DIGITAL FAIR SKILL 35.0
STAR TYPE CLASSIFICATION WITH

K-Nearest Neighbors

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INTRODUCTION

The dataset contains information about various types of stars, including temperature, luminosity, radius, and absolute magnitude.

Research on stars and their classification is essential in astronomy. K-Nearest Neighbors is a machine learning algorithm well-suited for classification tasks.

Objective: To apply the K-Nearest Neighbors algorithm to classify star types based on their characteristics.

LIBRARY IMPORT

```
[ ]  import pandas as pd  # Import the Pandas library for data manipulation and analysis
     import seaborn as sns  # Import the Seaborn library for creating data visualizations such as graphs or charts
     import matplotlib.pyplot as plt  # Import Matplotlib to generate graphs or plot data
     import numpy as np  # Import Numpy for mathematical operations such as arrays and statistical functions
     from scipy.stats import boxcox  # Import the Box-Cox function for data transformation to approximate a normal distribution
     from sklearn.preprocessing import LabelEncoder  # Import LabelEncoder to convert categorical data into numerical values
     from sklearn.model_selection import train_test_split  # Import the function to split data into training and testing sets
     from sklearn.preprocessing import StandardScaler  # Import StandardScaler for data standardization
     from sklearn.neighbors import KNeighborsClassifier  # Import the K-Nearest Neighbors algorithm for classification
     from sklearn.metrics import classification_report  # Import the function to generate a model evaluation report
     from sklearn.metrics import confusion_matrix  # Import the function to create a confusion matrix
```

DATA DESCRIPTION

Displays the last 5 rows and dataset size (number of rows and columns) using data.tail() and data.shape.

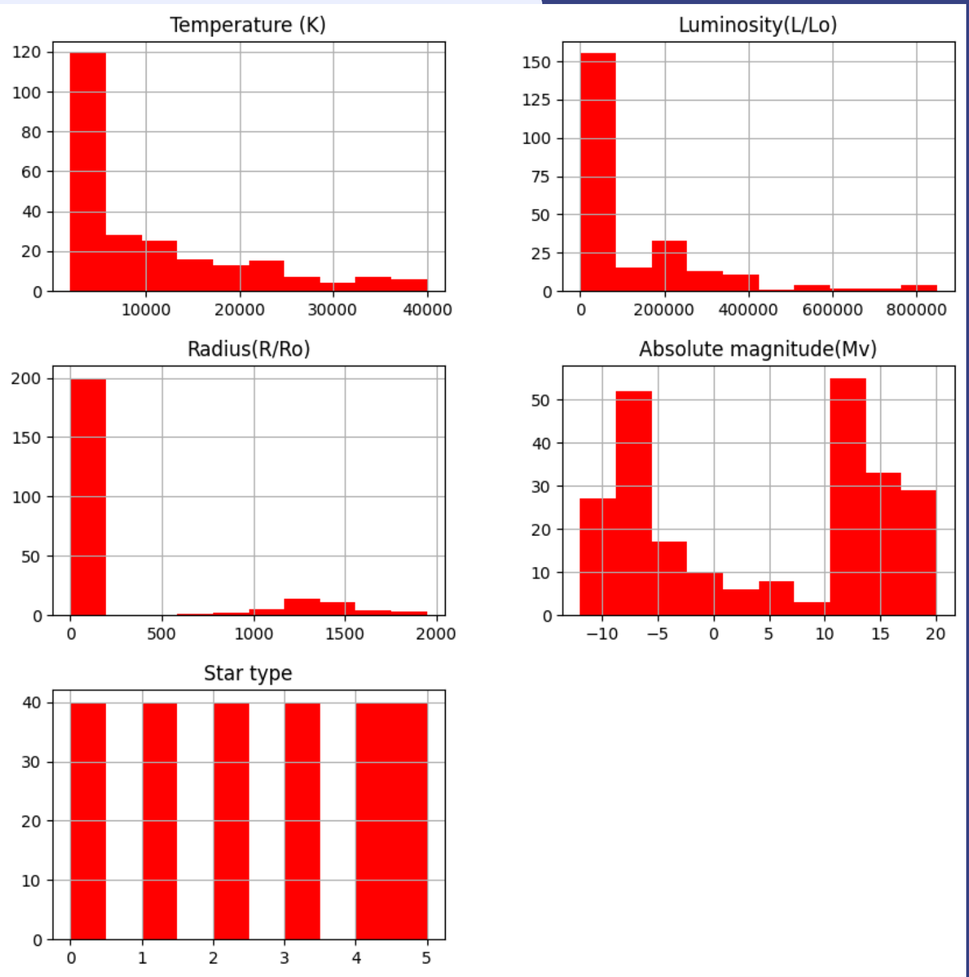
```
[ ]  data = pd.read_csv('/content/6 class csv.csv') # read file csv
     data.tail() # displat the last 5 lines of data
```

	Temperature (K)	Luminosity(L/Lo)	Radius(R/Ro)	Absolute magnitude(Mv)	Star type	Star color	Spectral Class
235	38940	374830.0	1356.0	-9.93	5	Blue	O
236	30839	834042.0	1194.0	-10.63	5	Blue	O
237	8829	537493.0	1423.0	-10.73	5	White	A
238	9235	404940.0	1112.0	-11.23	5	White	A
239	37882	294903.0	1783.0	-7.80	5	Blue	O

```
data.shape # Display the number of rows and columns
```

```
(240, 7)
```

DATA EXPLORATION



DATA VISUALIZATION

1. Histogram: Displays data distribution using data.hist().

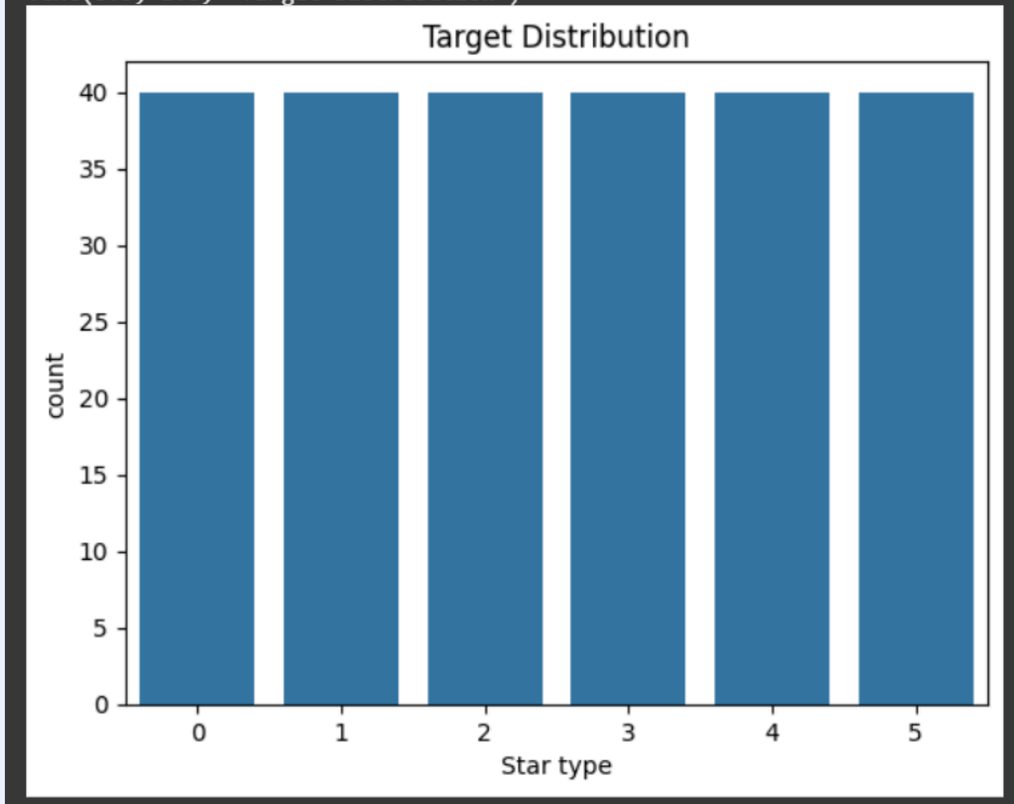
DATA VISUALIZATION

2. Boxplot: Detects outliers in each variable using the boxplot() function.

```
def boxplot(data):
    # Defines a function named 'boxplot' to create boxplots for multiple variables in the DataFrame 'data'

    variables = ['Star type', 'Temperature (K)', 'Luminosity(L/Lo)', 'Radius(R/Ro)', 'Absolute magnitude(Mv)', 'Spectral Class']

    fig, axes = plt.subplots(2, 3, figsize=(10, 5))
    # Creates a 2x3 grid for subplots with a total size of 10x5 inches

    fig.subplots_adjust(hspace=0.4, wspace=0.4)
    # Adjusts the spacing between plots both vertically and horizontally

    for i, var in enumerate(variables):
        row, col = i // 3, i % 3

        sns.boxplot(y=var, data=data, color='green', ax=axes[row, col])
        # Creates a boxplot for the variable 'var' in a specific subplot with the color green

        axes[row, col].set_title(var)
        # Sets the title for each subplot with the variable name

    plt.show()
```

```
# Creating count plot for variabel 'Star type' from DataFrame 'data_shorten'
sns.countplot(x='Star type', data=data_shorten)
plt.title('Target Distribution')
```

```
Text(0.5, 1.0, 'Target Distribution')
```



DATA VISUALIZATION

3 Countplot: Shows the distribution of the target class (star type) using sns.countplot().

DATA CLEANING

1. Removing outliers using the remove_outlier() function.

```
# to clean the data from outliers that can affect the data.
def remove_outlier(data):
  columns = data.select_dtypes(include=['int', 'float']).columns
  cleaned_data = data.copy()
  for column in columns:
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3-Q1
    lower_bound = Q1-1.5*IQR
    upper_bound = Q3+1.5*IQR
    cleaned_data = cleaned_data[(cleaned_data[column]>=lower_bound)&(cleaned_data[column]<=upper_bound)]

  return cleaned_data

data_shorten = remove_outlier(data_shorten)
```

DATA CLEANING

2. Removing missing values and duplicate data using data.dropna() and data.drop_duplicates().

```
[ ]  data = data.dropna()
```

```
[ ]  # remove duplicate data
     data.drop_duplicates(inplace= True)
```

```
     # displays unique data
     data.nunique()
```

	0
Temperature (K)	228
Luminosity(L/Lo)	208
Radius(R/Ro)	216
Absolute magnitude(Mv)	228
Star type	6
Star color	19
Spectral Class	7

dtype: int64

DATA PREPROCESSING

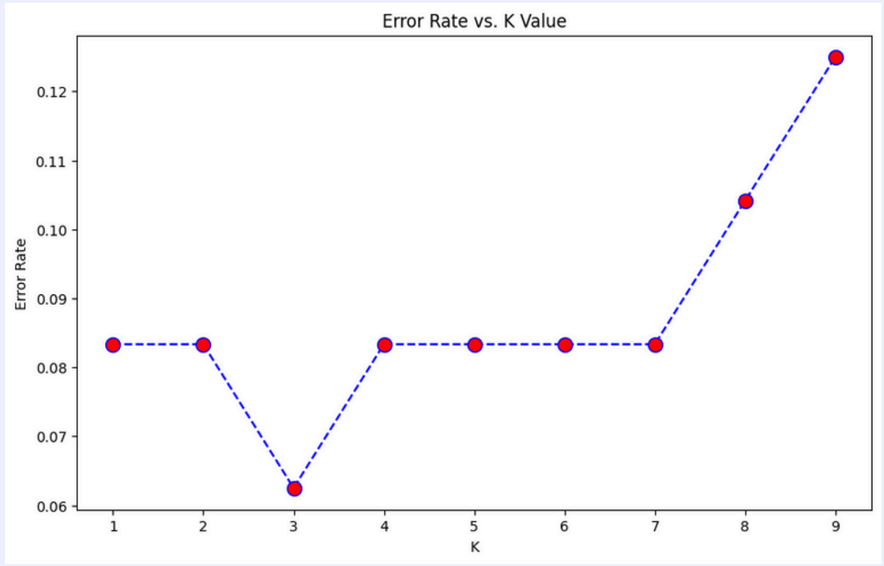
ENCODING

Converts categorical data into numerical values using LabelEncoder for columns such as 'Luminosity', 'Radius', 'Absolute Magnitude', 'Star Color', and 'Spectral Class'.
Standardization: Scales feature data using StandardScaler.
Data Splitting: Splits data into training (80%) and testing (20%) sets using train_test_split.

```
# coding process

le = LabelEncoder()

data['Luminosity(L/Lo)'] = le.fit_transform(data['Luminosity(L/Lo)'])
data['Radius(R/Ro)'] = le.fit_transform(data['Radius(R/Ro)'])
data['Absolute magnitude(Mv)'] = le.fit_transform(data['Absolute magnitude(Mv)'])
data['Star color'] = le.fit_transform(data['Star color'])
data['Spectral Class'] = le.fit_transform(data['Spectral Class'])
```

```
[ ] # separating features (independent variables) from targets (dependent variables)
    X = data.drop(columns='Star type')
    y = data['Star type']

[ ] # feature standardization (scaling the feature data)
    scaler = StandardScaler()
    X = scaler.fit_transform(X)

[ ] # splitting data by dividing 80% train data and 20% testing data
    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# determine the best value for parameter K (number of neighbors)
error_rate = []

for i in range(1,10):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(x_train,y_train)
    pred_i = knn.predict(x_test)
    error_rate.append(np.mean(pred_i != y_test))

plt.figure(figsize=(10,6))
plt.plot(range(1,10),error_rate,color="blue", linestyle="dashed", marker="o",
         markerfacecolor="red", markersize=10)
plt.title("Error Rate vs. K Value")
plt.xlabel("K")
plt.ylabel("Error Rate")
```



MODELING WITH K-NEAREST NEIGHBORS

1. CHOOSING K VALUE

Determines the optimal K value by analyzing error rates using loops and visualization.

2.MODEL TRAINING

Trains the KNN model with the optimal K value using knn.fit().

3.PREDICTION

Makes predictions on test data using knn.predict().

```python
# modeling process
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(x_train, y_train)
y_pred = knn.predict(x_test)
```

```python
# model evaluation
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         8
           1       0.88      1.00      0.93         7
           2       1.00      1.00      1.00         6
           3       0.88      0.88      0.88         8
           4       0.88      0.88      0.88         8
           5       1.00      0.91      0.95        11

    accuracy                           0.94        48
   macro avg       0.94      0.94      0.94        48
weighted avg       0.94      0.94      0.94        48
```

MODEL EVALUATION

1. CLASSIFICATION REPORT

Displays precision, recall, f1-score, and accuracy using classification_report().

2.CONFUSION MATRIX

Visualizes model performance using confusion_matrix() and sns.heatmap().

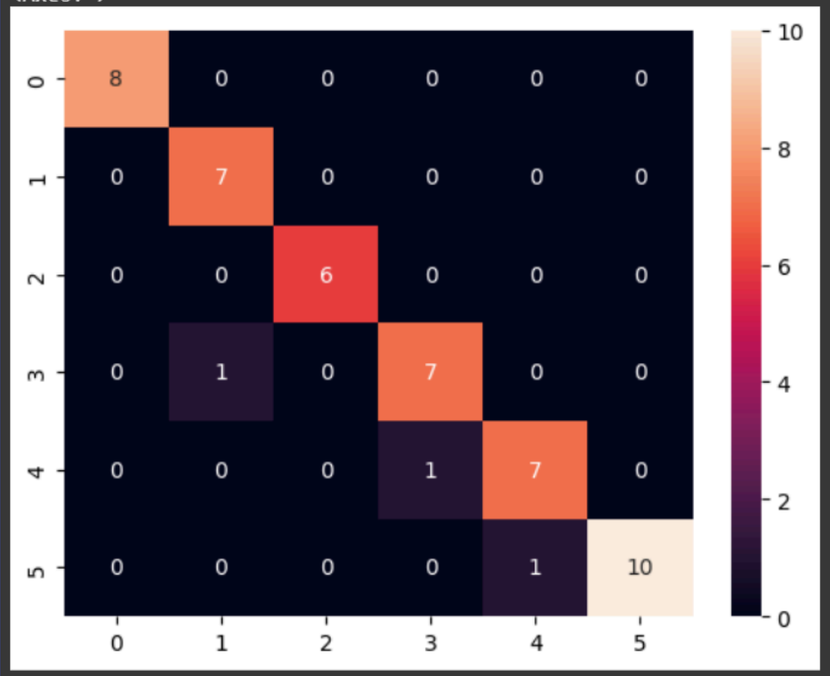
3.PREDICTION

Makes predictions on test data using knn.predict().

MODEL EVALUATION

```
# for calculating matrices and creating heatmaps for clearer visualization
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d')
```

```
<Axes: >
```




```
# to train the model and make predictions
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier(criterion='entropy', random_state=42)

dt.fit(x_train, y_train)

y_pred_dt_entropy = dt.predict(x_test)

print(classification_report(y_test, y_pred_dt_entropy))
```

```
              precision    recall  f1-score   support

           0       1.00      0.88      0.93         8
           1       0.88      1.00      0.93         7
           2       1.00      1.00      1.00         6
           3       1.00      0.88      0.93         8
           4       0.89      1.00      0.94         8
           5       1.00      1.00      1.00        11

    accuracy                           0.96        48
   macro avg       0.96      0.96      0.96        48
weighted avg       0.96      0.96      0.96        48
```

HANDLING DATA IMBALANCE (OVERSAMPLING)

1. SMOTE

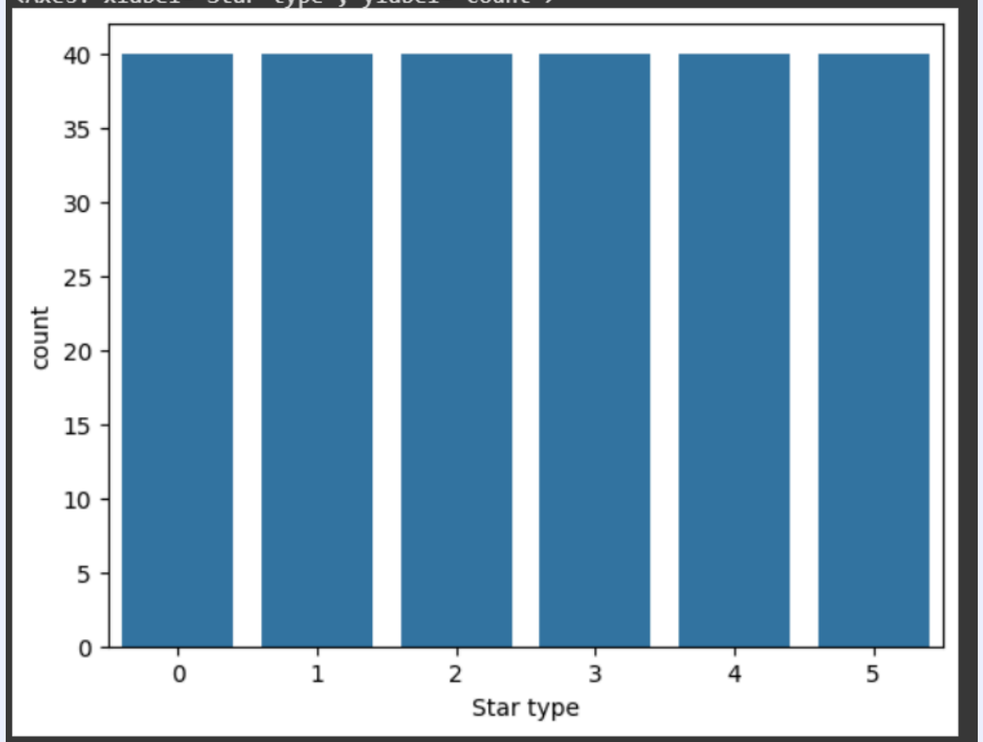
Applies the SMOTE technique to handle class imbalance using SMOTE().

2.MODEL EVALUATION

Retrains and reevaluates the KNN model using the oversampled dataset.

```
#oversampling
from imblearn.over_sampling import SMOTE

sm = SMOTE()
x_sm, y_sm = sm.fit_resample(X, y)

sns.countplot(x=y_sm)
```

```
<Axes: xlabel='Star type', ylabel='count'>
```



HANDLING DATA IMBALANCE (UNDERSAMPLING)

1. NEARMISS

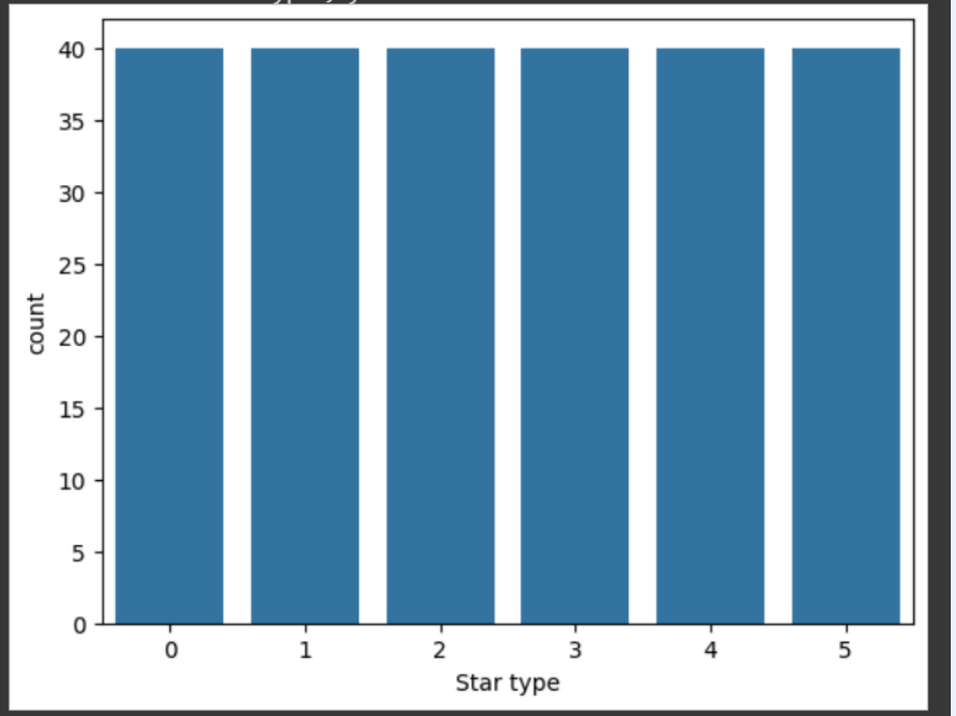
Applies the NearMiss undersampling technique using NearMiss().

2.MODEL EVALUATION

Retrains and reevaluates the KNN model using the undersampled dataset.

```
#Undersampling
from imblearn.under_sampling import NearMiss

nr = NearMiss()
x_nr, y_nr = nr.fit_resample(X, y)

sns.countplot(x=y_nr)
```

```
<Axes: xlabel='Star type', ylabel='count'>
```



DECISION TREE

1. MODELING WITH DECISION TREE

Trains a Decision Tree model using Gini and Entropy criteria.

2.MODEL EVALUATION

Evaluates the Decision Tree model using a classification report.

```
# to train the model and make predictions using 'DecisionTreeClassifier'
from sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier(criterion='gini', random_state=42)
dt.fit(x_train, y_train)
y_pred_dt_gini = dt.predict(x_test)
print(classification_report(y_test, y_pred_dt_gini))
```

```
              precision    recall  f1-score   support

           0       1.00      0.88      0.93         8
           1       0.88      1.00      0.93         7
           2       1.00      1.00      1.00         6
           3       1.00      0.88      0.93         8
           4       0.89      1.00      0.94         8
           5       1.00      1.00      1.00        11

    accuracy                           0.96        48
   macro avg       0.96      0.96      0.96        48
weighted avg       0.96      0.96      0.96        48
```

CONCLUSION

Summarizes the outcomes of KNN modeling, including model performance and the best technique for handling data imbalance.

Provides recommendations for model improvement or future research directions.

THANK YOU