1st sem (enrolle
d) is low AND Curricular units 1st sem (evaluations) is low AND Curricular units 2nd sem (enrolled) is medium AND
Application mode is high AND Mother's occupation is medium AND Age at enrollment is medium AND Curricular units 2n
d sem (evaluations) is medium AND Course is high AND Curricular units 1st sem (approved) is low THEN 0 (Confidenc
e: 1.00)
Rule 2: IF Curricular units 2nd sem (grade) is low AND Curricular units 2nd sem (approved) is low AND Previous qua
lification (grade) is medium AND Curricular units 1st sem (grade) is medium AND Curricular units 1st sem (enrolle
d) is medium AND Curricular units 1st sem (evaluations) is medium AND Curricular units 2nd sem (enrolled) is mediu
m AND Application mode is medium AND Mother's occupation is low AND Age at enrollment is high AND Curricular units
2nd sem (evaluations) is low AND Course is medium AND Curricular units 1st sem (approved) is medium THEN 0 (Confid
ence: 1.00)
Rule 3: IF Curricular units 2nd sem (grade) is low AND Curricular units 2nd sem (approved) is low AND Previous qua
lification (grade) is high AND Curricular units 1st sem (grade) is low AND Curricular units 1st sem (enrolled) is
low AND Curricular units 1st sem (evaluations) is low AND Curricular units 2nd sem (enrolled) is medium AND Applic
ation mode is medium AND Mother's occupation is medium AND Age at enrollment is low AND Curricular units 2nd sem
(evaluations) is low AND Course is medium AND Curricular units 1st sem (approved) is low THEN 0 (Confidence: 1.00)
Rule 4: IF Curricular units 2nd sem (grade) is medium AND Curricular units 2nd sem (approved) is low AND Previous
qualification (grade) is low AND Curricular units 1st sem (grade) is medium AND Curricular units 1st sem (enrolle
d) is medium AND Curricular units 1st sem (evaluations) is medium AND Curricular units 2nd sem (enrolled) is mediu
m AND Application mode is medium AND Mother's occupation is medium AND Age at enrollment is low AND Curricular uni
ts 2nd sem (evaluations) is low AND Course is medium AND Curricular units 1st sem (approved) is low THEN 0 (Confid
ence: 1.00)
Rule 5: IF Curricular units 2nd sem (grade) is low AND Curricular units 2nd sem (approved) is low AND Previous qua
lification (grade) is high AND Curricular units 1st sem (grade) is low AND Curricular units 1st sem (enrolled) is
medium AND Curricular units 1st sem (evaluations) is low AND Curricular units 2nd sem (enrolled) is medium AND App
lication mode is medium AND Mother's occupation is low AND Age at enrollment is medium AND Curricular units 2nd se
m (evaluations) is low AND Course is medium AND Curricular units 1st sem (approved) is low THEN 0 (Confidence: 1.0
0)
```

In [52]:

```
# import ipywidgets as widgets
# from IPython.display import display, clear_output
#
# feature_dropdown = widgets.Dropdown(
#     options=continuous_features,
#     description='Feature:',
#     layout=widgets.Layout(width='60%')
# )
# out_membership = widgets.Output()
#
# def on_feature_change(change):
#     if change['name'] == 'value':
#         feature = change['new']
#         with out_membership:
#             clear_output(wait=True)
#             # Plot membership functions
#             x = np.linspace(
#                 X_train_original[feature].min(),
#                 X_train_original[feature].max(),
#                 500
#             )
#             plt.figure(figsize=(6, 4))
#             for label, params in feature_fuzzy_params[feature].items():
#                 a, b, c, boundary = params
#                 y = [triangular_membership(val, a, b, c, boundary) for val in x]
#                 plt.plot(x, y, label=label, linewidth=2)
#             plt.title(f"Membership Functions for {feature}")
#             plt.xlabel(feature)
#             plt.ylabel('Membership Degree')
#             plt.grid(True, linestyle='--', alpha=0.01)
#             plt.legend()
#             plt.show()
#
# feature_dropdown.observe(on_feature_change, names='value')
# # Initial display
# on_feature_change({'name': 'value', 'new': feature_dropdown.value})
#
# tab1 = widgets.VBox([feature_dropdown, out_membership])
#
# # --- Tab 2: Rule Confidence ---
# rules_df = pd.DataFrame([
#     {
#         'Rule':
#             f"IF {' AND '.join([f'{feat} is {label}' for feat, label in rule[0]])} "
#             f"THEN {label_encoder.inverse_transform([rule[1]])[0]}",
#         'Confidence': rule_weights[(tuple(rule[0]), rule[1])]
#     }
#     for rule in selected_rules
# ])
# rules_df = rules_df.sort_values('Confidence', ascending=False).reset_index(drop=True)
# out_rules = widgets.Output()
#
# def show_top_rules(n=10):
#     with out_rules:
#         clear_output()
#         display(rules_df.head(n))
#
# show_top_rules(10)
#
# tab2 = widgets.VBox([
#     widgets.HTML(value='<b>Top Rules by Confidence</b>'),
#     out_rules
# ], width='100%')
#
# # --- Tab 3: Rule Activation for a Sample ---
# sample_slider = widgets.IntSlider(
#     value=1,
#     min=1,
#     max=min(50, len(fuzzy_X_test)),
#     step=1,
#     description='Sample:',
#     layout=widgets.Layout(width='50%')
# )
# thresh_slider = widgets.FloatSlider(
#     value=0.001,
#     min=0,
#     max=1,
#     step=0.001,
#     description='Thresh:',
#     layout=widgets.Layout(width='50%')
# )
# out_activation = widgets.Output()
#
# def update_activation(change=None):
#     idx = sample_slider.value - 1
#     sample = fuzzy_X_test.iloc[idx]
#     # Compute activations per rule
#     activations = []
#     for rule in selected_rules:
#         antecedent, _ = rule
#         conf = 1.0
```

```python
#         for feat, label in antecedent:
#             conf *= sample[f"{feat}_{label}"]
#         activations.append(conf)
#     # Prepare DataFrame
#     act_arr = np.array(activations)
#     df_act = pd.DataFrame({
#         'Rule': [f'R{i+1}' for i in range(len(selected_rules))],
#         'Activation': act_arr
#     })
#     # Filter by threshold
#     df_act = df_act[df_act['Activation'] >= thresh_slider.value]
#     df_act = df_act.sort_values('Activation', ascending=False).reset_index(drop=True)
#
#     with out_activation:
#         clear_output(wait=True)
#         display(df_act)
#
# sample_slider.observe(update_activation, names='value')
# thresh_slider.observe(update_activation, names='value')
# update_activation()
#
# tab3 = widgets.VBox([widgets.HBox([sample_slider, thresh_slider]), out_activation])
#
# # --- Assemble Tabs ---
# tabs = widgets.Tab([tab1, tab2, tab3])
# tabs.set_title(0, 'Membership')
# tabs.set_title(1, 'Rules')
# tabs.set_title(2, 'Activation')
#
# display(tabs)
```

In [53]:

```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC

# Comparison with Alternative Models
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X_train, y_train)
y_pred_dt = dt.predict(X_test)
accuracy_dt = accuracy_score(y_test, y_pred_dt)
precision_dt = precision_score(y_test, y_pred_dt, average='weighted')
recall_dt = recall_score(y_test, y_pred_dt, average='weighted')
f1_dt = f1_score(y_test, y_pred_dt, average='weighted')
print("Decision TreeEvaluation Metrics:")
print(f"Accuracy: {accuracy_dt:.4f}")
print(f"Precision: {precision_dt:.4f}")
print(f"Recall: {recall_dt:.4f}")
print(f"F1 Score: {f1_dt:.4f}")
```

```
Decision TreeEvaluation Metrics:
Accuracy: 0.6847
Precision: 0.6912
Recall: 0.6847
F1 Score: 0.6877
```

In [54]:

```python
svm = SVC(class_weight='balanced')
svm.fit(X_train, y_train)
y_pred_svm = svm.predict(X_test)
accuracy_svm = accuracy_score(y_test, y_pred_svm)
precision_svm = precision_score(y_test, y_pred_svm, average='weighted', zero_division=0)
recall_svm = recall_score(y_test, y_pred_svm, average='weighted', zero_division=0)
f1_svm = f1_score(y_test, y_pred_svm, average='weighted', zero_division=0)
print("\nSVM Evaluation Metrics:")
print(f"Accuracy: {accuracy_svm:.4f}")
print(f"Precision: {precision_svm:.4f}")
print(f"Recall: {recall_svm:.4f}")
print(f"F1 Score: {f1_svm:.4f}")
```

```
SVM Evaluation Metrics:
Accuracy: 0.1853
Precision: 0.1538
Recall: 0.1853
F1 Score: 0.0846
```

In [ ]: