IMPORT IMPORTANT LIBRARIES

In [339]:

```
import pandas as pd  ### to handle dataframe
import numpy as np   ### to perform numeric operation
import matplotlib.pyplot as plt  ### for visualization
import seaborn as sns ### for visualization

from sklearn.model_selection import train_test_split   ### for splitting the data
from sklearn.preprocessing import StandardScaler       ### normalize the data
from sklearn.metrics import accuracy_score             ### to get accuracy score

from sklearn.linear_model import LogisticRegression    ### logistic regression
from sklearn.neighbors import KNeighborsClassifier     ### knn
from sklearn.tree import DecisionTreeClassifier        ### Decision tree
from sklearn.ensemble import RandomForestClassifier    ### Random Forest
from sklearn.svm import SVC                            ### Support vector machine

from sklearn.model_selection import cross_val_score    ### for cross validation
from sklearn.metrics import roc_curve,auc              ### roc and auc
```

READING DATA

In [192]:

```
! pip install openpyxl ### to read (.xlsx) file first we have to install this library

df = pd.read_excel('train.xlsx') ### reading data
```

In [193]:

```
df
```

Out[193]:

	Index	BI_RADS	Age	Shape	Margin	Mass_Density	Severity
0	1	5.0	67.0	lobular	spiculated	low	1
1	2	4.0	43.0	round	circumscribed	NaN	1
2	3	5.0	58.0	irregular	spiculated	low	1
3	4	4.0	28.0	round	circumscribed	low	0
4	5	5.0	74.0	round	spiculated	NaN	1
...	...	...	...	...	...	...	...
806	807	5.0	62.0	irregular	ill-defined	iso	1
807	808	4.0	56.0	oval	circumscribed	low	0
808	809	5.0	58.0	irregular	ill-defined	low	1
809	810	4.0	NaN	round	ill-defined	low	0
810	811	5.0	75.0	irregular	spiculated	low	1

811 rows × 7 columns

EDA + FEATURE ENGINEERING

In [194]:

```
df.info()   ### to get all information about dataframe
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 811 entries, 0 to 810
Data columns (total 7 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Index         811 non-null    int64  
 1   BI_RADS       809 non-null    float64
 2   Age           723 non-null    float64
 3   Shape         781 non-null    object 
 4   Margin        764 non-null    object 
 5   Mass_Density  735 non-null    object 
 6   Severity      811 non-null    int64  
dtypes: float64(2), int64(2), object(3)
memory usage: 44.5+ KB
```

In [195]:

```
df.describe(include='all')
```

Out[195]:

	Index	BI_RADS	Age	Shape	Margin	Mass_Density	Severity
count	811.000000	809.000000	723.000000	781	764	735	811.000000
unique	NaN	NaN	NaN	4	5	4	NaN
top	NaN	NaN	NaN	irregular	circumscribed	low	NaN
freq	NaN	NaN	NaN	340	298	663	NaN
mean	406.000000	4.379481	55.887967	NaN	NaN	NaN	0.459926
std	234.259827	1.914800	16.886616	NaN	NaN	NaN	0.498699
min	1.000000	0.000000	5.000000	NaN	NaN	NaN	0.000000
25%	203.500000	4.000000	45.000000	NaN	NaN	NaN	0.000000
50%	406.000000	4.000000	56.000000	NaN	NaN	NaN	0.000000
75%	608.500000	5.000000	66.000000	NaN	NaN	NaN	1.000000
max	811.000000	55.000000	130.000000	NaN	NaN	NaN	1.000000

HANDELING MISSING VALUES

QUESTION NO - 9

Q - What techniques have been used for treating missing values to prepare features for model building?

Ans - Handeling missing values totally depend on type of data

```
 1 - if the data is continous numerical data then we can use imputation method in
 which we replace the nan values with
     mean,median or mode values.

 2 - if the data is categorical data then we replace nan values with other categor
ical data

     - if the number of missing value is less then we replace the missing values w
ith most frequent category

     - if the number of missing values is more then we replace the missing values
 with new category
```

In [338]:

```
df.isna() ### checking whether null values are present or not , True = Present
```

Out[338]:

	Age	Shape	Margin	Mass_Density	Severity
0	False	False	False	False	False
1	False	False	False	False	False
2	False	False	False	False	False
3	False	False	False	False	False
4	False	False	False	False	False
...	...	...	...	...	...
806	False	False	False	False	False
807	False	False	False	False	False
808	False	False	False	False	False
809	False	False	False	False	False
810	False	False	False	False	False

811 rows × 5 columns

In [197]:

```
df.drop(['Index'],axis = 1,inplace = True) ### we dont need index column so drop it
```

BI_RADS

In [198]:

```
### as mentioned in the porblem statement BI_RADS is no-predictive so itll not be useful
### for prediction so iam going to drop BI_RADS

df['BI_RADS'].isna().sum()
```

Out[198]:

```
2
```

In [199]:

```
df['BI_RADS'].isna().value_counts() ### to check the values and their counts
```

Out[199]:

```
False    809
True       2
Name: BI_RADS, dtype: int64
```

In [200]:

```
df['BI_RADS'].unique() ### to get unique values
```

Out[200]:

```
array([ 5.,  4.,  3., nan,  2., 55.,  0.,  6.])
```

Age

In [201]:

```
### Age attribute having continous numeric data so we can go for imputation method
```

In [202]:

```
df['Age'].isna().sum()
```

Out[202]:

```
88
```

In [203]:

```
df['Age'].isna().value_counts()
```

Out[203]:

```
False    723
True      88
Name: Age, dtype: int64
```

In [204]:

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

Out[204]:

```
array([ 67.,  43.,  58.,  28.,  74.,  65.,  70.,  42.,  57.,  60.,  76.,
        64.,  36.,  54.,  52.,  59.,  40.,  66.,  56.,  nan,  45.,  55.,
        46.,  39.,  81.,  77.,  48.,  78.,  50.,  61.,  62.,  44.,  23.,
        80.,  63.,  53.,  49.,  51.,  25.,  72.,  73.,  68.,  33.,  47.,
        29.,  34.,  71., 130.,  24.,  75.,  41.,  87.,  21.,  19.,  35.,
        37.,  79.,  69.,  38.,  32.,  27.,  83.,  88.,  26.,   5.,  18.,
        93.,  22.,  96.])
```

In [205]:

```
df['Age'].mean()
```

Out[205]:

```
55.88796680497925
```

In [206]:

```
df['Age'].median() ### for attribute Age we fill null values with median value of Age
                   ### because mean and mode value is close to median value
```

Out[206]:

```
56.0
```

In [207]:

```
df['Age'].mode()[0]
```

Out[207]:

```
59.0
```

In [208]:

```
### filling null values with median value

df['Age'].fillna(df['Age'].median(),inplace = True)
```

In [209]:

```
df['Age'].isna().sum()
```

Out[209]:

```
0
```

Shape

In [210]:

```
### Attribute Shape having categorical data so we cant use imputation method so we can repl
```

In [211]:

```
df['Shape'].isna().sum()
```

Out[211]:

```
30
```

In [212]:

```
df['Shape'].value_counts()
```

Out[212]:

```
irregular    340
round        192
oval         177
lobular       72
Name: Shape, dtype: int64
```

In [213]:

```
df['Shape'].isna().value_counts()
```

Out[213]:

```
False    781
True      30
Name: Shape, dtype: int64
```

In [214]:

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

Out[214]:

```
array(['lobular', 'round', 'irregular', nan, 'oval'], dtype=object)
```

In [215]:

```
df['Shape'].value_counts().to_dict()
```

Out[215]:

```
{'irregular': 340, 'round': 192, 'oval': 177, 'lobular': 72}
```

In [216]:

```
### we dont have too many nan values so i will replace the nan values with the most frequen
### which is 'irregular'

df['Shape'].fillna('irregular',inplace = True)
```

In [217]:

```
df['Shape'].isna().sum()
```

Out[217]:

```
0
```

In [218]:

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

Out[218]:

```
array(['lobular', 'round', 'irregular', 'oval'], dtype=object)
```

Margin

In [219]:

```
df['Margin'].isna().sum()
```

Out[219]:

```
47
```

In [220]:

```
df['Margin'].isna().value_counts()
```

Out[220]:

```
False    764
True      47
Name: Margin, dtype: int64
```

In [221]:

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

Out[221]:

```
array(['spiculated', 'circumscribed', nan, 'ill-defined', 'obscured',
       'microlobulated'], dtype=object)
```

In [222]:

```
df['Margin'].value_counts()
```

Out[222]:

```
circumscribed     298
ill-defined       236
spiculated        116
obscured           97
microlobulated     17
Name: Margin, dtype: int64
```

In [223]:

```
### we dont have too many nan values so i will replace the nan values with the most frequen
### which is 'circumscribed'

df['Margin'].fillna('circumscribed',inplace = True)
```

In [224]:

```
df['Margin'].isna().sum()
```

Out[224]:

```
0
```

Mass_Density

In [225]:

```
df['Mass_Density'].isna().sum()
```

Out[225]:

```
76
```

In [226]:

```
df['Mass_Density'].isna().value_counts()
```

Out[226]:

```
False    735
True      76
Name: Mass_Density, dtype: int64
```

In [227]:

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

Out[227]:

```
array(['low', nan, 'high', 'iso', 'fat-containing'], dtype=object)
```

In [228]:

```
df['Mass_Density'].value_counts()
```

Out[228]:

```
low               663
iso                49
high               13
fat-containing     10
Name: Mass_Density, dtype: int64
```

In [229]:

```
### we dont have too many nan values so i will replace the nan values with the most frequen
### which is 'Low'

df['Mass_Density'].fillna('low',inplace = True)
```

In [230]:

```
df['Mass_Density'].isna().sum()
```

Out[230]:

```
0
```

Severity

In [231]:

```
### this is target column and dont have any nan value so ill skip this attribute

df['Severity'].isna().sum()
```

Out[231]:

```
0
```

In [232]:

```
df['Severity'].isna().value_counts()
```

Out[232]:

```
False    811
Name: Severity, dtype: int64
```

In [233]:

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

Out[233]:

```
array([1, 0], dtype=int64)
```

DATATYPE HANDELING

In [234]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 811 entries, 0 to 810
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   BI_RADS       809 non-null    float64
 1   Age           811 non-null    float64
 2   Shape         811 non-null    object 
 3   Margin        811 non-null    object 
 4   Mass_Density  811 non-null    object 
 5   Severity      811 non-null    int64  
dtypes: float64(2), int64(1), object(3)
memory usage: 38.1+ KB
```

1 - Shape

In [235]:

```
df['Shape'].value_counts()
```

Out[235]:

```
irregular    370
round        192
oval         177
lobular       72
Name: Shape, dtype: int64
```

In [236]:

```
df['Shape'].value_counts().to_dict()
```

Out[236]:

```
{'irregular': 370, 'round': 192, 'oval': 177, 'lobular': 72}
```

In [237]:

```
### Using Replace method

df['Shape'].replace({'irregular': 4, 'round': 1, 'oval': 2, 'lobular': 3},inplace = True)
```

In [238]:

```
df.head()
```

Out[238]:

	BI_RADS	Age	Shape	Margin	Mass_Density	Severity
0	5.0	67.0	3	spiculated	low	1
1	4.0	43.0	1	circumscribed	low	1
2	5.0	58.0	4	spiculated	low	1
3	4.0	28.0	1	circumscribed	low	0
4	5.0	74.0	1	spiculated	low	1

In [239]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 811 entries, 0 to 810
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   BI_RADS       809 non-null    float64
 1   Age           811 non-null    float64
 2   Shape         811 non-null    int64  
 3   Margin        811 non-null    object 
 4   Mass_Density  811 non-null    object 
 5   Severity      811 non-null    int64  
dtypes: float64(2), int64(2), object(2)
memory usage: 38.1+ KB
```

2 - Margin

In [240]:

```
df['Margin'].value_counts()
```

Out[240]:

```
circumscribed     345
ill-defined       236
spiculated        116
obscured           97
microlobulated     17
Name: Margin, dtype: int64
```

In [241]:

```
df['Margin'].value_counts().to_dict()
```

Out[241]:

```
{'circumscribed': 345,
 'ill-defined': 236,
 'spiculated': 116,
 'obscured': 97,
 'microlobulated': 17}
```

In [242]:

```
df['Margin'].replace({'circumscribed': 1,
 'ill-defined': 4,
 'spiculated': 5,
 'obscured': 3,
 'microlobulated': 2}, inplace = True)
```

In [243]:

```
df.head()
```

Out[243]:

	BI_RADS	Age	Shape	Margin	Mass_Density	Severity
0	5.0	67.0	3	5	low	1
1	4.0	43.0	1	1	low	1
2	5.0	58.0	4	5	low	1
3	4.0	28.0	1	1	low	0
4	5.0	74.0	1	5	low	1

In [244]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 811 entries, 0 to 810
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   BI_RADS       809 non-null    float64
 1   Age           811 non-null    float64
 2   Shape         811 non-null    int64  
 3   Margin        811 non-null    int64  
 4   Mass_Density  811 non-null    object 
 5   Severity      811 non-null    int64  
dtypes: float64(2), int64(3), object(1)
memory usage: 38.1+ KB
```

3 - Mass Density

In [245]:

```
df['Mass_Density'].value_counts()
```

Out[245]:

```
low               739
iso                49
high               13
fat-containing     10
Name: Mass_Density, dtype: int64
```

In [246]:

```
df['Mass_Density'].value_counts().to_dict()
```

Out[246]:

```
{'low': 739, 'iso': 49, 'high': 13, 'fat-containing': 10}
```

In [247]:

```
df['Mass_Density'].replace({'low': 3, 'iso': 2, 'high': 1, 'fat-containing': 4},inplace = T
```

In [248]:

```
df.head()
```

Out[248]:

	BI_RADS	Age	Shape	Margin	Mass_Density	Severity
0	5.0	67.0	3	5	3	1
1	4.0	43.0	1	1	3	1
2	5.0	58.0	4	5	3	1
3	4.0	28.0	1	1	3	0
4	5.0	74.0	1	5	3	1

In [249]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 811 entries, 0 to 810
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   BI_RADS       809 non-null    float64
 1   Age           811 non-null    float64
 2   Shape         811 non-null    int64  
 3   Margin        811 non-null    int64  
 4   Mass_Density  811 non-null    int64  
 5   Severity      811 non-null    int64  
dtypes: float64(2), int64(4)
memory usage: 38.1 KB
```

FEATURE SELECTION

QUESTION NO - 3

Q - What features would you want to create for your prediction model based on data provided?

Ans - BI_RADS attribute is non predictive so drop this attribute and proceed with all other attributes

In [255]:

```
df.drop(['BI_RADS'],axis = 1,inplace = True)
```

In [256]:

```
df.head()
```

Out[256]:

	Age	Shape	Margin	Mass_Density	Severity
0	67.0	3	5	3	1
1	43.0	1	1	3	1
2	58.0	4	5	3	1
3	28.0	1	1	3	0
4	74.0	1	5	3	1

So Age, Shape , Margin , Mass_Density will be input feature and Severity will be output feature

DATA VISUALISATION

QUESTION NO - 6

Q - Determine whether the data is normally distributed visually and statistically.

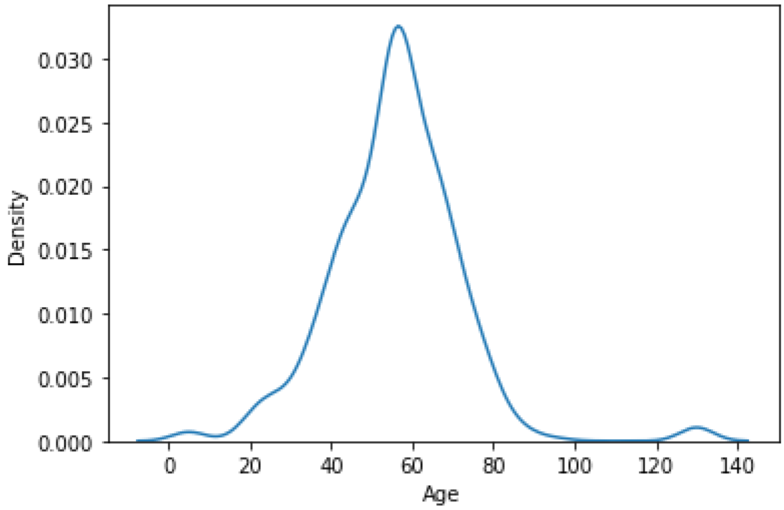
Ans - data is normally distributed as per we can see the kdeplot little bit random distributed in case of Margin and Shape but we can say that data is normally distributed

In [258]:

```
sns.kdeplot(df['Age'])
```

Out[258]:

<AxesSubplot:xlabel='Age', ylabel='Density'>



In [ ]:

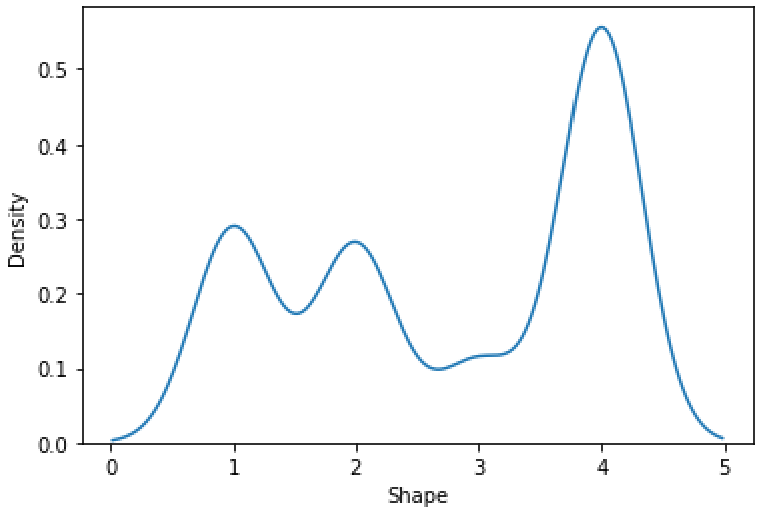
```

```

In [259]:

```
sns.kdeplot(df['Shape'])
```

Out[259]:

<AxesSubplot:xlabel='Shape', ylabel='Density'>



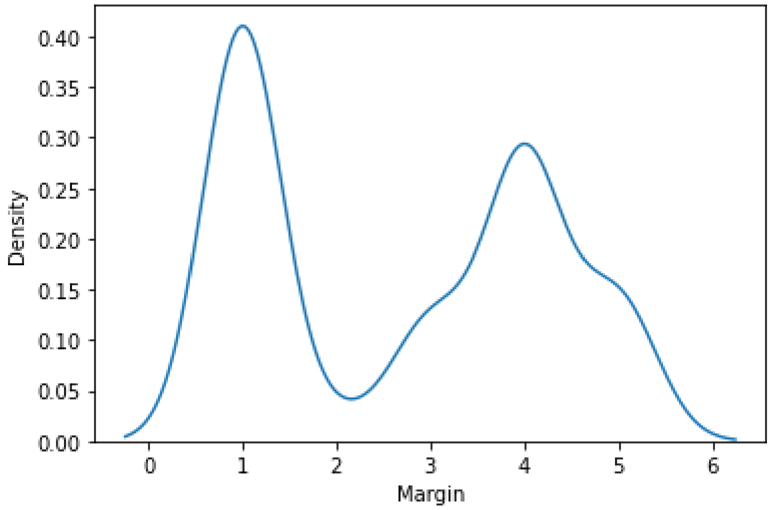
In [ ]:

In [260]:

```
sns.kdeplot(df['Margin'])
```

Out[260]:

<AxesSubplot:xlabel='Margin', ylabel='Density'>



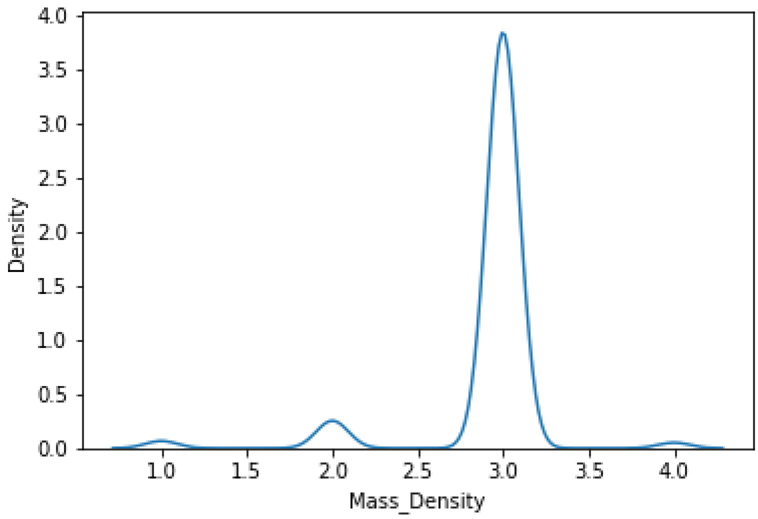
In [ ]:

In [261]:

```
sns.kdeplot(df['Mass_Density'])
```

Out[261]:

<AxesSubplot:xlabel='Mass_Density', ylabel='Density'>



DETECTING AND HANDELING OUTLIERS

QUESTION NO - 8

Q - How are you detecting and treating outliers in the dataset for better convergence?

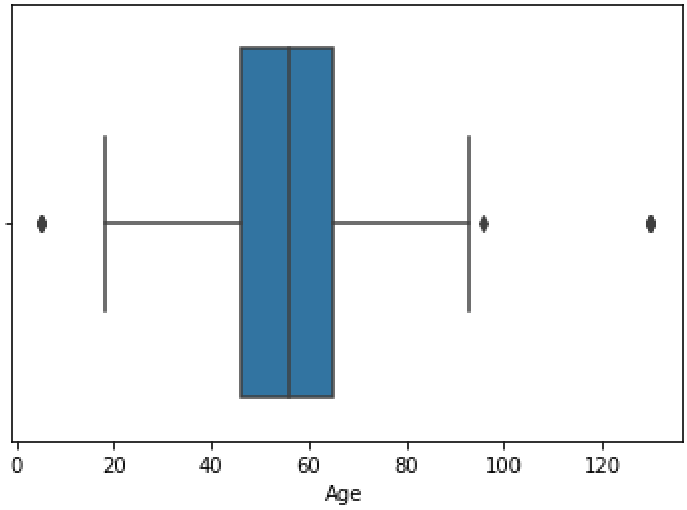
Ans - to detect the outliers ill use boxplot

In [269]:

```
sns.boxplot(x=df['Age'])

### in Age attribute we can see three dots shown in fig below those three dots are outliers
### lets find out the upper tail so we can get clearance about those outliers
```

Out[269]:

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



In [270]:

```
q1 = df['Age'].quantile(0.25)
q3 = df['Age'].quantile(0.75)
iqr = q3-q1

upper_tail = q3+(1.5*iqr)
upper_tail
```

Out[270]:

```
93.5
```

In [271]:

```
df.loc[df['Age'] > upper_tail]
```

Out[271]:

	Age	Shape	Margin	Mass_Density	Severity
119	130.0	4	5	3	0
132	130.0	4	4	3	0
169	130.0	4	5	3	1
195	130.0	4	4	3	1
330	130.0	3	5	3	1
466	130.0	4	5	3	1
578	130.0	3	2	3	1
596	130.0	4	3	3	1
609	130.0	3	4	3	1
726	96.0	3	4	3	1

In [ ]:

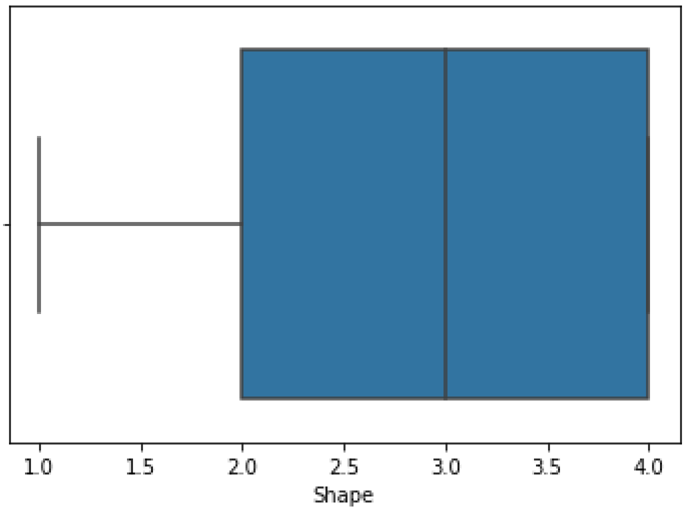
```
### so basically the outliers are age value higher than upper tail
### age is important attribute in our data frame so we cant consider it as outliers
### so we just skip
```

In [272]:

```
sns.boxplot(x=df['Shape'])

### there is no outlier in Shape attribute
```

Out[272]:

<AxesSubplot:xlabel='Shape'>

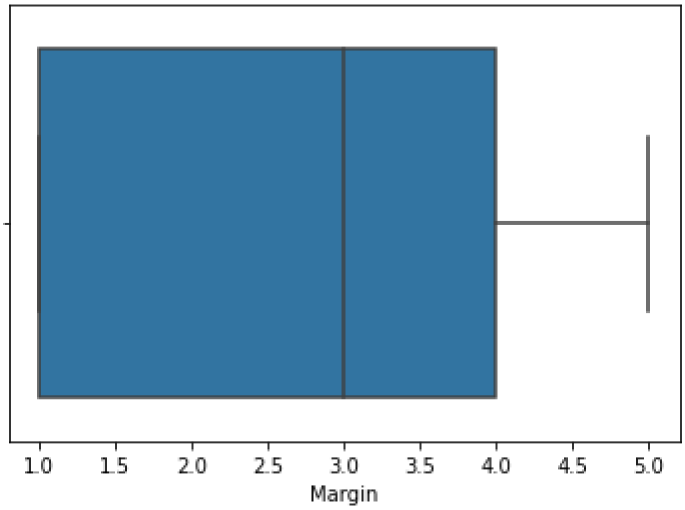


In [273]:

```
sns.boxplot(x=df['Margin'])

### there is no outlier in Margin attribute
```

Out[273]:

```
&lt;AxesSubplot:xlabel='Margin'&gt;
```

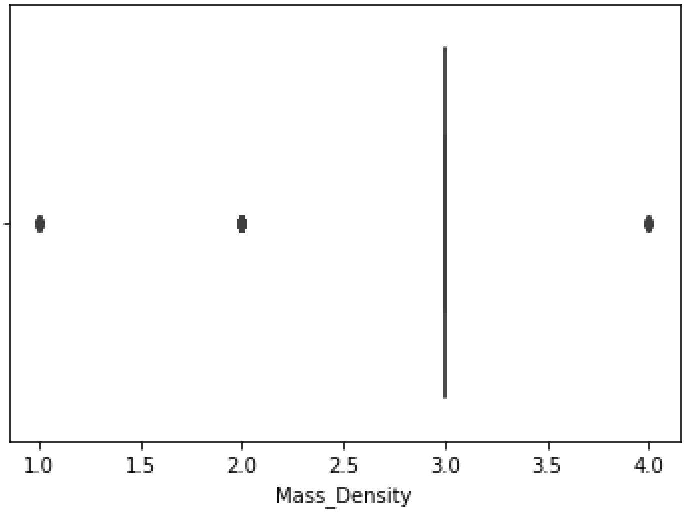


In [274]:

```
sns.boxplot(x=df['Mass_Density'])

### we can see the outliers but those are important as per our data so we can skip
```

Out[274]:

```
&lt;AxesSubplot:xlabel='Mass_Density'&gt;
```



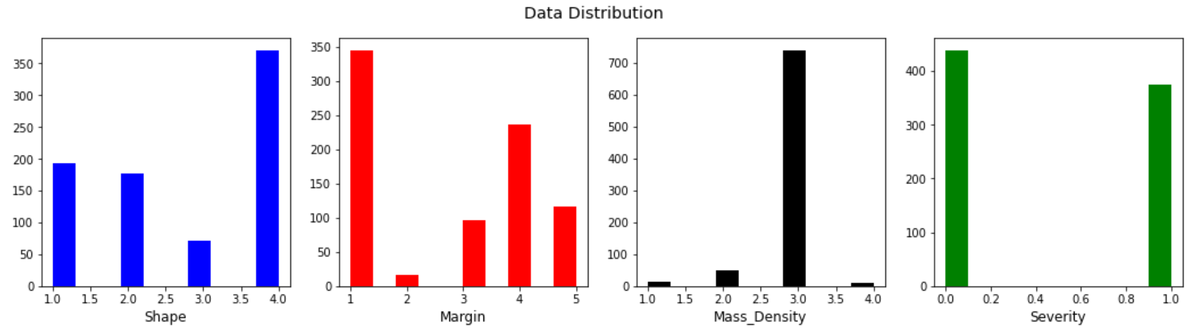
QUESTION NO - 10

Q - What is the distribution of target with respect to categorical columns?

Ans - We have three categorical columns named Shape, Margin, Mass_Density and Age is not categorical column and with the help of histogram we can see the data distribution of the columns

In [282]:

```
figure,axes = plt.subplots(1,4, sharey = False,figsize = (18,4))
x1,x2,x3,x4 = axes.flatten()
x1.hist(df['Shape'],bins = 10,color = "blue")
x2.hist(df['Margin'],bins = 10,color = "red")
x3.hist(df['Mass_Density'],bins = 10,color = "black")
x4.hist(df['Severity'],bins = 10,color = "green")

x1.set_xlabel('Shape',fontsize = 'large')
x2.set_xlabel('Margin',fontsize = 'large')
x3.set_xlabel('Mass_Density',fontsize = 'large')
x4.set_xlabel('Severity',fontsize = 'large')

plt.suptitle('Data Distribution',ha='center',fontsize = 'x-large')
plt.show()
```



MODEL BUILDING AND MODELTRAINING

QUESTION NO - 1

Q - Build Statistical Classification model to detect severity

Ans - i will use five different classification algorithm and compair the performance

1 - Decision Tree

2 - Random Forest

3 - KNN

4 - SVM

5 - Logistic Regression

In [292]:

```
### Assigning values for x and y

x = df.drop('Severity',axis = 1)
y = df['Severity']
```

In [286]:

```
### Scaling the input attributes to normalize the data within a particular range
### with the help of StandardScalar we can normalize the data

###why?
### Ans - as we seen in above kde plot we have some fetures having slight random distributi
### we using Standard Scalar to normalize the data

scalar = StandardScaler()
x = scalar.fit_transform(x)
print(x)
```

```
[[ 0.6966527   0.18819935  1.45162835  0.22191151]
 [-0.80964014 -1.41001715 -1.07877593  0.22191151]
 [ 0.13179288  0.98730761  1.45162835  0.22191151]
 ...
 [ 0.13179288  0.98730761  0.81902728  0.22191151]
 [ 0.00626848 -1.41001715  0.81902728  0.22191151]
 [ 1.19875031  0.98730761  1.45162835  0.22191151]]
```

In [288]:

```
### Splitting the data

x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2,random_state=0)

### 80% data for training
### 20% data for testing
```

In [319]:

```
df['Severity'].value_counts()
```

Out[319]:

```
0    438
1    373
Name: Severity, dtype: int64
```

QUESTION NO - 5

Q - What is your model evaluation criteria? What are the assumptions and limitations of your approach?

Ans - so as per value counts of our target variable data distribution is nearly equal so we can say that the data is balanced so we can directly find the accuracy score. in below cell we training the model and find out the accuracy score

what if the data is imbalanced?

- if the data is imbalanced then we have to find out the confusion matrix then calculate the precision ,recall and f-beta score

In [328]:

```
### ill create dictionary of all the different algorithms and train the models

dictionary = {SVC(kernel = 'rbf', C = 1 ,gamma = 1000 , probability = True):"Support Vector
             LogisticRegression(solver = 'liblinear', random_state = 0):"Logistic Regressio
             KNeighborsClassifier(n_neighbors = 10):"K-Neighbors Classifier",
             RandomForestClassifier(max_depth = 3 , n_estimators = 100 , random_state = 0):
             DecisionTreeClassifier(random_state = 0):"Decision Tree Classifier"}

for model in dictionary:
    model.fit(x_train,y_train)

    y_pred = model.predict(x_test)

    accuracy = accuracy_score(y_test,y_pred)

    print("Model Accuracy of", dictionary[model]," = ",accuracy.round(3))
```

```
Model Accuracy of Support Vector Classifier  =  0.644
Model Accuracy of Logistic Regression  =  0.791
Model Accuracy of K-Neighbors Classifier  =  0.804
Model Accuracy of Random Forest  =  0.81
Model Accuracy of Decision Tree Classifier  =  0.693
```

QUESTION NO - 4

Q - How have you performed hyper-parameter tuning and model optimization? What are the reasons for your decision choices for these steps?

Ans - talking about hyperparameter i did not used hyperparameter tuning but some default hyperparameters are given below

Logistic regression --> solver = liblinear

k Neighbors --> n_neighbors = 10 --> we can give range for this

SVM --> kernel = 'rbf'

Random Forest --> max_depth = 3 and n_estimators = 100

In [322]:

```
### as we see above we get more accuracy by using random forest algorithm
### now i can use k-fold cross validation to check wether our model accuracy is getting bet
### k-fold is used for improving model prediction
```

In [334]:

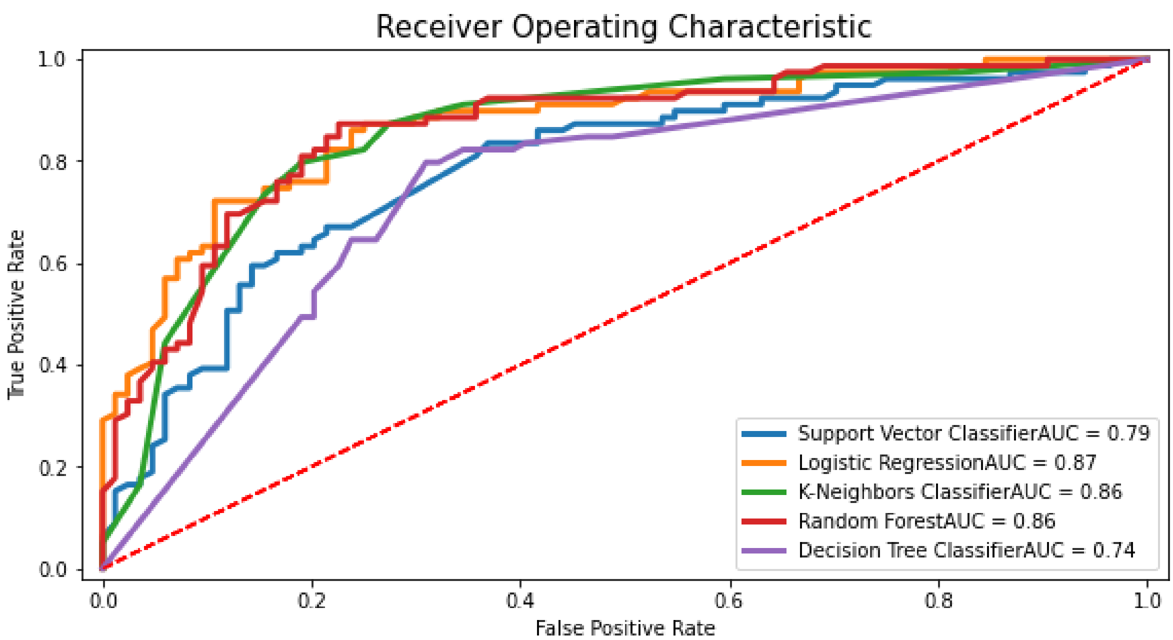
```
from sklearn.model_selection import cross_val_score

for model in dictionary:
    cvscore = cross_val_score(model,x,y,cv = 10)
    print("Model Accuracy of", dictionary[model],"with cross validation is = ",'{:3.2f}'.fo
```

```
Model Accuracy of Support Vector Classifier with cross validation is =  0.70
Model Accuracy of Logistic Regression with cross validation is =  0.79
Model Accuracy of K-Neighbors Classifier with cross validation is =  0.77
Model Accuracy of Random Forest with cross validation is =  0.81
Model Accuracy of Decision Tree Classifier with cross validation is =  0.74
```

ROC AND AUC CURVE TO CHECK THE DIFFERENT MODEL PERFORMANCE

In [337]:

```
from sklearn.metrics import roc_curve,auc  ### import roc and auc

dictionary = {SVC(kernel = 'rbf', C = 1 ,gamma = 1000 , probability = True):"Support Vector
              LogisticRegression(solver = 'liblinear', random_state = 0):"Logistic Regressio
              KNeighborsClassifier(n_neighbors = 10):"K-Neighbors Classifier",
              RandomForestClassifier(max_depth = 3 , n_estimators = 100 , random_state = 0):
              DecisionTreeClassifier(random_state = 0):"Decision Tree Classifier"}

for model in dictionary:
    model.fit(x_train,y_train)

    prob = model.predict_proba(x_test)

    fpr,tpr,thresholds=roc_curve(y_test,prob[:,1])

    roc_auc = auc(fpr,tpr)

    plt.plot(fpr,tpr,lw = 3, label = dictionary[model]+'AUC = %0.2f'% roc_auc)

    plt.legend(loc = 'lower right')
    plt.plot([0,1],[0,1],'r--')
    plt.title('Receiver Operating Characteristic', fontsize = 15)

plt.xlim([-0.02, 1.02])
plt.ylim([-0.02, 1.02])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.rcParams['figure.figsize'] = (10,5)
plt.show()
```



In [ ]:

```
### a curve pulled close to the upper left corner indicates a better performance
```

QUESTION NO - 2

Q - What considerations have been used for model selection?

Ans - for model selection my way to select the best model is to feed data to all classification or regression models and compair the accuracy as per our case Random forest is giving more accuracy even after cross validation than other classification models so ill go for Random Forest for my final model Selection

QUESTION NO - 11

Q - Comment on any other observations or recommendations based on your analysis

Ans - 1 - by observation we can see that we got 81% accuracy using random forest even after cross validation we can increase the accuracy by changing the default hyperparametrs that we have used during training or also we can go for hyperparameter tuning using grid and randomized search for those default hyperparameters

2 - we replaced null values with the most common data in the data frame instead of that we can go for dropping all the null vlaue we might get better accuracy

3 - we had some outliers in the dataframe columns but those outliers are important values and cant be ignored so if those values not present in the data set then our model performance might be different

In [ ]:

```

```