MET Bhujbal Knowledge City, Nashik

DATA MINING AND WAREHOUSING MINI-PROJECT REPORT

SUBMITTED BY

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Contents

Problem Statement

Consider a labeled dataset belonging to an application domain. Apply suitable data preprocessing steps such as handling of null values, data reduction, discretization. For prediction of class labels of given data instances, build classifier models using different techniques (minimum 3), analyze the confusion matrix and compare these models.

Also apply cross validation while preparing the training and testing datasets.

Abstract

Celestial bodies such as stars are classified into categories such as Red Dwarf, Brown Dwarf, White Dwarf, MainSequence , Super Giants, Hyper Giants. This categorisation is based on properties such as size, temperature and contents.

However, categorising these bodies can be quite tedious.Hence, in this assignment, we train different types of machine learning models to categorize these bodies and compare their performance

Star Type Classification :

Dataset consists of the following features:

Temperature -- K

L -- L/Lo (Relative Luminosity)

R -- R/Ro (Relative Radius)

AM -- Mv (Absolute Magnitude)

Color -- General Color of Spectrum

Spectral_Class -- O,B,A,F,G,K,M / SMASS - https://en.wikipedia.org/wiki/Asteroid_spectral_types

Type -- Red Dwarf, Brown Dwarf, White Dwarf, Main Sequence , Super Giants, Hyper Giants

TARGET: Type

from 0 to 5

Red Dwarf - 0 Brown Dwarf - 1 White Dwarf - 2 Main Sequence - 3 Super Giants - 4 Hyper Giants - 5

MATH:

Lo = 3.828 x 10^26 Watts (Avg Luminosity of Sun)

Ro = 6.9551 x 10^8 m (Avg Radius of Sun)

Datasets :

```
[ ] import pandas as pd
    import numpy as np
    import matplotlib.pyplot as plt
    import seaborn as sns

    %matplotlib inline
```

```
df = pd.read_csv('Stars.csv')
df.head()
```

	Temperature	L	R	A_M	Color	Spectral_Class	Type
0	3068	0.002400	0.1700	16.12	Red	M	0
1	3042	0.000500	0.1542	16.60	Red	M	0
2	2600	0.000300	0.1020	18.70	Red	M	0
3	2800	0.000200	0.1600	16.65	Red	M	0
4	1939	0.000138	0.1030	20.06	Red	M	0

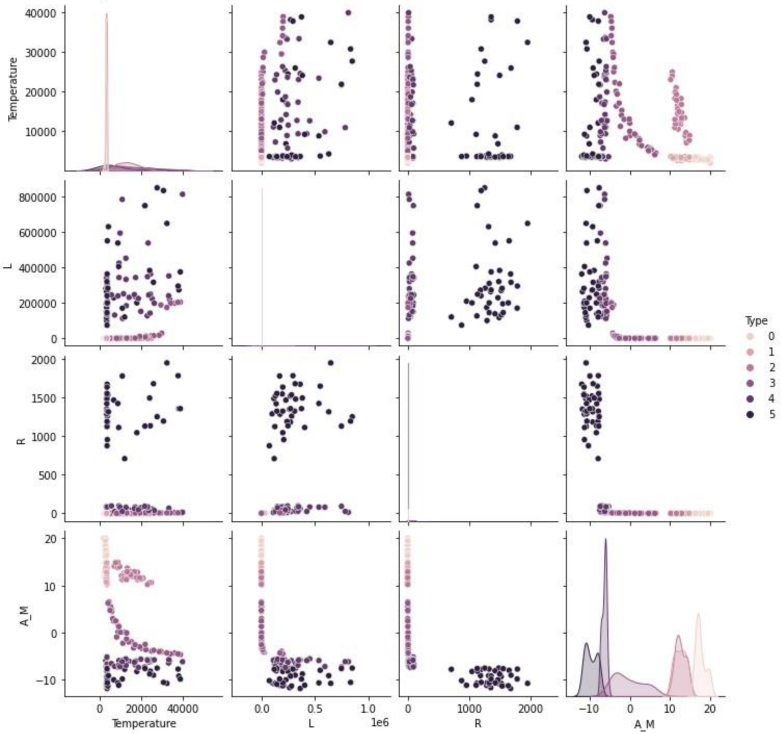
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 240 entries, 0 to 239
Data columns (total 7 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Temperature     240 non-null    int64  
 1   L               240 non-null    float64
 2   R               240 non-null    float64
 3   A_M             240 non-null    float64
 4   Color           240 non-null    object 
 5   Spectral_Class  240 non-null    object 
 6   Type            240 non-null    int64  
dtypes: float64(3), int64(2), object(2)
memory usage: 13.2+ KB
```

Data Visualization :

```
sns.pairplot(df,hue='Type')
```

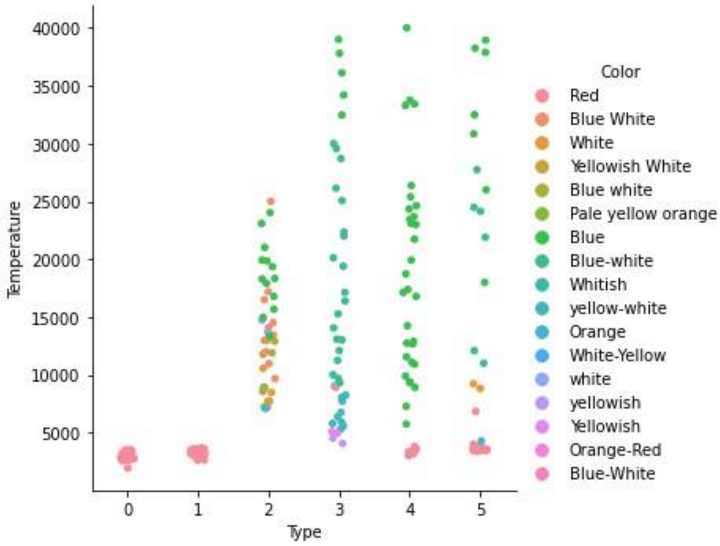
```
<seaborn.axisgrid.PairGrid at 0x7f2882427b90>
```



```
sns.catplot(data=df, x='Type', y='Temperature', hue='Color')

# type 0 and 1 have temperature less than 5000K while other categories are spread over various ranges
# type 3,4,5 can have higher temperature values
# type 2,3,4,5 have temperature >= 5000K
```

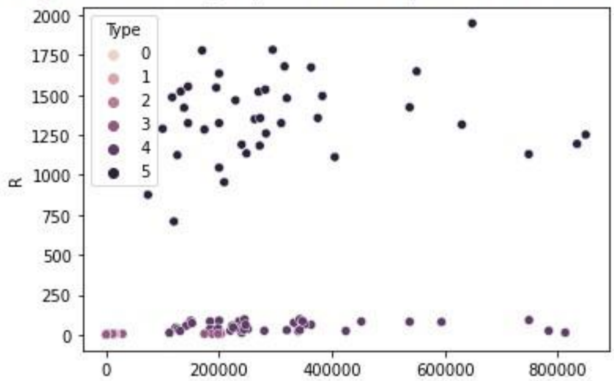
```
<seaborn.axisgrid.FacetGrid at 0x7f2882290d50>
```




```
sns.scatterplot(data=df, x='L',y='R',hue='Type')

#type 5 stars have higher R value
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2874bea250>
```



Preprocessing :

```
[ ] df.describe()
```

	Temperature	L	R	A_M	Type
count	240.000000	240.000000	240.000000	240.000000	240.000000
mean	10497.462500	107188.361635	237.157781	4.382396	2.500000
std	9552.425037	179432.244940	517.155763	10.532512	1.711394
min	1939.000000	0.000080	0.008400	-11.920000	0.000000
25%	3344.250000	0.000865	0.102750	-6.232500	1.000000
50%	5776.000000	0.070500	0.762500	8.313000	2.500000
75%	15055.500000	198050.000000	42.750000	13.697500	4.000000
max	40000.000000	849420.000000	1948.500000	20.060000	5.000000

```
[ ] df.head()
    # Rescale : Temperature, L, R, A_M
    # Encode : Color, Spectral_Class
```

	Temperature	L	R	A_M	Color	Spectral_Class	Type
0	3068	0.002400	0.1700	16.12	Red	M	0
1	3042	0.000500	0.1542	16.60	Red	M	0
2	2600	0.000300	0.1020	18.70	Red	M	0
3	2800	0.000200	0.1600	16.65	Red	M	0
4	1939	0.000138	0.1030	20.06	Red	M	0

```
[ ] df['Color'].unique()
```

```
array(['Red', 'Blue White', 'White', 'Yellowish White', 'Blue white',
       'Pale yellow orange', 'Blue', 'Blue-white', 'Whitish',
       'yellow-white', 'Orange', 'White-Yellow', 'white', 'yellowish',
       'Yellowish', 'Orange-Red', 'Blue-White'], dtype=object)
```

```
[ ] #removing typos

    df['Color'] = df['Color'].apply(lambda x:x.lower())
    df['Color'] = df['Color'].str.replace('-',' ')
    df['Color'] = df['Color'].str.replace('ish','')
    df['Color'] = df['Color'].str.replace('pale ','')
    df['Color'] = df['Color'].str.replace('white yellow','yellow white')
    df['Color'] = df['Color'].replace('whit','white')

    df['Color'].unique()
```

```
array(['red', 'blue white', 'white', 'yellow white', 'yellow orange',
       'blue', 'orange', 'yellow', 'orange red'], dtype=object)
```

```
[ ] df['Spectral_Class'].unique()
```

```
array(['M', 'B', 'A', 'F', 'O', 'K', 'G'], dtype=object)
```

```
[ ] #encoding labels

    from sklearn.preprocessing import LabelEncoder

    encoder = LabelEncoder()

    df['Color'] = encoder.fit_transform(df['Color'])
    df['Spectral_Class'] = encoder.fit_transform(df['Spectral_Class'])

    df.head()
```

	Temperature	L	R	A_M	Color	Spectral_Class	Type
0	3068	0.002400	0.1700	16.12	4	5	0
1	3042	0.000500	0.1542	16.60	4	5	0
2	2600	0.000300	0.1020	18.70	4	5	0
3	2800	0.000200	0.1600	16.65	4	5	0
4	1939	0.000138	0.1030	20.06	4	5	0

```python
#rescaling non categorical features

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scalable = ['Temperature','L','R','A_M']
scaledColumns = pd.DataFrame(scaler.fit_transform(df[scalable]),columns=scalable)
scaledColumns.describe()
```

	Temperature	L	R	A_M
count	2.400000e+02	2.400000e+02	2.400000e+02	2.400000e+02
mean	1.850372e-17	-2.127927e-17	-1.850372e-17	-9.344377e-17
std	1.002090e+00	1.002090e+00	1.002090e+00	1.002090e+00
min	-8.978190e-01	-5.986236e-01	-4.595230e-01	-1.551051e+00
25%	-7.504023e-01	-5.986236e-01	-4.593402e-01	-1.009928e+00
50%	-4.953014e-01	-5.986232e-01	-4.580618e-01	3.739676e-01
75%	4.781574e-01	5.074424e-01	-3.767029e-01	8.862626e-01
max	3.094941e+00	4.145201e+00	3.316058e+00	1.491607e+00

```python
df.drop(scalable,inplace=True,axis=1)
df = pd.concat([df,scaledColumns],axis=1)
df.head()
```

	Color	Spectral_Class	Type	Temperature	L	R	A_M
0	4	5	0	-0.779382	-0.598624	-0.459210	1.116745
1	4	5	0	-0.782110	-0.598624	-0.459241	1.162414
2	4	5	0	-0.828477	-0.598624	-0.459342	1.362213
3	4	5	0	-0.807496	-0.598624	-0.459229	1.167171
4	4	5	0	-0.897819	-0.598624	-0.459340	1.491607

KNN Classifier :

```
[ ] from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
    from sklearn.model_selection import cross_val_score
```

```
[ ] from sklearn.neighbors import KNeighborsClassifier

    knnModel = KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                         metric_params=None, n_jobs=None, n_neighbors=6, p=2,
                         weights='uniform')

    knnModel= KNeighborsClassifier().fit(X_train,y_train.values.ravel())
```

```
[ ] cv_lr = cross_val_score(estimator = knnModel, X = X_train, y = y_train, cv = 10)
    print("CV: ", cv_lr.mean())
```

```
CV:  0.870879120879121
```

```
[ ] #metrics and cross validation
    y_pred= knnModel.predict(X_train)
    print(classification_report(y_train,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        21
           1       0.88      1.00      0.93        21
           2       0.88      1.00      0.94        22
           3       0.95      0.73      0.83        26
           4       0.87      0.95      0.91        21
           5       1.00      0.90      0.95        21

    accuracy                           0.92       132
   macro avg       0.93      0.93      0.93       132
weighted avg       0.93      0.92      0.92       132
```

```
[ ] y_test_pred = knnModel.predict(X_test)
    print(classification_report(y_test,y_test_pred))
    #for knn training data accuracy is 0.92 where as testing data accuracy is 0.94
```

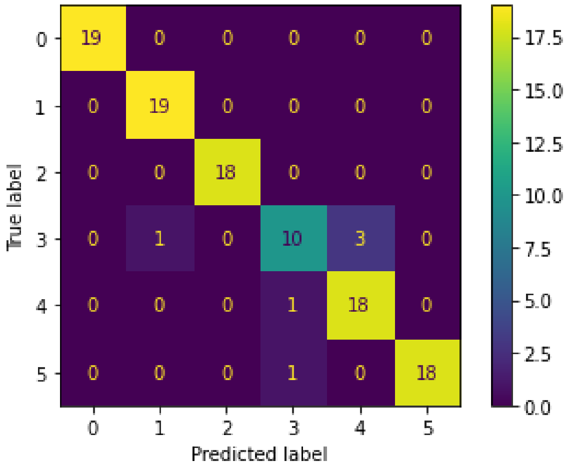
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       0.95      1.00      0.97        19
           2       1.00      1.00      1.00        18
           3       0.83      0.71      0.77        14
           4       0.86      0.95      0.90        19
           5       1.00      0.95      0.97        19

    accuracy                           0.94       108
   macro avg       0.94      0.93      0.94       108
weighted avg       0.94      0.94      0.94       108
```

```
[ ] ConfusionMatrixDisplay.from_estimator(knnModel,X_test,y_test)
```

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f28709108d0>



Decision Tree Classifier :

```
[ ]  from sklearn.tree import DecisionTreeClassifier

     tree = DecisionTreeClassifier(max_depth=4)
     tree.fit(X_train,y_train)
```

```
DecisionTreeClassifier(max_depth=4)
```

```
[ ]  cv_lr = cross_val_score(estimator = tree, X = X_train, y = y_train, cv = 10)
     print("CV: ", cv_lr.mean())
```

```
CV:  0.9923076923076923
```

```
[ ]  y_train_pred = tree.predict(X_train)
     print(classification_report(y_train,y_train_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        21
           1       1.00      1.00      1.00        21
           2       1.00      1.00      1.00        22
           3       1.00      1.00      1.00        26
           4       1.00      1.00      1.00        21
           5       1.00      1.00      1.00        21

    accuracy                           1.00       132
   macro avg       1.00      1.00      1.00       132
weighted avg       1.00      1.00      1.00       132
```

```
[ ] y_test_pred = tree.predict(X_test)
    print(classification_report(y_test,y_test_pred))

    #for decision tree training accuracy is 1.00 where as testing accuracy is 0.99
    #error found was in type 3 and 4 which can be reduced by increasing dataset size
```

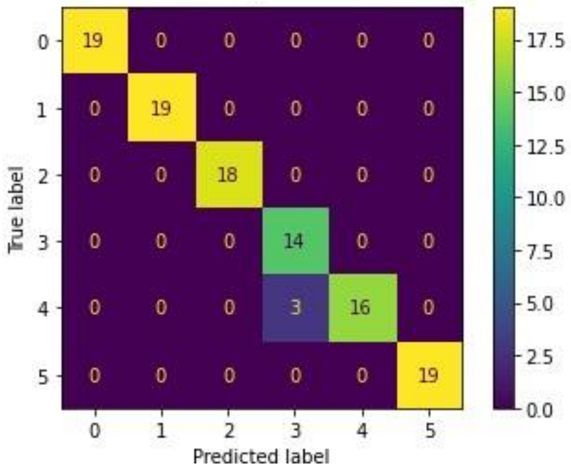
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      1.00      1.00        19
           2       1.00      1.00      1.00        18
           3       0.82      1.00      0.90        14
           4       1.00      0.84      0.91        19
           5       1.00      1.00      1.00        19

    accuracy                           0.97       108
   macro avg       0.97      0.97      0.97       108
weighted avg       0.98      0.97      0.97       108
```

```
[ ] ConfusionMatrixDisplay.from_estimator(tree,X_test,y_test)
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f286f756dd0>
```



Random Forest Classifier :

```
[ ] from sklearn.ensemble import RandomForestClassifier
    rf = RandomForestClassifier(criterion = 'entropy', max_features = 4, n_estimators = 800, random_state=69)
    rf.fit(X_train, y_train.ravel())
```

```
RandomForestClassifier(criterion='entropy', max_features=4, n_estimators=800,
                       random_state=69)
```

```
[ ] cv_lr = cross_val_score(estimator = rf, X = X_train, y = y_train, cv = 10)
    print("CV: ", cv_lr.mean())
```

```
CV:  1.0
```

```
[ ] y_train_pred = rf.predict(X_train)
    print(classification_report(y_train,y_train_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        21
           1       1.00      1.00      1.00        21
           2       1.00      1.00      1.00        22
           3       1.00      1.00      1.00        26
           4       1.00      1.00      1.00        21
           5       1.00      1.00      1.00        21

    accuracy                           1.00       132
   macro avg       1.00      1.00      1.00       132
weighted avg       1.00      1.00      1.00       132
```

```
[ ] y_test_pred = rf.predict(X_test)
    print(classification_report(y_test,y_test_pred))
    #for random forest training accuracy is 1.00 where as testing accuracy is 0.98
```

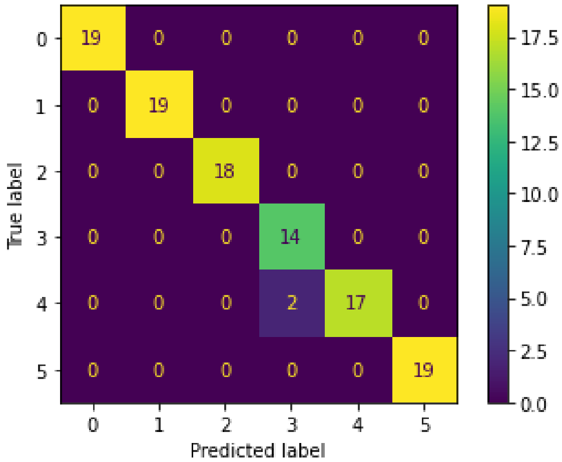
```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        19
           1       1.00      1.00      1.00        19
           2       1.00      1.00      1.00        18
           3       0.88      1.00      0.93        14
           4       1.00      0.89      0.94        19
           5       1.00      1.00      1.00        19

    accuracy                           0.98       108
   macro avg       0.98      0.98      0.98       108
weighted avg       0.98      0.98      0.98       108
```

```
[ ] ConfusionMatrixDisplay.from_estimator(rf,X_test,y_test)
```

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7f286df00650>
```



Logistic Regression :

```
[ ] from sklearn.linear_model import LogisticRegression
    lr = LogisticRegression(random_state=69,max_iter=10000)
    lr.fit(X_train,y_train.ravel())
```

```
LogisticRegression(max_iter=10000, random_state=69)
```

```
[ ] cv_lr = cross_val_score(estimator = lr, X = X_train, y = y_train, cv = 10)
    print("CV: ", cv_lr.mean())
```

```
CV:  0.9543956043956043
```

```
[ ] y_train_pred = lr.predict(X_train)
    print(classification_report(y_train,y_train_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        21
           1       1.00      1.00      1.00        21
           2       1.00      1.00      1.00        22
           3       0.96      0.92      0.94        26
           4       0.91      0.95      0.93        21
           5       1.00      1.00      1.00        21

    accuracy                           0.98       132
   macro avg       0.98      0.98      0.98       132
weighted avg       0.98      0.98      0.98       132
```

Conclusion

Thus we have created classifiers for the given dataset and obtained the following results.

Model	Precision	Recall	Accuracy
KNN	0.94	0.94	0.94
Decision Tree	0.98	0.97	0.97
Random Forest	0.98	0.98	0.98
Logistic Regression	0.98	0.98	0.98