# WELCOME TO MY NOTEBOOK

## MAIN OBJECTIVE

This Notebook will be More focused on Predicting the Classification of the target Variable in the Dataset Selected (that is explained below) so "Objective is to Classification" in the Conclusion of this analysis will give Best possible Classification and with that try to explain the Features.

### Dataset Description

This Dataset is about the Students Knowledge Level with explainable columns. This is beginner level data set has 403 rows and 6 columns. It is a real dataset about the students' knowledge status about the subject of Electrical DC Machines.

#### ***Attributes***

- STG - The degree of study time for goal object materials
- SCG - The degree of repetition number of user for goal object materials
- STR - The degree of study time of user for related objects with goal object
- LPR - The exam performance of user for related objects with goal object
- PEG - The exam performance of user for goal objects
- UNS - The knowledge level of user (Very Low, Low, Middle, High)

UNS is the Target variable we try to predict. It has four classes namely

1. Very Low
2. Low
3. Middle
4. High.

#### ***Dataset source***

This data set has been sourced from the Machine Learning Repository of University of California, Irvine User Knowledge Modeling Data Set (UC Irvine).

# Data Exploration

In [2]:

```
# Importing Lib's
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

#### ***@Loading Data from Disk to Notebook***

In [3]:

```
data=pd.read_csv('Predict_student_ knowledge_level.csv')
data # Data overview
```

Out[3]:

| | STG | SCG | STR | LPR | PEG | UNS | Unnamed: 6 | Unnamed: 7 | Unnamed: 8 |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | very_low | NaN | NaN | NaN |
| **1** | 0.08 | 0.08 | 0.10 | 0.24 | 0.90 | High | NaN | NaN | NaN |
| **2** | 0.06 | 0.06 | 0.05 | 0.25 | 0.33 | Low | NaN | NaN | NaN |
| **3** | 0.10 | 0.10 | 0.15 | 0.65 | 0.30 | Middle | NaN | NaN | NaN |
| **4** | 0.08 | 0.08 | 0.08 | 0.98 | 0.24 | Low | NaN | NaN | NaN |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **398** | 0.90 | 0.78 | 0.62 | 0.32 | 0.89 | High | NaN | NaN | NaN |
| **399** | 0.85 | 0.82 | 0.66 | 0.83 | 0.83 | High | NaN | NaN | NaN |
| **400** | 0.56 | 0.60 | 0.77 | 0.13 | 0.32 | Low | NaN | NaN | NaN |
| **401** | 0.66 | 0.68 | 0.81 | 0.57 | 0.57 | Middle | NaN | NaN | NaN |
| **402** | 0.68 | 0.64 | 0.79 | 0.97 | 0.24 | Middle | NaN | NaN | NaN |

403 rows × 9 columns

In [4]:

```
data.shape #data shape(rows,columns)
```

Out[4]:

```
(403, 9)
```

***Removing that empty cloumns***

In [5]:

```
data=data.drop(columns=['Unnamed: 6','Unnamed: 7','Unnamed: 8'],axis=1)
data.head()
```

Out[5]:

| | STG | SCG | STR | LPR | PEG | UNS |
|---|---|---|---|---|---|---|
| **0** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | very_low |
| **1** | 0.08 | 0.08 | 0.10 | 0.24 | 0.90 | High |
| **2** | 0.06 | 0.06 | 0.05 | 0.25 | 0.33 | Low |
| **3** | 0.10 | 0.10 | 0.15 | 0.65 | 0.30 | Middle |
| **4** | 0.08 | 0.08 | 0.08 | 0.98 | 0.24 | Low |

***General Info about the data***

In [6]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 403 entries, 0 to 402
Data columns (total 6 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   STG     403 non-null    float64
 1   SCG     403 non-null    float64
 2   STR     403 non-null    float64
 3   LPR     403 non-null    float64
 4   PEG     403 non-null    float64
 5    UNS    403 non-null    object 
dtypes: float64(5), object(1)
memory usage: 19.0+ KB
```

In [7]:

```
data.STG.unique()
```

Out[7]:

```
array([0.   , 0.08 , 0.06 , 0.1  , 0.09 , 0.15 , 0.2  , 0.18 , 0.12 ,
       0.05 , 0.04 , 0.19 , 0.02 , 0.14 , 0.115, 0.17 , 0.13 , 0.23 ,
       0.24 , 0.25 , 0.32 , 0.29 , 0.28 , 0.3  , 0.27 , 0.31 , 0.255,
       0.265, 0.275, 0.245, 0.295, 0.315, 0.248, 0.325, 0.258, 0.251,
       0.288, 0.323, 0.243, 0.299, 0.26 , 0.305, 0.276, 0.329, 0.285,
       0.312, 0.39 , 0.4  , 0.45 , 0.48 , 0.41 , 0.38 , 0.37 , 0.33 ,
       0.42 , 0.44 , 0.46 , 0.365, 0.345, 0.49 , 0.334, 0.36 , 0.43 ,
       0.495, 0.465, 0.475, 0.348, 0.385, 0.445, 0.34 , 0.35 , 0.6  ,
       0.55 , 0.68 , 0.73 , 0.78 , 0.59 , 0.64 , 0.69 , 0.62 , 0.7  ,
       0.75 , 0.85 , 0.8  , 0.9  , 0.76 , 0.72 , 0.52 , 0.51 , 0.58 ,
       0.61 , 0.77 , 0.79 , 0.71 , 0.88 , 0.99 , 0.83 , 0.66 , 0.523,
       0.5  , 0.91 , 0.89 , 0.56 , 0.54 , 0.22 , 0.16 , 0.11 , 0.21 ,
       0.47 , 0.65 , 0.87 , 0.57 ])
```

In [8]:

```
data['UNS']=data[' UNS']
data=data.drop([' UNS'],axis=1)
```

Description

In [9]:

```
data.describe()
```

Out[9]:

| | STG | SCG | STR | LPR | PEG |
|---|---|---|---|---|---|
| **count** | 403.000000 | 403.000000 | 403.000000 | 403.000000 | 403.000000 |
| **mean** | 0.353141 | 0.355940 | 0.457655 | 0.431342 | 0.456360 |
| **std** | 0.212018 | 0.215531 | 0.246684 | 0.257545 | 0.266775 |
| **min** | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| **25%** | 0.200000 | 0.200000 | 0.265000 | 0.250000 | 0.250000 |
| **50%** | 0.300000 | 0.300000 | 0.440000 | 0.330000 | 0.400000 |
| **75%** | 0.480000 | 0.510000 | 0.680000 | 0.650000 | 0.660000 |
| **max** | 0.990000 | 0.900000 | 0.950000 | 0.990000 | 0.990000 |

In [10]:

```
data.UNS.unique()
```

Out[10]:

```
array(['very_low', 'High', 'Low', 'Middle', 'Very Low'], dtype=object)
```

***There is same type of class with different name***

```
making it correct.
```

In [11]:

```
data.UNS = [each.lower().replace("very low","very_low") for each in data.UNS]
data.UNS.value_counts()
```

Out[11]:

```
low         129
middle      122
high        102
very_low     50
Name: UNS, dtype: int64
```

In [12]:

```
data['UNS'].unique()
```

Out[12]:

```
array(['very_low', 'high', 'low', 'middle'], dtype=object)
```

Now looks good.

***Checking for null Values***

In [13]:

```
data.isnull().sum()
```

Out[13]:

```
STG    0
SCG    0
STR    0
LPR    0
PEG    0
UNS    0
dtype: int64
```

No null values.

***Checking the Data type in each columns.***

In [14]:

```
data.dtypes
```

Out[14]:

```
STG    float64
SCG    float64
STR    float64
LPR    float64
PEG    float64
UNS     object
dtype: object
```

***The data is Scaled. we can see below.***

In [15]:

```
pd.concat([data.min(),data.max()],axis=1)
```

Out[15]:

| | 0 | 1 |
|---|---|---|
| **STG** | 0.0 | 0.99 |
| **SCG** | 0.0 | 0.9 |
| **STR** | 0.0 | 0.95 |
| **LPR** | 0.0 | 0.99 |
| **PEG** | 0.0 | 0.99 |
| **UNS** | high | very_low |

***This data has nothing to clean and fill.***

**Target Variable**

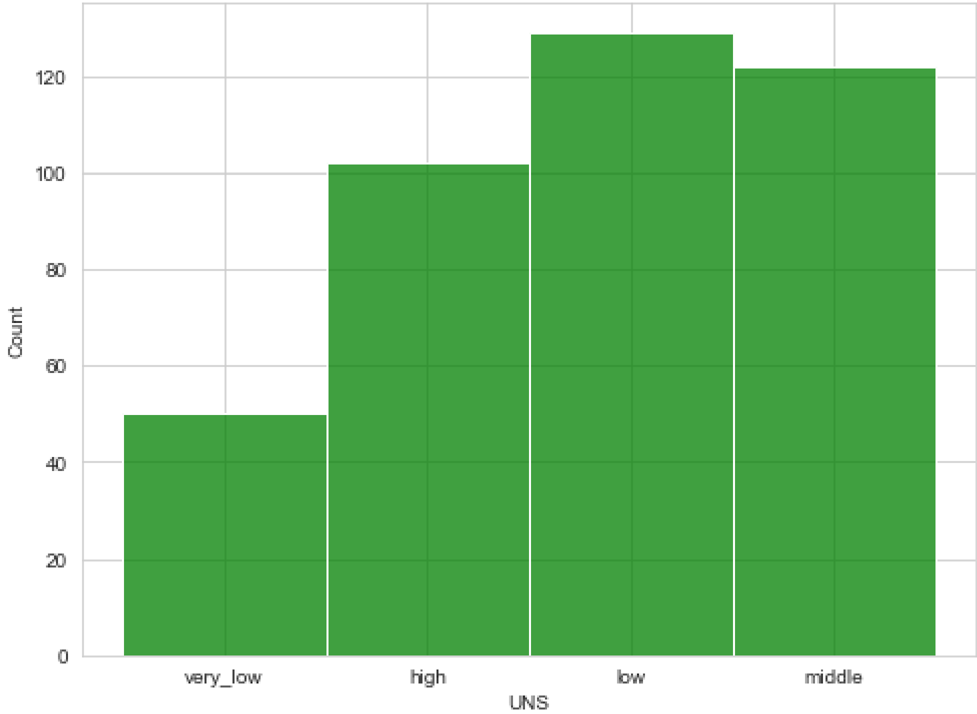
**Target variable**

In [17]:

```
plt.figure(figsize=(8,6))
sns.histplot(data=data,x=data['UNS'],color='green')
```

Out[17]:

```
<AxesSubplot:xlabel='UNS', ylabel='Count'>
```



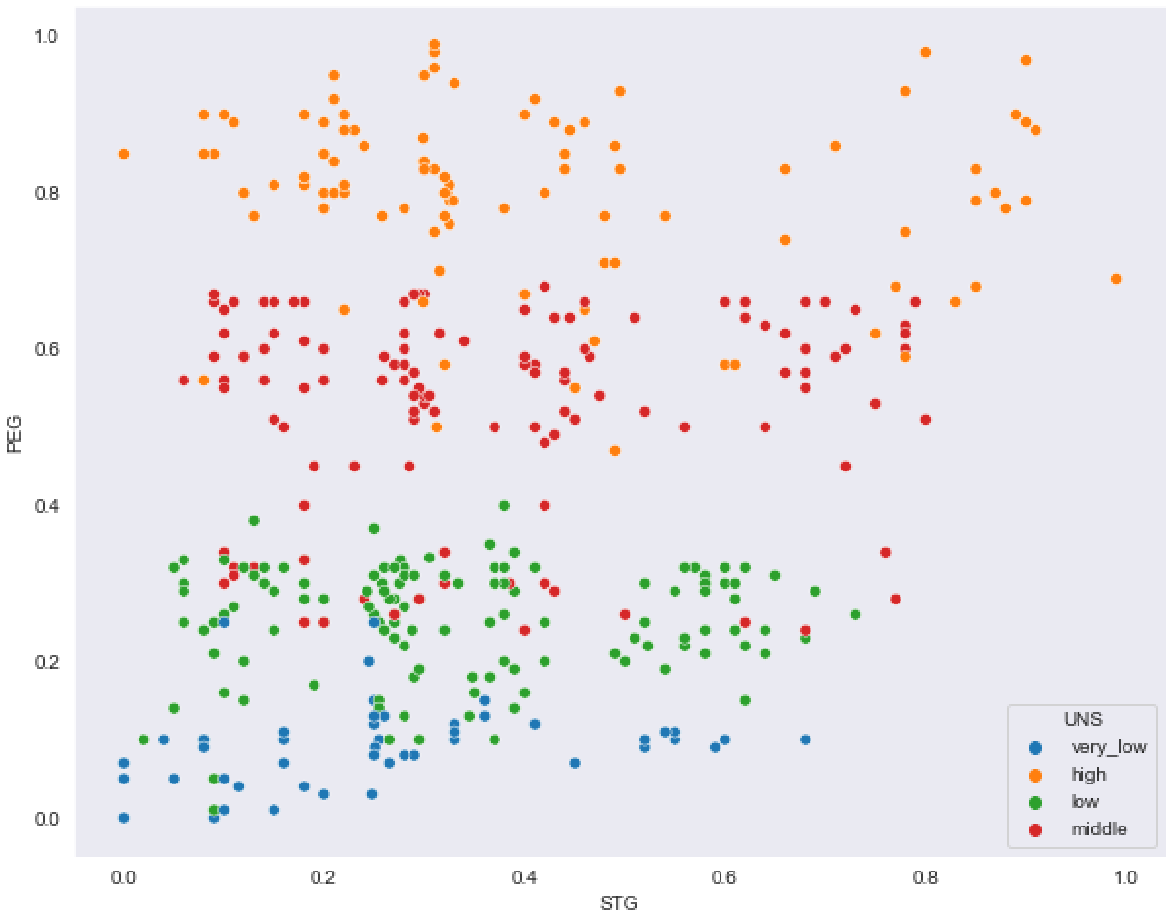

***Scatter plot of study time with respect to exam performance.***

In [18]:

```
pp=plt.figure(figsize=(10,8))
sns.set_style('dark')
sns.scatterplot(data=data,x=data.STG,y=data.PEG,hue='UNS')
```

Out[18]:

```
<AxesSubplot:xlabel='STG', ylabel='PEG'>
```



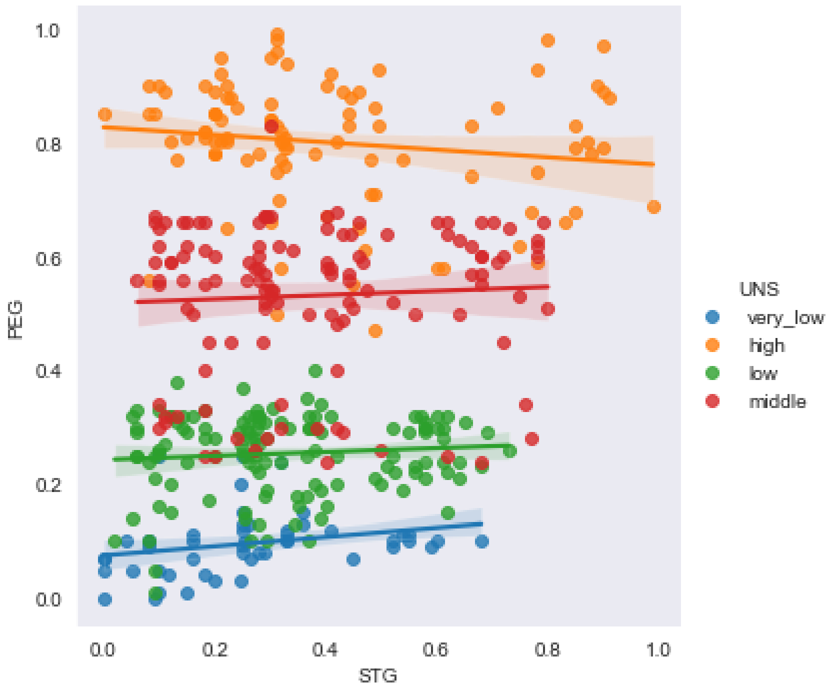
***Correlation of study time with respect to exam performance.***

In [19]:

```
sns.lmplot(data=data,x='STG',y='PEG',hue='UNS')
```

Out[19]:

```
<seaborn.axisgrid.FacetGrid at 0x21354180490>
```

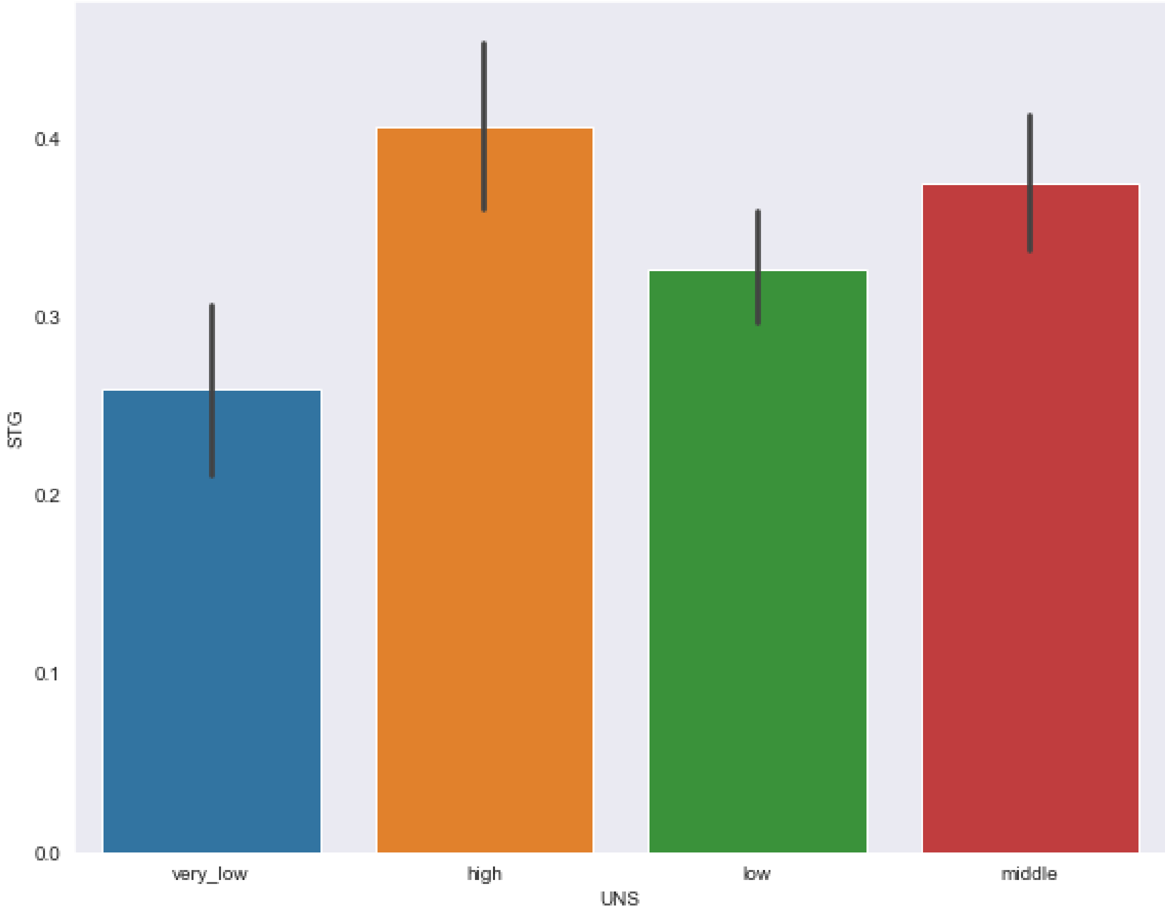


In [20]:

```
pp=plt.figure(figsize=(10,8))
sns.set_style('dark')
sns.barplot(x=data.UNS,y=data.STG) #study time of user for related objects with goal object
```

Out[20]:

```
<AxesSubplot:xlabel='UNS', ylabel='STG'>
```



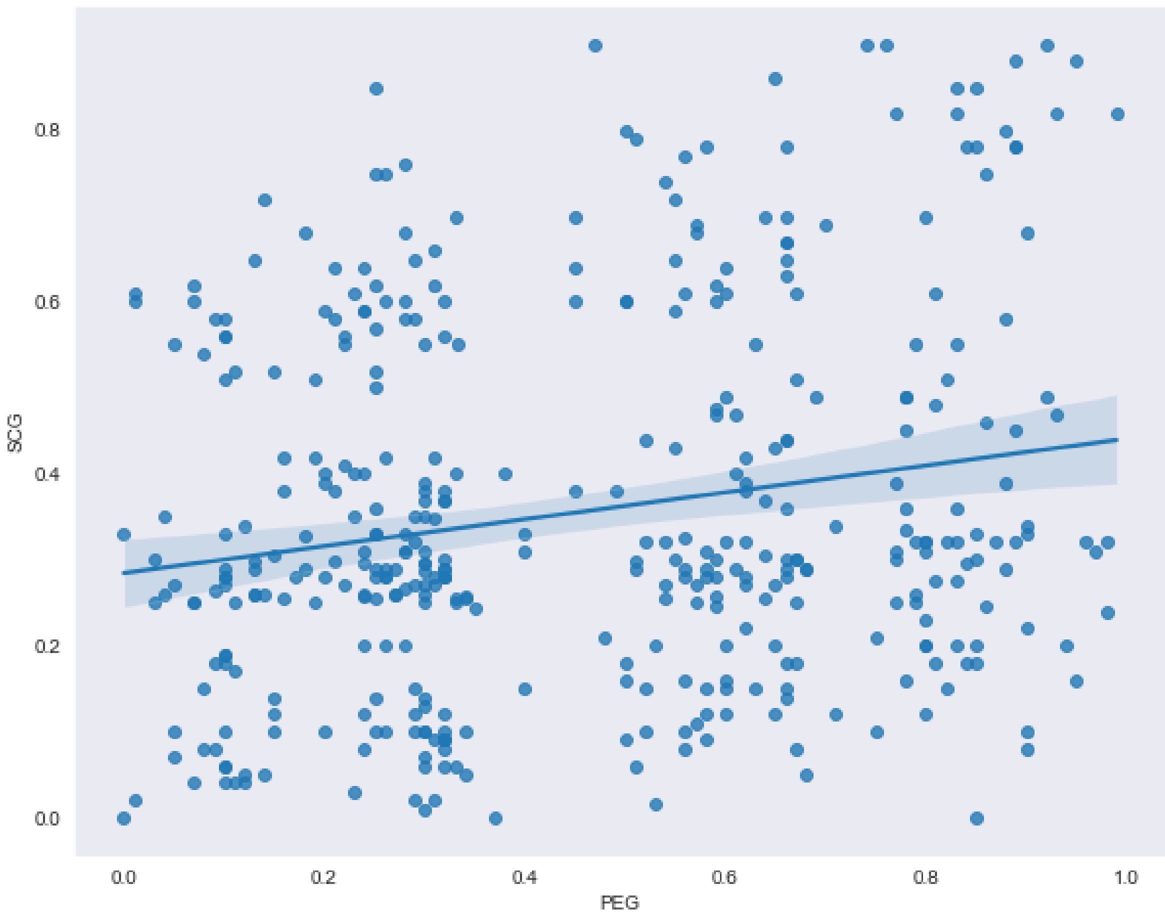
***Scatter plot of repetition number of user for goal object with respect to exam performance.***

In [21]:

```
plt.figure(figsize=(10,8))
sns.regplot(x=data.PEG,y=data.SCG)
```

Out[21]:

```
<AxesSubplot:xlabel='PEG', ylabel='SCG'>
```




***Relation beteen knowledge level of user vs exam performance of use**

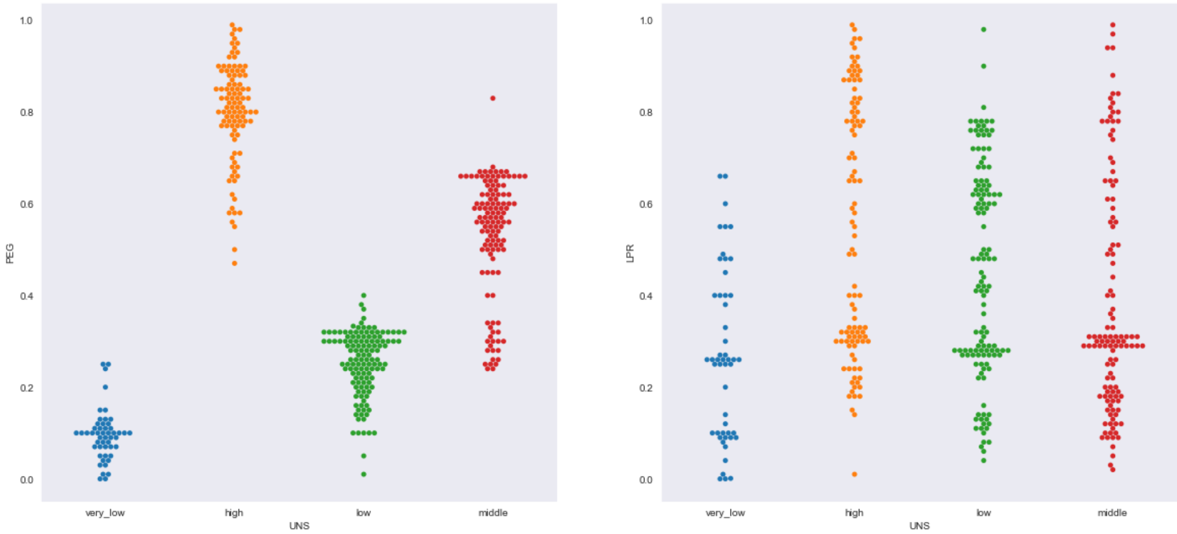
***Relation beteen knowledge level of user vs exam performance of user for related objects**

In [22]:

```
fig,axes =plt.subplots(1,2,figsize=(20,9))
sns.swarmplot(ax=axes[0],x=data.UNS,y=data.PEG)
sns.swarmplot(ax=axes[1],x=data.UNS,y=data.LPR)
```

Out[22]:

```
<AxesSubplot:xlabel='UNS', ylabel='LPR'>
```



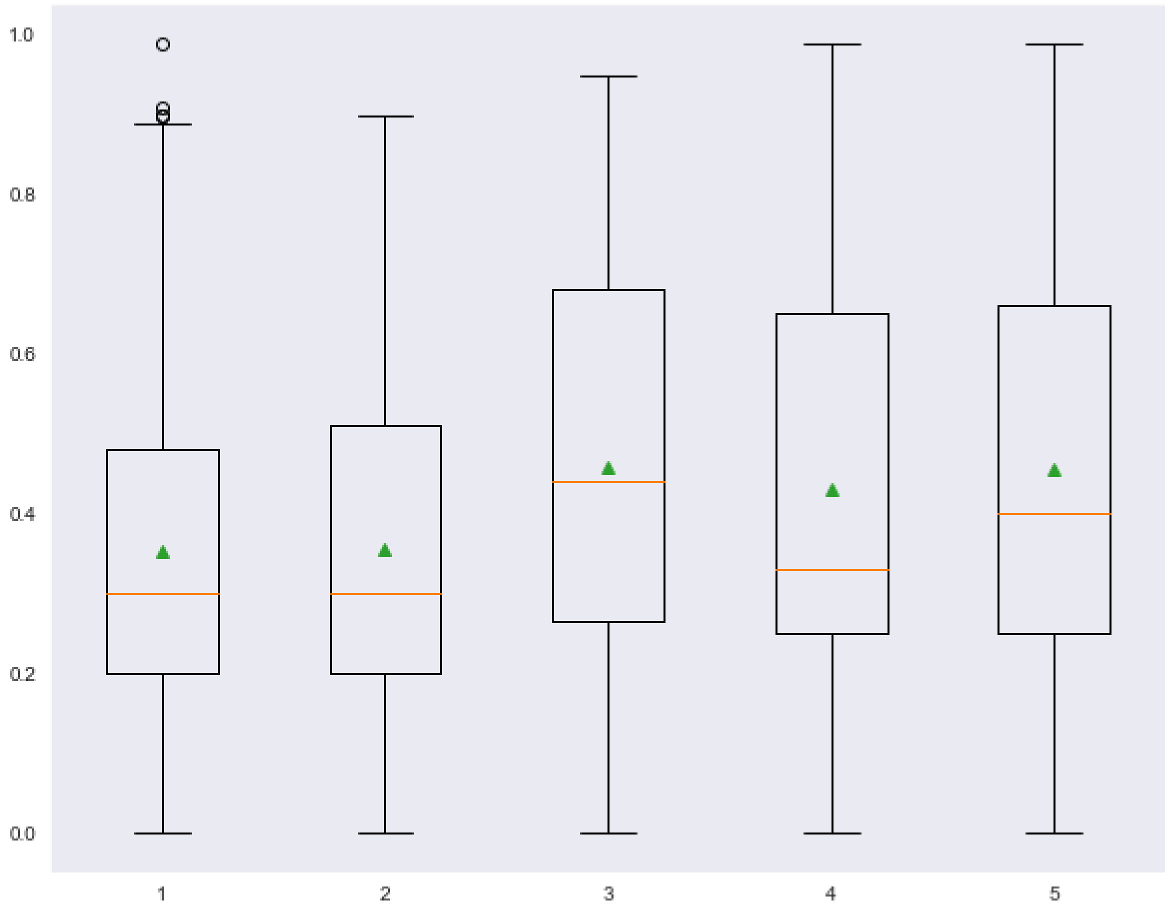

***checking for outliers using Boxplot***

In [23]:

```
plt.figure(figsize=(10,8))
plt.boxplot(data.iloc[:,:-1],showmeans=True)
```

Out[23]:

```
{'whiskers': [<matplotlib.lines.Line2D at 0x21354b08c70>,
  <matplotlib.lines.Line2D at 0x21354b08f40>,
  <matplotlib.lines.Line2D at 0x21354b1f370>,
  <matplotlib.lines.Line2D at 0x21354b1f640>,
  <matplotlib.lines.Line2D at 0x21354b32a30>,
  <matplotlib.lines.Line2D at 0x21354b32d00>,
  <matplotlib.lines.Line2D at 0x21354b4b130>,
  <matplotlib.lines.Line2D at 0x21354b4b400>,
  <matplotlib.lines.Line2D at 0x21354b547f0>,
  <matplotlib.lines.Line2D at 0x21354b54ac0>],
 'caps': [<matplotlib.lines.Line2D at 0x21354b17250>,
  <matplotlib.lines.Line2D at 0x21354b17520>,
  <matplotlib.lines.Line2D at 0x21354b1f910>,
  <matplotlib.lines.Line2D at 0x21354b1fbe0>,
  <matplotlib.lines.Line2D at 0x21354b32fd0>,
  <matplotlib.lines.Line2D at 0x21354b3e2e0>,
  <matplotlib.lines.Line2D at 0x21354b4b6d0>,
  <matplotlib.lines.Line2D at 0x21354b4b9a0>,
  <matplotlib.lines.Line2D at 0x21354b54d90>,
  <matplotlib.lines.Line2D at 0x21354b640a0>],
 'boxes': [<matplotlib.lines.Line2D at 0x21354b08970>,
  <matplotlib.lines.Line2D at 0x21354b1f0a0>,
  <matplotlib.lines.Line2D at 0x21354b32760>,
  <matplotlib.lines.Line2D at 0x21354b3ee20>,
  <matplotlib.lines.Line2D at 0x21354b54520>],
 'medians': [<matplotlib.lines.Line2D at 0x21354b177f0>,
  <matplotlib.lines.Line2D at 0x21354b1feb0>,
  <matplotlib.lines.Line2D at 0x21354b3e5b0>,
  <matplotlib.lines.Line2D at 0x21354b4bc70>,
  <matplotlib.lines.Line2D at 0x21354b64370>],
 'fliers': [<matplotlib.lines.Line2D at 0x21354b17d90>,
  <matplotlib.lines.Line2D at 0x21354b32490>,
  <matplotlib.lines.Line2D at 0x21354b3eb50>,
  <matplotlib.lines.Line2D at 0x21354b54250>,
  <matplotlib.lines.Line2D at 0x21354b64910>],
 'means': [<matplotlib.lines.Line2D at 0x21354b17ac0>,
  <matplotlib.lines.Line2D at 0x21354b321c0>,
  <matplotlib.lines.Line2D at 0x21354b3e880>,
  <matplotlib.lines.Line2D at 0x21354b4bf40>,
  <matplotlib.lines.Line2D at 0x21354b64640>]}
```




Doesn't seems to big deal.

# MODE BUILDING & TRAINING.

### Importing necessary lib's.

In [24]:

```
from sklearn.preprocessing import StandardScaler,MinMaxScaler,PolynomialFeatures,LabelEncod
from sklearn.model_selection import train_test_split,ShuffleSplit,StratifiedKFold,Stratifie
from sklearn.linear_model import LogisticRegression,LogisticRegressionCV
from sklearn.metrics import accuracy_score,precision_recall_fscore_support,precision_recall
```

***segregation the X and Y columns.***

In [25]:

```
x=data.iloc[:,:-1]
Y=data.iloc[:,-1:]
```

In [26]:

```
Y.head()
```

Out[26]:

| | UNS |
|---|---|
| 0 | very_low |
| 1 | high |
| 2 | low |
| 3 | middle |
| 4 | low |

***Encoding the target variable.***

In [27]:

```
le=LabelEncoder()
y=le.fit_transform(Y.values.ravel())
c=le.inverse_transform(y)
```

In [28]:

```
c[1:6]
```

Out[28]:

```
array(['high', 'low', 'middle', 'low', 'middle'], dtype=object)
```

***Train test split with stratification.***

In [29]:

```
x_train, x_test, y_train, y_test =train_test_split(x,y,test_size=0.3,stratify=y,random_stat
```

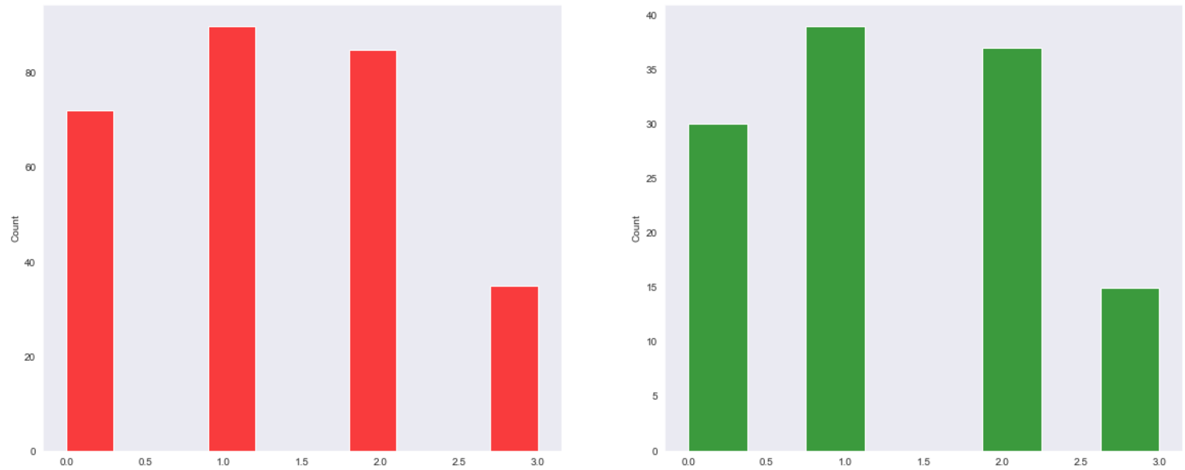
**The stratified split of y is below with equally splitted.**

In [30]:

```
fig,axes=plt.subplots(1,2,figsize=(20,8))
sns.histplot(ax=axes[0],x=y_train,color='red')
sns.histplot(ax=axes[1],x=y_test,color='green')
```

Out[30]:

```
<AxesSubplot:ylabel='Count'>
```




In [31]:

```
print(x_train.shape,y_train.shape)
print(x_test.shape,y_test.shape)
```

```
(282, 5) (282,)
(121, 5) (121,)
```

# Model Building --

## Fitting Logistic Regression Model.

In [32]:

```
lo=LogisticRegression()
lo.fit(x_train,y_train)
ypredlo=lo.predict(x_test)
```

#### Getting Accuracy score, Precision, Recall, F1 Score

In [37]:

```
precision,recall,f1score,support=precision_recall_fscore_support(y_test,ypredlo)
all={'acuracy':accuracy_score(y_test,ypredlo),'precision':precision,'recal':recall,'f1score
```

In [38]:

```
all
```

Out[38]:

```
{'acuracy': 0.8429752066115702,
 'precision': array([1.        , 0.67857143, 1.        , 0.83333333]),
 'recal': array([1.        , 0.97435897, 0.78378378, 0.33333333]),
 'f1score': array([1.        , 0.8       , 0.87878788, 0.47619048])}
```

**Defining function for getting All the Scores.**

In [41]:

```
def scores(yt,yp):
    acuracy=accuracy_score(yt,yp)
    precision,recall,f1score,support=precision_recall_fscore_support(yt,yp)
    sc={'acuracy':acuracy,'precision':precision,'recall':recall,'f1score':f1score}
    return  pd.DataFrame(sc).set_index(keys=np.array(['verylow','high','middle','low']))
```

In [42]:

```
scores(y_test,ypredlo)
```

Out[42]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.842975 | 1.000000 | 1.000000 | 1.000000 |
| **high** | 0.842975 | 0.678571 | 0.974359 | 0.800000 |
| **middle** | 0.842975 | 1.000000 | 0.783784 | 0.878788 |
| **low** | 0.842975 | 0.833333 | 0.333333 | 0.476190 |

In [43]:

```
lo.coef_
```

Out[43]:

```
array([[ 0.20489559,  0.84782216,  0.64348579,  2.31302463,  6.34364977],
       [ 0.02740854, -0.37122048, -0.21419144, -0.00848867, -3.14867644],
       [ 0.83710923,  0.19982656,  0.42504269, -0.18131524,  1.64860852],
       [-1.06941336, -0.67642825, -0.85433704, -2.12322071, -4.84358185]])
```

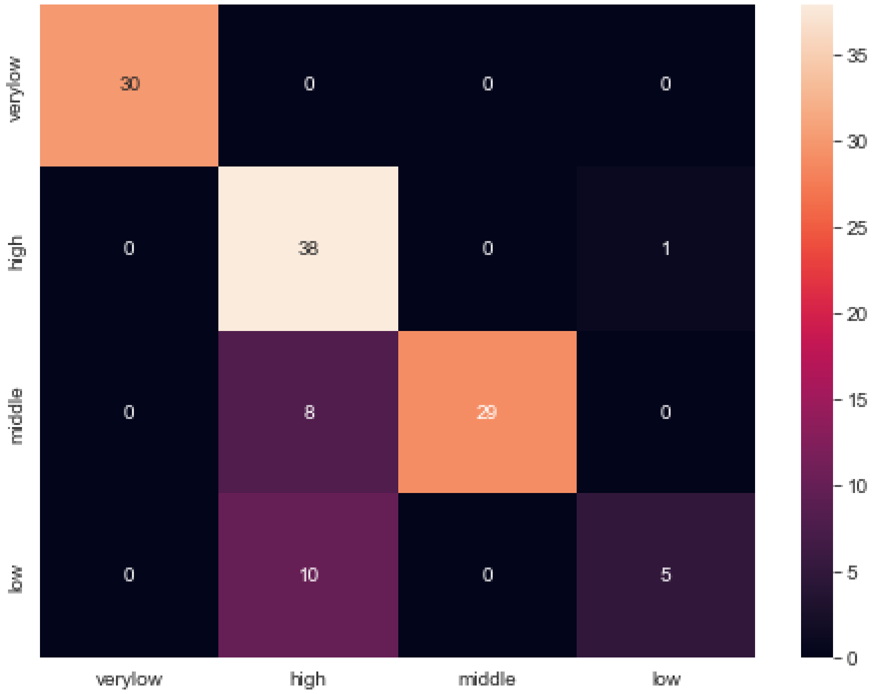
***Creating confusion matrix for the Logistic Regression.***

In [44]:

```
cflo=confusion_matrix(y_test,ypredlo)
plt.figure(figsize=(8,6))
sns.heatmap(cflo,annot=True,xticklabels=['verylow','high','middle','low'],yticklabels=['ver
```

Out[44]:

```
<AxesSubplot:>
```




**Logistic Regression with custom values.**

In [45]:

```
l2_model = LogisticRegression(random_state=42, penalty='l2', multi_class='multinomial', sol
l2_model.fit(x_train,y_train)
ypredl2=l2_model.predict(x_test)
ypredl2t=l2_model.predict(x_train)
```

**Test Set Score.**

In [46]:

```
print('TEST SCORES:')
scores(y_test,ypredl2)
```

TEST SCORES:

Out[46]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.842975 | 1.000000 | 1.000000 | 1.000000 |
| **high** | 0.842975 | 0.678571 | 0.974359 | 0.800000 |
| **middle** | 0.842975 | 1.000000 | 0.783784 | 0.878788 |
| **low** | 0.842975 | 0.833333 | 0.333333 | 0.476190 |

**Above Looks same as Logistic Regression with Default values.**

## Train set Score.

In [47]:

```
print('TRAIN SCORES:')
scores(y_train,ypredl2t)
```

TRAIN SCORES:

Out[47]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.826241 | 0.946667 | 0.986111 | 0.965986 |
| **high** | 0.826241 | 0.674242 | 0.988889 | 0.801802 |
| **middle** | 0.826241 | 0.970149 | 0.764706 | 0.855263 |
| **low** | 0.826241 | 1.000000 | 0.228571 | 0.372093 |

**For this model class LOW is not getting much Recall score.**

In [52]:

```
l2_model.coef_
```

Out[52]:

```
array([[ 0.20489559,  0.84782216,  0.64348579,  2.31302463,  6.34364977],
       [ 0.02740854, -0.37122048, -0.21419144, -0.00848867, -3.14867644],
       [ 0.83710923,  0.19982656,  0.42504269, -0.18131524,  1.64860852],
       [-1.06941336, -0.67642825, -0.85433704, -2.12322071, -4.84358185]])
```

## Creating Confusion Matrix for both Train and Test set.

In [117]:

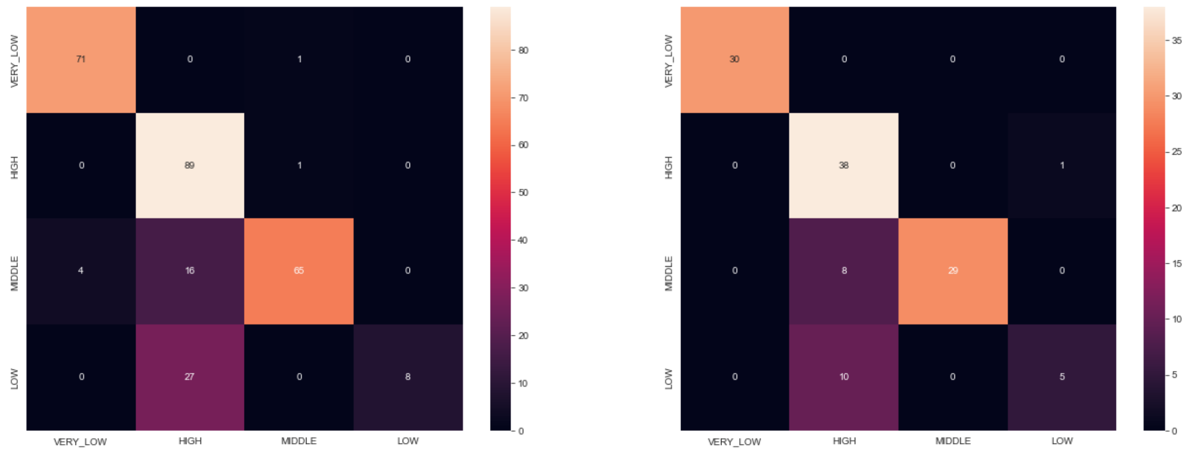
```
cfl2=confusion_matrix(y_test,ypredl2)
cfl2t=confusion_matrix(y_train,ypredl2t)

plt.figure(figsize=(8,6))
fig,axes=plt.subplots(1,2,figsize=(22,8))
sns.heatmap(ax=axes[0],data=cfl2t,annot=True,xticklabels=['VERY_LOW','HIGH','MIDDLE','LOW']
sns.heatmap(ax=axes[1],data=cfl2,annot=True,xticklabels=['VERY_LOW','HIGH','MIDDLE','LOW'],
```

Out[117]:

```
&lt;AxesSubplot:&gt;
```

```
&lt;Figure size 576x432 with 0 Axes&gt;
```




# Logistic Rgression with L1 penalty.

In [54]:

```
l1_model = LogisticRegression(random_state=42, penalty='l1', multi_class='multinomial', sol
l1_model.fit(x_train,y_train)
ypredl1=l1_model.predict(x_test)
ypredl1t=l1_model.predict(x_train)
```

In [55]:

```
print('TEST SCORES:')
scores(y_test,ypredl1)
```

```
TEST SCORES:
```

Out[55]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.92562 | 1.0000 | 1.000000 | 1.000000 |
| **high** | 0.92562 | 0.8125 | 1.000000 | 0.896552 |
| **middle** | 0.92562 | 1.0000 | 0.837838 | 0.911765 |
| **low** | 0.92562 | 1.0000 | 0.800000 | 0.888889 |

In [56]:

```
print('TRAIN SCORES:')
scores(y_train,ypredl1t)
```

TRAIN SCORES:

Out[56]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.925532 | 0.985915 | 0.972222 | 0.979021 |
| **high** | 0.925532 | 0.839623 | 0.988889 | 0.908163 |
| **middle** | 0.925532 | 0.973684 | 0.870588 | 0.919255 |
| **low** | 0.925532 | 0.965517 | 0.800000 | 0.875000 |

**Model with L1 penalty seems to giving better results.**

In [57]:

```
l1_model.score(x_train,y_train),l1_model.score(x_test,y_test)
```

Out[57]:

```
(0.925531914893617, 0.9256198347107438)
```

In [58]:

```
l1_model.coef_
```

Out[58]:

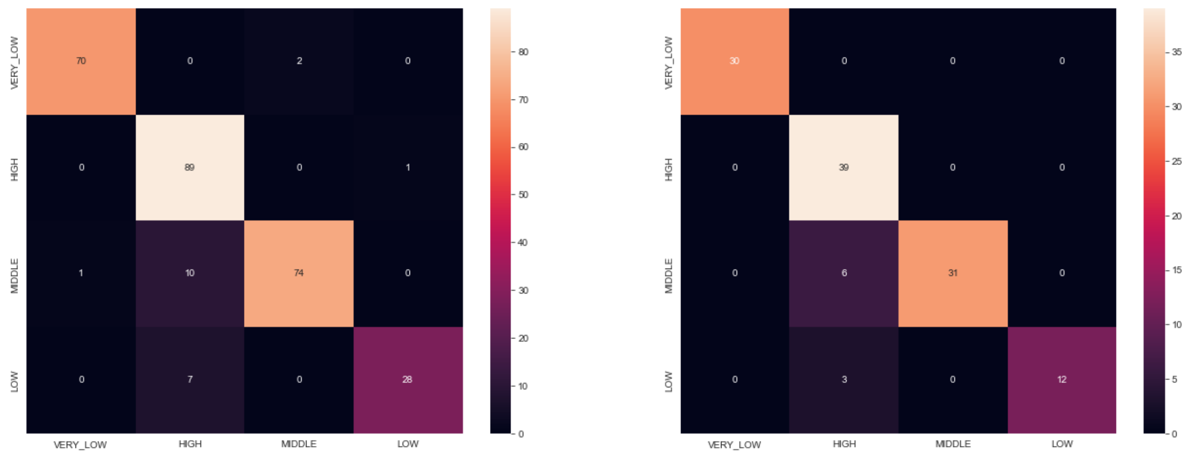
```
array([[  0.        ,   0.        ,   0.        ,   7.30776828,
         22.80753956],
       [  0.        ,   0.        ,   0.        ,  -1.53841778,
         -6.82349608],
       [  0.29876925,   0.        ,   0.06083014,   1.13679844,
          6.22333495],
       [  0.        ,   0.        ,  -0.45493062,  -6.30773541,
        -22.2114645 ]])
```

In [116]:

```
cfl1=confusion_matrix(y_test,ypredl1)
cfl1t=confusion_matrix(y_train,ypredl1t)
fig,axes=plt.subplots(1,2,figsize=(22,8))
#plt.figure(figsize=(8,6))
sns.heatmap(ax=axes[0],data=cfl1t,annot=True,xticklabels=['VERY_LOW','HIGH','MIDDLE','LOW']
sns.heatmap(ax=axes[1],data=cfl1,annot=True,xticklabels=['VERY_LOW','HIGH','MIDDLE','LOW'],
```

Out[116]:

```
<AxesSubplot:>
```




# Importing Flaml lib.

In [61]:

```
import flaml as fl
```

In [62]:

```
from flaml import AutoML
```

## Using AutoML for getting better score.

In [64]:

```
automl=AutoML()
automl.fit(x_train,y_train,task='classification')
ypredml=automl.predict(x_test)
ypredmlt=automl.predict(x_train)
```

...

In [65]:

```
scores(y_test,ypredml)
```

Out[65]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.975207 | 1.000000 | 1.000000 | 1.000000 |
| **high** | 0.975207 | 0.928571 | 1.000000 | 0.962963 |
| **middle** | 0.975207 | 1.000000 | 0.918919 | 0.957746 |
| **low** | 0.975207 | 1.000000 | 1.000000 | 1.000000 |

In [66]:

```
scores(y_train,ypredmlt)
```

Out[66]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 1.0 | 1.0 | 1.0 | 1.0 |
| **high** | 1.0 | 1.0 | 1.0 | 1.0 |
| **middle** | 1.0 | 1.0 | 1.0 | 1.0 |
| **low** | 1.0 | 1.0 | 1.0 | 1.0 |

***Likewise this gives much better scores.***

In [67]:

```
automl.score(x_train,y_train),automl.score(x_test,y_test)
```

Out[67]:

```
(1.0, 0.9752066115702479)
```

In [68]:

```
automl.best_result
```

Out[68]:

```
{'pred_time': 0.02319636195898056,
 'wall_clock_time': 11.55249547958374,
 'metric_for_logging': {'pred_time': 0.02319636195898056},
 'val_loss': 0.3018192903929744,
 'training_iteration': 1,
 'config': {'n_estimators': 2047,
  'max_features': 1.0,
  'max_leaves': 18344,
  'criterion': 'entropy'},
 'config/n_estimators': 2047,
 'config/max_features': 1.0,
 'config/max_leaves': 18344,
 'config/criterion': 'entropy',
 'experiment_tag': 'exp',
 'time_total_s': 3.005923271179199}
```

***All models with its loss.***

In [86]:

```
automl.best_loss_per_estimator
```

Out[86]:

```
{'rf': 1.2329927782380166,
 'lgbm': 0.6005965633922834,
 'xgboost': 0.3911803248702199,
 'extra_tree': 0.3018192903929744,
 'xgb_limitdepth': 0.39102573465788737,
 'lrl1': 1.1905604675716568}
```

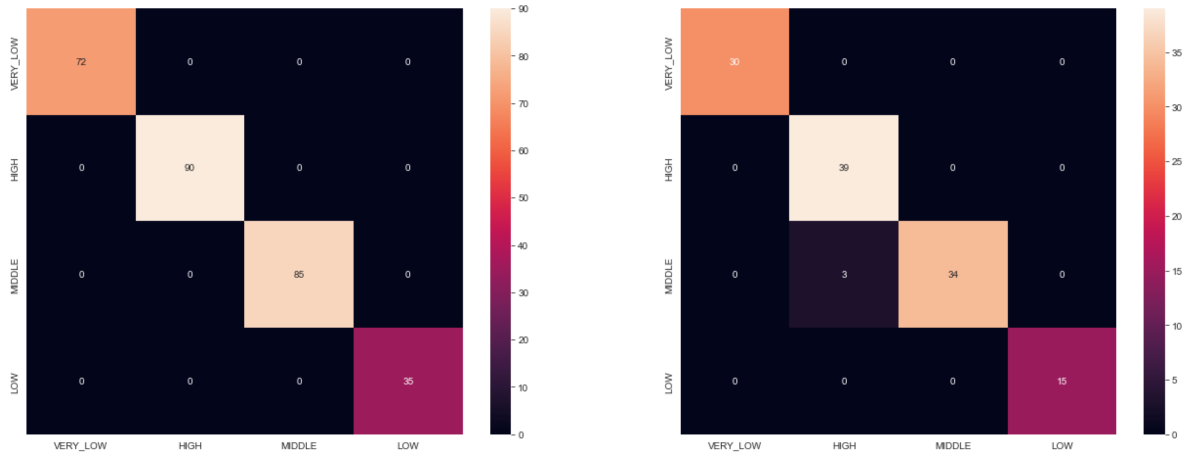
**Creating Confusion matrix for both train and test sets.**

In [115]:

```
cfml = confusion_matrix(y_test, ypredml)
cfmlt = confusion_matrix(y_train, ypredmlt)
fig, axes = plt.subplots(1, 2, figsize=(22, 8))
#plt.figure(figsize=(8,6))
sns.heatmap(ax=axes[0], data=cfmlt, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE',
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=cfml, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', '
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[115]:

<AxesSubplot:>




## knn model

In [88]:

```
from sklearn.neighbors import KNeighborsClassifier
```

In [89]:

```
knn=KNeighborsClassifier(n_neighbors=10,weights='distance')
knn.fit(x_train,y_train)
ypredknn=knn.predict(x_test)
ypredknnt=knn.predict(x_train)
```

In [92]:

```
accuracy_score(y_test,ypredknn)
```

Out[92]:

0.9008264462809917

In [93]:

```
f1_score(y_test,ypredknn,average=None)    #[None, 'micro', 'macro', 'weighted'].
```

Out[93]:

```
array([0.98305085, 0.87356322, 0.90140845, 0.8       ])
```

In [94]:

```
precision_recall_fscore_support(y_test,ypredknn)
```

Out[94]:

```
(array([1.        , 0.79166667, 0.94117647, 1.        ]),
 array([0.96666667, 0.97435897, 0.86486486, 0.66666667]),
 array([0.98305085, 0.87356322, 0.90140845, 0.8       ]),
 array([30, 39, 37, 15], dtype=int64))
```

In [95]:

```
scores(y_train,ypredknnt)
```

Out[95]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 1.0 | 1.0 | 1.0 | 1.0 |
| **high** | 1.0 | 1.0 | 1.0 | 1.0 |
| **middle** | 1.0 | 1.0 | 1.0 | 1.0 |
| **low** | 1.0 | 1.0 | 1.0 | 1.0 |

In [96]:

```
scores(y_test,ypredknn)
```

Out[96]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.900826 | 1.000000 | 0.966667 | 0.983051 |
| **high** | 0.900826 | 0.791667 | 0.974359 | 0.873563 |
| **middle** | 0.900826 | 0.941176 | 0.864865 | 0.901408 |
| **low** | 0.900826 | 1.000000 | 0.666667 | 0.800000 |

### To find best n neighbors

In [97]:

```
max_no=40
error_rate=[]
f1scores=[]
for i in range(1,max_no):
    knn1=KNeighborsClassifier(n_neighbors=i,weights='distance')
    knn1.fit(x_train,y_train)
    ypr=knn1.predict(x_test)
    precision,recall,f1score,support=precision_recall_fscore_support(y_test,ypr,average=Non
    error=1-round(accuracy_score(y_test,ypr),2)
    error_rate.append((i,error))
    f1scores.append((i,f1score))
f1sc=pd.DataFrame(f1scores,columns=['k','f1score'])
errorrate=pd.DataFrame(error_rate,columns=['k','error'])
```

In [98]:

```
errorrate
```

Out[98]:

| | k | error |
|---|---|---|
| **0** | 1 | 0.16 |
| **1** | 2 | 0.16 |
| **2** | 3 | 0.13 |
| **3** | 4 | 0.12 |
| **4** | 5 | 0.12 |
| **5** | 6 | 0.11 |
| **6** | 7 | 0.10 |
| **7** | 8 | 0.09 |
| **8** | 9 | 0.11 |
| **9** | 10 | 0.10 |
| **10** | 11 | 0.10 |

***no of k's with minimum error.***

In [104]:

```
errorrate[errorrate.error==errorrate.error.min()]
```

Out[104]:

| | k | error |
|---|---|---|
| **11** | 12 | 0.08 |
| **12** | 13 | 0.08 |

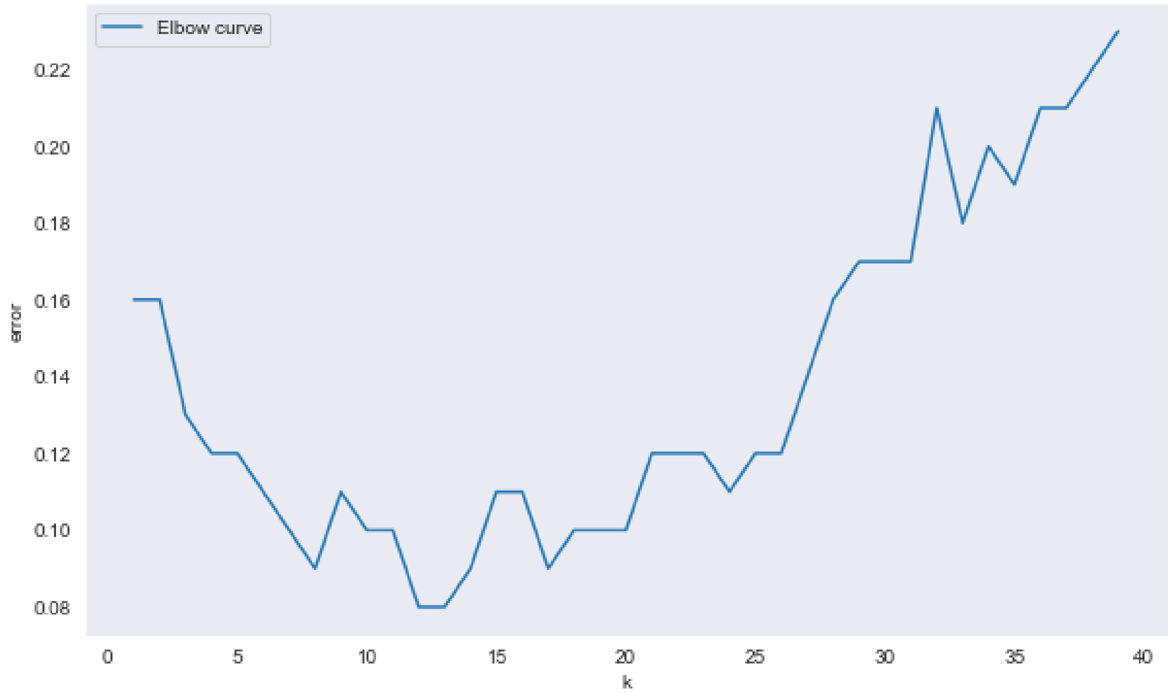
**Plotting error rates to get best n no of neighbors**

In [105]:

```
plt.figure(figsize=(10,6))
sns.lineplot(x=errorrate['k'],y=errorrate['error'],label='Elbow curve')
```

Out[105]:

```
<AxesSubplot:xlabel='k', ylabel='error'>
```




**Assigning the no of n neighbours with low error(12) in below KNN**

In [118]:

```
knn1=KNeighborsClassifier(n_neighbors=12,weights='distance')
knn1.fit(x_train,y_train)
ypredknn1=knn1.predict(x_test)
ypredknn1t=knn1.predict(x_train)
```

In [119]:

```
scores(y_train,ypredknn1t),scores(y_test,ypredknn1)
```

Out[119]:

```
(          acuracy  precision  recall  f1score
 verylow       1.0        1.0     1.0      1.0
 high          1.0        1.0     1.0      1.0
 middle        1.0        1.0     1.0      1.0
 low           1.0        1.0     1.0      1.0,
           acuracy  precision    recall   f1score
 verylow  0.917355   1.000000  0.966667  0.983051
 high     0.917355   0.812500  1.000000  0.896552
 middle   0.917355   0.970588  0.891892  0.929577
 low      0.917355   1.000000  0.666667  0.800000)
```

***Got best score.***

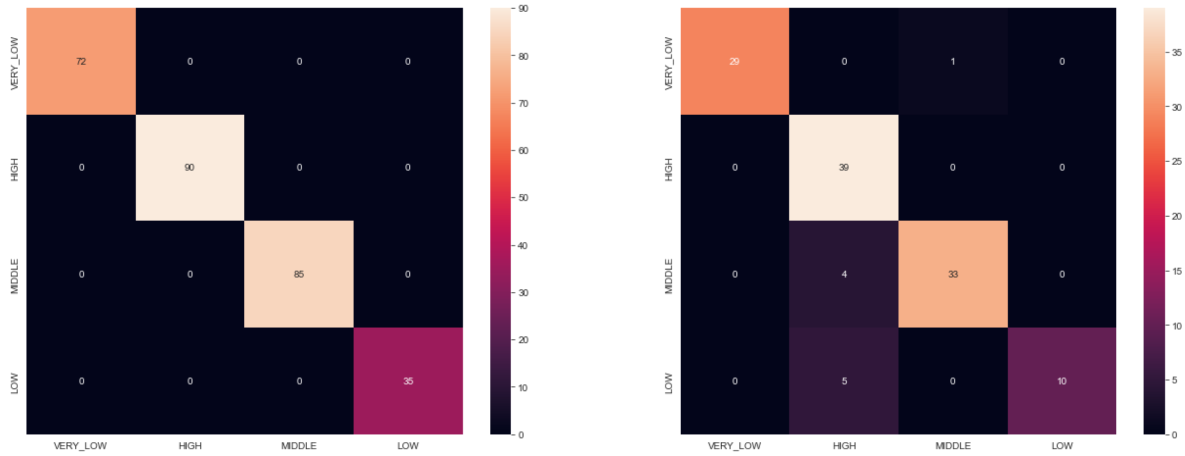
**plotting confusion matrix.**

In [122]:

```
cfknn = confusion_matrix(y_test, ypredknn1)
cfknnt = confusion_matrix(y_train, ypredknn1t)
fig, axes = plt.subplots(1, 2, figsize=(22, 8))
#plt.figure(figsize=(8,6))
sns.heatmap(ax=axes[0], data=cfknnt, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE',
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=cfknn, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE',
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[122]:

```
<AxesSubplot:>
```




# support vector machines

## svm L1 penalty

In [123]:

```
from sklearn.svm import LinearSVC
lsvml1=LinearSVC(penalty='l1',dual=False)
lsvml1.fit(x_train,y_train)
ypredlsvml1=lsvml1.predict(x_test)
ypredlsvmtl1=lsvml1.predict(x_train)
```

```
C:\Users\vignesh\AppData\Local\Programs\Python\Python39\lib\site-packages\sk
learn\svm\_base.py:1206: ConvergenceWarning: Liblinear failed to converge, i
ncrease the number of iterations.
  warnings.warn(
```

In [124]:

```
lsvml1.score(x_train,y_train),lsvml1.score(x_test,y_test)
```

Out[124]:

```
(0.8900709219858156, 0.8760330578512396)
```

In [125]:

```
scores(y_test,ypredlsvml1)
```

Out[125]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.876033 | 0.967742 | 1.000000 | 0.983607 |
| **high** | 0.876033 | 0.735849 | 1.000000 | 0.847826 |
| **middle** | 0.876033 | 1.000000 | 0.675676 | 0.806452 |
| **low** | 0.876033 | 1.000000 | 0.800000 | 0.888889 |

In [126]:

```
scores(y_train,ypredlsvmtl1)
```

Out[126]:

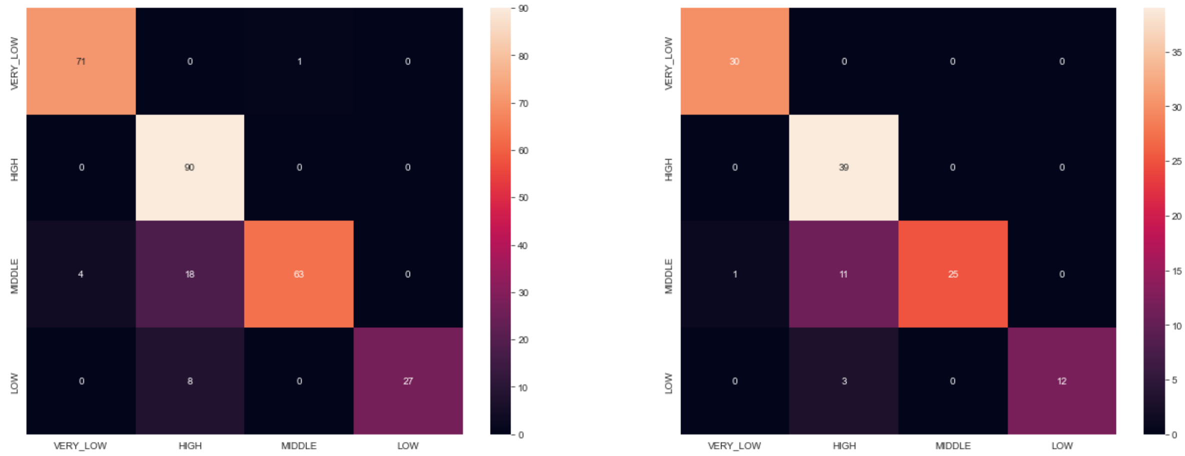
| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.890071 | 0.946667 | 0.986111 | 0.965986 |
| **high** | 0.890071 | 0.775862 | 1.000000 | 0.873786 |
| **middle** | 0.890071 | 0.984375 | 0.741176 | 0.845638 |
| **low** | 0.890071 | 1.000000 | 0.771429 | 0.870968 |

In [127]:

```
lsvml1cont=confusion_matrix(y_train,ypredlsvmtl1)
lsvml1con=confusion_matrix(y_test,ypredlsvml1)
fig,axes=plt.subplots(1,2, figsize=(22,8))
sns.heatmap(ax=axes[0], data=lsvml1cont, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDD
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=lsvml1con, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDL
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[127]:

<AxesSubplot:>




## svm L2 penalty

In [128]:

```
lsvml2=LinearSVC()
lsvml2.fit(x_train,y_train)
ypredlsvml2=lsvml2.predict(x_test)
ypredlsvml2t=lsvml2.predict(x_train)
```

In [129]:

```
accuracy_score(y_train,ypredlsvml2t),accuracy_score(y_test,ypredlsvml2)
```

Out[129]:

(0.8475177304964538, 0.8429752066115702)

In [130]:

```
scores(y_train,ypredlsvml2t)
```

Out[130]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.847518 | 0.898734 | 0.986111 | 0.940397 |
| **high** | 0.847518 | 0.729508 | 0.988889 | 0.839623 |
| **middle** | 0.847518 | 0.967213 | 0.694118 | 0.808219 |
| **low** | 0.847518 | 1.000000 | 0.571429 | 0.727273 |

In [131]:

```
scores(y_test,ypredlsvml2)
```

Out[131]:

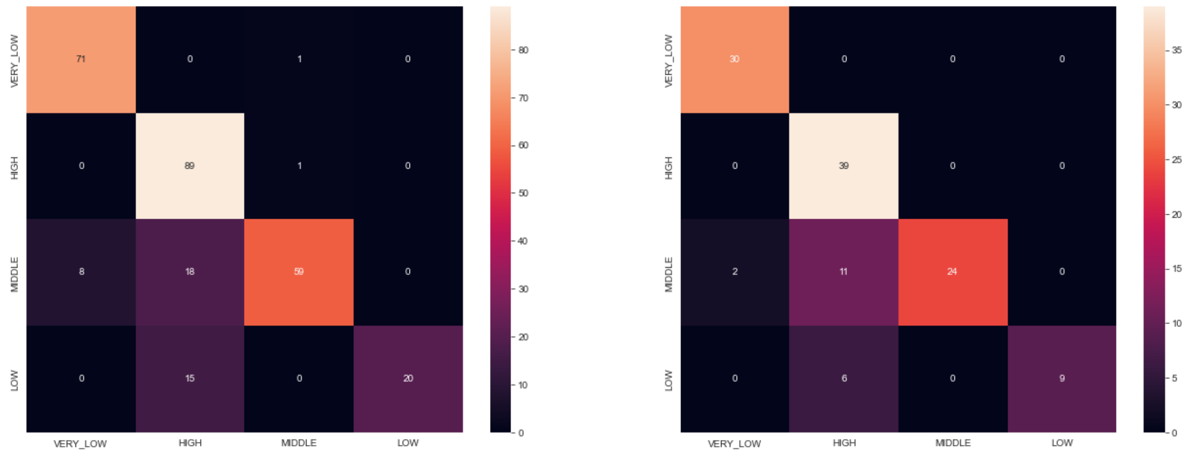
| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.842975 | 0.937500 | 1.000000 | 0.967742 |
| **high** | 0.842975 | 0.696429 | 1.000000 | 0.821053 |
| **middle** | 0.842975 | 1.000000 | 0.648649 | 0.786885 |
| **low** | 0.842975 | 1.000000 | 0.600000 | 0.750000 |

In [132]:

```
lsvml2cont=confusion_matrix(y_train,ypredlsvml2t)
lsvml2con=confusion_matrix(y_test,ypredlsvml2)
fig,axes=plt.subplots(1,2, figsize=(22,8))
sns.heatmap(ax=axes[0], data=lsvml2cont, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDD
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=lsvml2con, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDL
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[132]:

```
<AxesSubplot:>
```




## svm with kernals

In [133]:

```
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
```

In [140]:

```
param_gr = {
    'C': [0.001, 1, 100],
    'gamma':[0.1,100,100],
    'kernel':['rbf','poly','sigmoid']}
```

In [141]:

```
svc=SVC()
grid=GridSearchCV(estimator=svc,param_grid=param_gr,scoring='f1',cv=3,verbose=1)
grid.fit(x_train,y_train)
```

...

In [142]:

```
grid.best_params_
```

Out[142]:

```
{'C': 0.001, 'gamma': 0.1, 'kernel': 'rbf'}
```

In [143]:

```
ypredgrsvm=grid.predict(x_test)
ypredgrsvmt=grid.predict(x_train)
accuracy_score(y_train,ypredgrsvmt),accuracy_score(y_test,ypredgrsvm)
```

Out[143]:

```
(0.3191489361702128, 0.32231404958677684)
```

In [144]:

```
scores(y_train,ypredgrsvmt)
```

```
C:\Users\vignesh\AppData\Local\Programs\Python\Python39\lib\site-packages\sk
learn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and
F-score are ill-defined and being set to 0.0 in labels with no predicted sam
ples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Out[144]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.319149 | 0.000000 | 0.0 | 0.000000 |
| **high** | 0.319149 | 0.319149 | 1.0 | 0.483871 |
| **middle** | 0.319149 | 0.000000 | 0.0 | 0.000000 |
| **low** | 0.319149 | 0.000000 | 0.0 | 0.000000 |

In [145]:

```
scores(y_test,ypredgrsvm)
```

```
C:\Users\vignesh\AppData\Local\Programs\Python\Python39\lib\site-packages\sk
learn\metrics\_classification.py:1318: UndefinedMetricWarning: Precision and
F-score are ill-defined and being set to 0.0 in labels with no predicted sam
ples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Out[145]:

| | acuracy | precision | recall | f1score |
|---|---|---|---|---|
| **verylow** | 0.322314 | 0.000000 | 0.0 | 0.0000 |
| **high** | 0.322314 | 0.322314 | 1.0 | 0.4875 |
| **middle** | 0.322314 | 0.000000 | 0.0 | 0.0000 |
| **low** | 0.322314 | 0.000000 | 0.0 | 0.0000 |

### svc kernal method is not promising.

# Decision tree

***with 'gini' criterion.***

In [146]:

```
from sklearn.tree import DecisionTreeClassifier
dtc=DecisionTreeClassifier(random_state=42,criterion="gini")#criterion="entropy"
dtc.fit(x_train,y_train)
ypreddtc=dtc.predict(x_test)
ypreddtct=dtc.predict(x_train)
```

In [147]:

```
dtc.tree_.node_count,dtc.tree_.max_depth
```

Out[147]:

```
(51, 9)
```

feature importance.

In [149]:

```
dtc.tree_.compute_feature_importances()
```

Out[149]:

```
array([0.00813289, 0.01643467, 0.0222702 , 0.22154755, 0.73161469])
```

In [150]:

```
dtc.tree_.weighted_n_node_samples
```

Out[150]:

```
array([282., 138.,  36.,  28.,   8.,   6.,   2.,   1.,   1., 102.,  87.,
         2.,  85.,   7.,   3.,   4.,  78.,  74.,  68.,  10.,   1.,   9.,
        58.,   6.,   4.,   2.,   4.,   2.,   2.,  15.,   6.,   5.,   1.,
         9., 144.,  83.,  72.,  71.,   3.,   1.,   2.,  68.,   1.,  11.,
        61.,  54.,   7.,   2.,   1.,   1.,   5.])
```

In [151]:

```
dtc.score(x_train,y_train),dtc.score(x_test,y_test)
```

Out[151]:

```
(1.0, 0.9338842975206612)
```

In [152]:

```
scores(y_train,ypreddtct),scores(y_test,ypreddtc)
```

Out[152]:

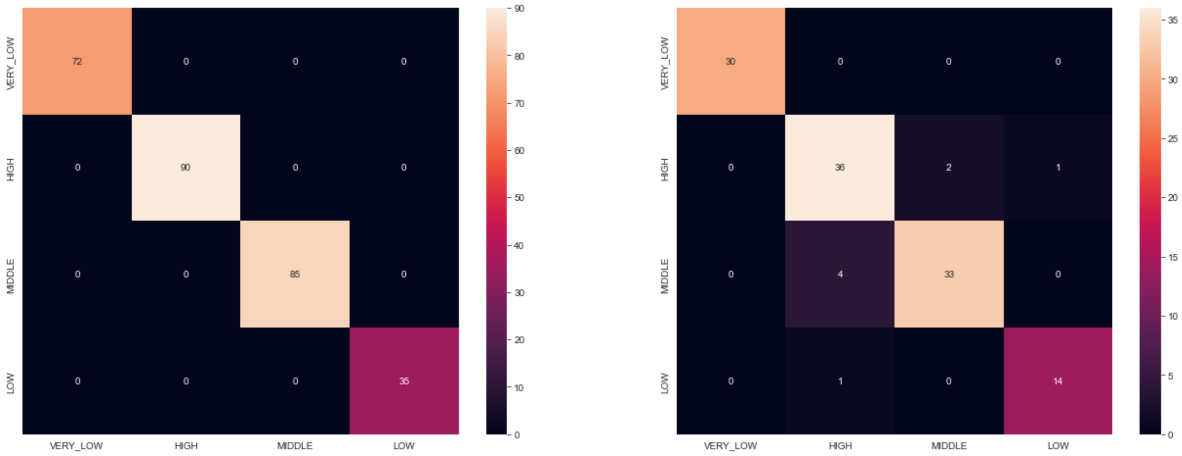
```
(         acuracy  precision  recall  f1score
 verylow      1.0        1.0     1.0      1.0
 high         1.0        1.0     1.0      1.0
 middle       1.0        1.0     1.0      1.0
 low          1.0        1.0     1.0      1.0,
           acuracy  precision    recall   f1score
 verylow  0.933884   1.000000  1.000000  1.000000
 high     0.933884   0.878049  0.923077  0.900000
 middle   0.933884   0.942857  0.891892  0.916667
 low      0.933884   0.933333  0.933333  0.933333)
```

In [153]:

```
dtctcon=confusion_matrix(y_train,ypreddtct)
dtccon=confusion_matrix(y_test,ypreddtc)
fig,axes=plt.subplots(1,2,figsize=(22,8))
sns.heatmap(ax=axes[0], data=dtctcon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE'
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=dtccon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE',
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[153]:

```
<AxesSubplot:>
```




## Using GridSearchCV to find best parameters.

In [176]:

```
paramdtc={'criterion':['entropy','gini'],'max_depth':range(1,100),
          'max_features':range(1,6)
          }
griddtc=DecisionTreeClassifier(random_state=42) #can use criterion gini or entropy in grids
griddtcmod=GridSearchCV(estimator=griddtc,param_grid=paramdtc,scoring='accuracy',cv=3,verbo
griddtcmod.fit(x_train,y_train)
```

Out[172]:

```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(random_state=42),
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': range(1, 100),
                         'max_features': range(1, 6)},
             scoring='accuracy', verbose=1)
```

```
Fitting 3 folds for each of 990 candidates, totalling 2970 fits
```

Out[173]:

```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(random_state=42),
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': range(1, 100),
                         'max_features': range(1, 6)},
             scoring='accuracy', verbose=1)
```

```
Fitting 3 folds for each of 990 candidates, totalling 2970 fits
```

Out[174]:

```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(random_state=42),
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': range(1, 100),
                         'max_features': range(1, 6)},
             scoring='accuracy', verbose=1)
```

```
Fitting 3 folds for each of 990 candidates, totalling 2970 fits
```

Out[175]:

```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(random_state=42),
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': range(1, 100),
                         'max_features': range(1, 6)},
             scoring='accuracy', verbose=1)
```

```
Fitting 3 folds for each of 990 candidates, totalling 2970 fits
```

Out[176]:

```
GridSearchCV(cv=3, estimator=DecisionTreeClassifier(random_state=42),
             param_grid={'criterion': ['entropy', 'gini'],
                         'max_depth': range(1, 100),
                         'max_features': range(1, 6)},
             scoring='accuracy', verbose=1)
```

In [177]:

```
ypredgrdtct=griddtcmod.predict(x_train)
ypredgrdtc=griddtcmod.predict(x_test)
```

In [178]:

```
griddtcmod.best_estimator_,griddtcmod.best_score_
```

Out[178]:

```
(DecisionTreeClassifier(criterion='entropy', max_depth=6, max_features=5,
                        random_state=42),
 0.900709219858156)
```

In [179]:

```
griddtcmod.best_estimator_.tree_.node_count,griddtcmod.best_estimator_.tree_.max_depth
```

Out[179]:

```
(41, 6)
```

In [180]:

```
scores(y_train,ypredgrdtct),scores(y_test,ypredgrdtc)
```

Out[180]:

```
(          acuracy  precision    recall   f1score
 verylow  0.989362   1.000000  1.000000  1.000000
 high     0.989362   0.967742  1.000000  0.983607
 middle   0.989362   1.000000  0.988235  0.994083
 low      0.989362   1.000000  0.942857  0.970588,
           acuracy  precision    recall   f1score
 verylow  0.933884   1.000000  1.000000  1.000000
 high     0.933884   0.918919  0.871795  0.894737
 middle   0.933884   0.871795  0.918919  0.894737
 low      0.933884   1.000000  1.000000  1.000000)
```

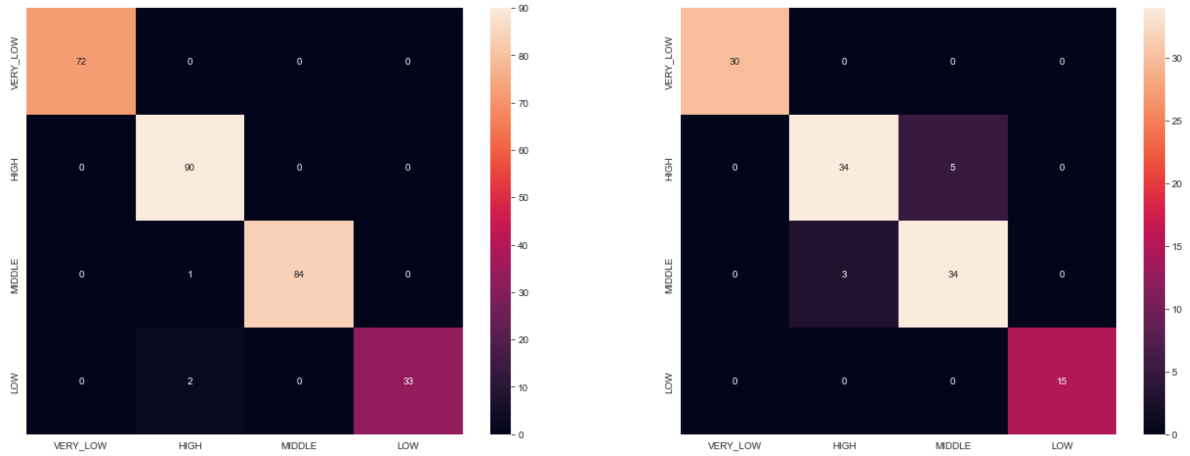
***plotting matrix.***

In [181]:

```
grdtctcon=confusion_matrix(y_train,ypredgrdtct)
grdtccon=confusion_matrix(y_test,ypredgrdtc)
fig,axes=plt.subplots(1,2,figsize=(22,8))
sns.heatmap(ax=axes[0], data=grdtctcon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDL
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=grdtccon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[181]:

```
<AxesSubplot:>
```




# Ensemble based models.

## Bagging

In [182]:

```
from sklearn.ensemble import BaggingClassifier
bc=BaggingClassifier(n_estimators=50)
bc.fit(x_train,y_train)
ypredbct=bc.predict(x_train)
ypredbc=bc.predict(x_test)
```

n estimator = 50 as told in course

In [183]:

```
scores(y_train,ypredbct),scores(y_test,ypredbc)
```

Out[183]:

```
(          acuracy  precision    recall   f1score
 verylow  0.996454   1.000000  1.000000  1.000000
 high     0.996454   0.989011  1.000000  0.994475
 middle   0.996454   1.000000  1.000000  1.000000
 low      0.996454   1.000000  0.971429  0.985507,
           acuracy  precision    recall   f1score
 verylow  0.950413   1.000000  1.000000  1.000000
 high     0.950413   0.902439  0.948718  0.925000
 middle   0.950413   0.944444  0.918919  0.931507
 low      0.950413   1.000000  0.933333  0.965517)
```

In [184]:

```
parambc={'n_estimators':range(1,100)}
mod=BaggingClassifier(random_state=42)
gridbc=GridSearchCV(mod,parambc,cv=3,verbose=1)
gridbc.fit(x_train,y_train)
ypredgrbct=gridbc.predict(x_train)
ypredgrbc=gridbc.predict(x_test)
```

```
Fitting 3 folds for each of 99 candidates, totalling 297 fits
```

In [185]:

```
accuracy_score(y_train,ypredgrbct),accuracy_score(y_test,ypredgrbc)
```

Out[185]:

```
(1.0, 0.9586776859504132)
```

In [186]:

```
gridbc.best_params_,gridbc.best_score_
```

Out[186]:

```
({'n_estimators': 32}, 0.9042553191489362)
```

In [187]:

```
scores(y_train,ypredgrbct),scores(y_test,ypredgrbc)
```

Out[187]:

```
(         acuracy  precision  recall  f1score
 verylow      1.0        1.0     1.0      1.0
 high         1.0        1.0     1.0      1.0
 middle       1.0        1.0     1.0      1.0
 low          1.0        1.0     1.0      1.0,
           acuracy  precision    recall   f1score
 verylow  0.958678   1.000000  1.000000  1.000000
 high     0.958678   0.904762  0.974359  0.938272
 middle   0.958678   0.971429  0.918919  0.944444
 low      0.958678   1.000000  0.933333  0.965517)
```

**find out of bag error to get eficient n_estimators**

In [188]:

```
bago=BaggingClassifier(oob_score=True,random_state=42,n_jobs=1,warm_start=False,bootstrap=T
oob_list=[]
for n_trees in range(1,100):
    bago.set_params(n_estimators=n_trees)
    bago.fit(x_train,y_train)
    oob_error=1 - bago.oob_score_
    oob_list.append(pd.Series({'n_trees':n_trees,'error':round(oob_error,4)}))
oob_err=pd.concat(oob_list,axis=1).T.set_index('n_trees')
oob_err
```

...

In [189]:

```
oob_err.error.min()
```

Out[189]:

```
0.0745
```

found that 50 is good.

In [190]:

```
oob_err[oob_err.error==0.0745]
```

Out[190]:

| | error |
|---|---|
| **n_trees** | |
| **50.0** | 0.0745 |

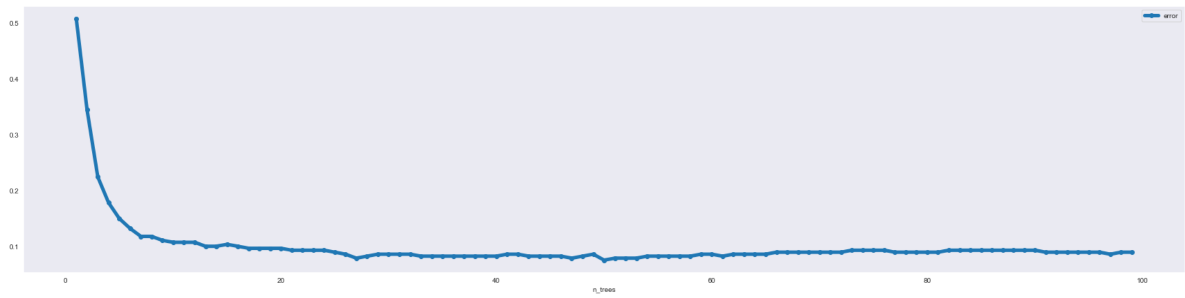
In [192]:

```
plt.figure(figsize=(28,7))
oob_err.plot(marker='o', figsize=(30, 7), linewidth=5)
```

Out[192]:

```
<AxesSubplot:xlabel='n_trees'>
```

```
<Figure size 2016x504 with 0 Axes>
```




# Random forest

In [193]:

```
from sklearn.ensemble import RandomForestClassifier
rf=RandomForestClassifier(n_estimators=49,random_state=2)
```

In [194]:

```
rf.fit(x_train,y_train)
ypredrft=rf.predict(x_train)
ypredrf=rf.predict(x_test)
```

In [195]:

```
rf.score(x_train,y_train),rf.score(x_test,y_test)
```

Out[195]:

```
(1.0, 0.9752066115702479)
```

In [196]:

```
scores(y_train,ypredrft),scores(y_test,ypredrf)
```

Out[196]:

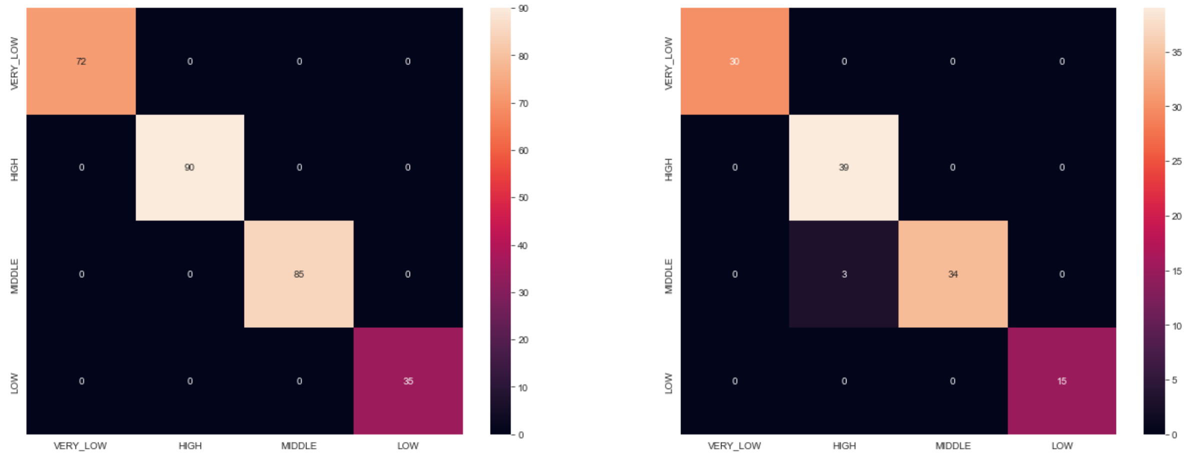
```
(         acuracy  precision  recall  f1score
 verylow      1.0        1.0     1.0      1.0
 high         1.0        1.0     1.0      1.0
 middle       1.0        1.0     1.0      1.0
 low          1.0        1.0     1.0      1.0,
           acuracy  precision    recall   f1score
 verylow  0.975207   1.000000  1.000000  1.000000
 high     0.975207   0.928571  1.000000  0.962963
 middle   0.975207   1.000000  0.918919  0.957746
 low      0.975207   1.000000  1.000000  1.000000)
```

In [201]:

```
rftcon=confusion_matrix(y_train,ypredrft)
rfcon=confusion_matrix(y_test,ypredrf)
fig,axes=plt.subplots(1,2,figsize=(22,8))
sns.heatmap(ax=axes[0], data=rftcon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE',
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=rfcon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE',
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[201]:

```
<AxesSubplot:>
```




In [202]:

```
param_gridrf = {'n_estimators': range(100),
               'max_depth' : range(15) ,
               'max_features':["auto", "sqrt", "log2"]}
model=RandomForestClassifier(random_state=2)
```

In [203]:

```
gridrf=GridSearchCV(estimator=model, param_grid=param_gridrf,scoring='accuracy',cv=3,return
gridrf.fit(x_train, y_train)
```

...

In [204]:

```
ypredgrrft=gridrf.predict(x_train)
ypredgrrf=gridrf.predict(x_test)
```

In [205]:

```
gridrf.best_score_,gridrf.best_params_
```

Out[205]:

```
(0.9148936170212766,
 {'max_depth': 8, 'max_features': 'auto', 'n_estimators': 19})
```

In [206]:

```
scores(y_train,ypredgrrft),scores(y_test,ypredgrrf)
```

Out[206]:

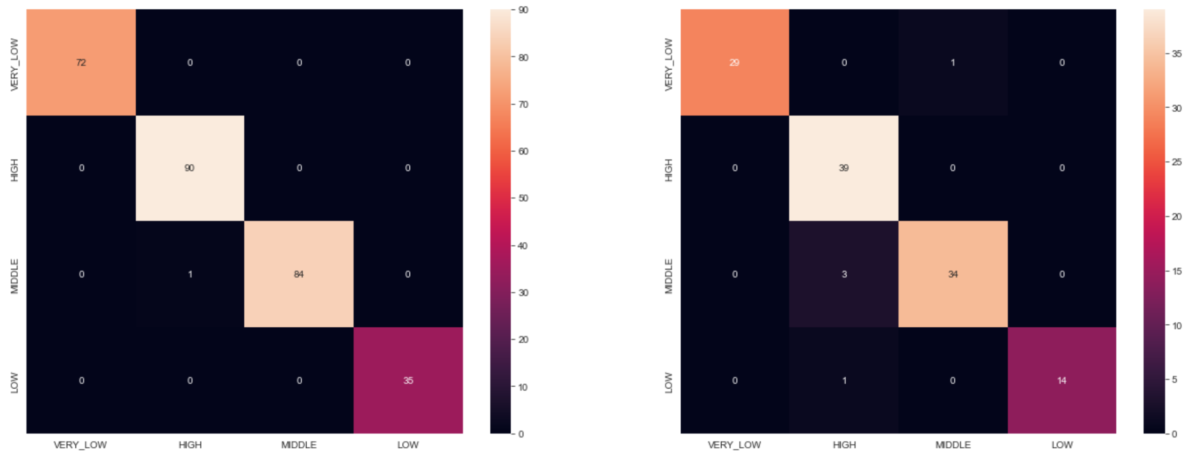
```
(          acuracy  precision    recall   f1score
 verylow  0.996454   1.000000  1.000000  1.000000
 high     0.996454   0.989011  1.000000  0.994475
 middle   0.996454   1.000000  0.988235  0.994083
 low      0.996454   1.000000  1.000000  1.000000,
           acuracy  precision    recall   f1score
 verylow  0.958678   1.000000  0.966667  0.983051
 high     0.958678   0.906977  1.000000  0.951220
 middle   0.958678   0.971429  0.918919  0.944444
 low      0.958678   1.000000  0.933333  0.965517)
```

In [207]:

```
grdrftcon=confusion_matrix(y_train,ypredgrrft)
grdrfcon=confusion_matrix(y_test,ypredgrrf)
fig,axes=plt.subplots(1,2,figsize=(22,8))
sns.heatmap(ax=axes[0], data=grdrftcon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDL
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
sns.heatmap(ax=axes[1], data=grdrfcon, annot=True, xticklabels=['VERY_LOW', 'HIGH', 'MIDDLE
            yticklabels=['VERY_LOW', 'HIGH', 'MIDDLE', 'LOW'])
```

Out[207]:

```
<AxesSubplot:>
```




## Extra tree classifier

In [211]:

```
from sklearn.ensemble import ExtraTreesClassifier
ex=ExtraTreesClassifier(n_estimators=50,random_state=10)
```

In [212]:

```
ex.fit(x_train,y_train)
ypredex=ex.predict(x_test)
ypredext=ex.predict(x_train)
```

In [213]:

```
ex.score(x_train,y_train),ex.score(x_test,y_test)
```

Out[213]:

```
(1.0, 0.9669421487603306)
```

***we can do grid seachcv for this above also***

***and oob score method***

In [214]:

```
oobex=ExtraTreesClassifier(oob_score=True,random_state=42,n_jobs=1,bootstrap=True)
oobex_list=[]
for n_trees in range(1,100):
    oobex.set_params(n_estimators=n_trees)
    oobex.fit(x_train,y_train)
    oobex_error=1 - oobex.oob_score_
    oobex_list.append(pd.Series({'n_trees':n_trees,'error':round(oobex_error,4)}))
oobex_err=pd.concat(oobex_list,axis=1).T.set_index('n_trees')
oobex_err
```

```
scores. This probably means too few trees were used to compute any reliabl
e OOB estimates.
  warn(
C:\Users\vignesh\AppData\Local\Programs\Python\Python39\lib\site-packages
\sklearn\ensemble\_forest.py:560: UserWarning: Some inputs do not have OOB
scores. This probably means too few trees were used to compute any reliabl
e OOB estimates.
  warn(
```

Out[214]:

| | error |
|---|---|
| **n_trees** | |
| **1.0** | 0.5496 |
| **2.0** | 0.3901 |
| **3.0** | 0.3085 |
| **4.0** | 0.2624 |

In [215]:

```
oobex_err.min()
```

Out[215]:

```
error    0.0567
dtype: float64
```

In [216]:

```
topl=oobex_err[40:80]
oobex_err[oobex_err.error==0.0567]
```

Out[216]:

| | error |
|---|---|
| **n_trees** | |
| **68.0** | 0.0567 |

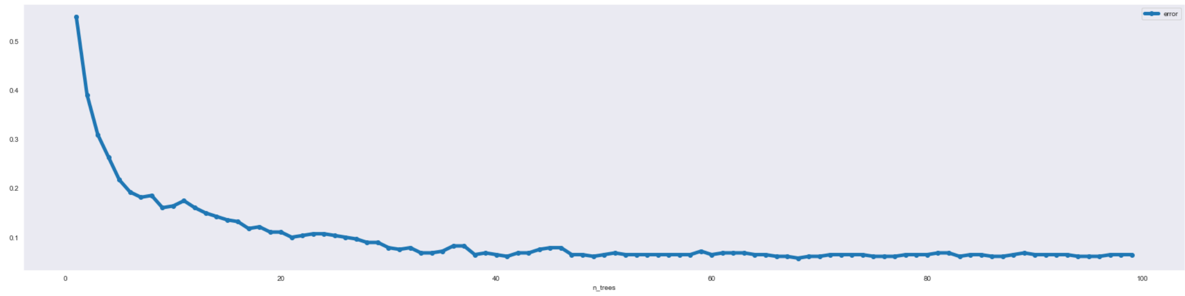
In [220]:

```
plt.figure(figsize=(20,10))
oobex_err.plot(marker='o', figsize=(30, 7), linewidth=5)
```

Out[220]:

```
<AxesSubplot:xlabel='n_trees'>
```

```
<Figure size 1440x720 with 0 Axes>
```




***found that 68 is good.***

In [221]:

```
ex1=ExtraTreesClassifier(n_estimators=68,random_state=10)
ex1.fit(x_train,y_train)
ypredex1=ex1.predict(x_test)
ypredext1=ex1.predict(x_train)
ex1.score(x_train,y_train),ex1.score(x_test,y_test)
```

Out[221]:

```
(1.0, 0.9669421487603306)
```

In [223]:

```
scores(y_train,ypredext1),scores(y_test,ypredex1)
```

Out[223]:

```
(         acuracy  precision  recall  f1score
 verylow      1.0        1.0     1.0      1.0
 high         1.0        1.0     1.0      1.0
 middle       1.0        1.0     1.0      1.0
 low          1.0        1.0     1.0      1.0,
           acuracy  precision    recall   f1score
 verylow  0.966942   1.000000  1.000000  1.000000
 high     0.966942   0.926829  0.974359  0.950000
 middle   0.966942   0.971429  0.918919  0.944444
 low      0.966942   1.000000  1.000000  1.000000)
```

# Best model is 'Random Forest' in terms of accuracy.

This model gives best accuracy score for the test dataset and generalize well for new data here it is test set. It gives of

### 97%

of accuracy same as the AutoML. Hence Random Forset is the 'Model of the Analysis'. And also the best F1 scores of

- 100%
- 96.2%
- 95.7%
- 100% for the consecutive classes in the target Attribute.

# Summary

This Dataset is not having many more data points maybe that's why this notebook is simple to interpret when even reading about the description of the data. So, that explains that Random forest came with Best score out of all the Models that are fitted. From Logistic Regression, SVM, Decision tree to the ensemble models along with the AutoML used in this notebook good Fit is random Forest and the AutoML.

# Suggestions.

This Dataset is so simple and easy to interpret and To do analysis i would suggest there is another student Performance Dataset available in Kaggle to use. This data maybe worth doing analysis but with more number of data points and some more features. the features in this dataset is simple and Also not complex enough and even the Knowledge level of a student is not solely depend on the 'performence' or 'number of time studying' at all. that's why more number of features can be helpful in further more Interpretation of these kind of analysis.

# Thank you