In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import skew
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score,mean_absolute_error
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVR
```

In [2]:
```
def print_title(title):
    print(f'\n{'-'*60}\n\033[1m{title}\033[0m')
def print_section(title):
    print(f'{'-'*60}\n{title}\n{'-'*60}')
```

(1) Loading and Preprocessing

loding the California Housing dataset using the fetch_California_Housing function from sklearn

In [4]:
```
from sklearn.datasets import fetch_california_housing
data = fetch_california_housing()
```

In [5]:
```
x = data.data
y = data.target
feature = data.feature_names
```

In [6]:
```
print_section('This data from sklearndataset contains the average house value as target
```

```
------------------------------------------------------------
This data from sklearndataset contains the average house value as target variable
and the following indepentend variables (features): average income,
housing average age, average rooms, average bedrooms, population,
average occupation, latitude, and longitude in that order.
------------------------------------------------------------
```

Converging the dataset into a pandas DataFrame for easier handling.

In [8]:
```
ch = pd.DataFrame(x,columns = feature)
ch['MedHouseVal'] = y
```

In [9]:
```
#data frame basic exploratory data analysis
print_title("DataFrame Info")
print_section(ch.info())
print_title("DataFrame null values sum")
print_section(ch.isnull().sum())
print_title("DataFrame Description")
print_section(ch.describe())
```

```
------------------------------------------------------------
DataFrame Info
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
```

```
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
------------------------------------------------------------
None
------------------------------------------------------------

------------------------------------------------------------
DataFrame null values sum
------------------------------------------------------------
MedInc         0
HouseAge       0
AveRooms       0
AveBedrms      0
Population     0
AveOccup       0
Latitude       0
Longitude      0
MedHouseVal    0
dtype: int64
------------------------------------------------------------

------------------------------------------------------------
DataFrame Description
------------------------------------------------------------
             MedInc      HouseAge      AveRooms     AveBedrms    Population  \
count  20640.000000  20640.000000  20640.000000  20640.000000  20640.000000   
mean       3.870671     28.639486      5.429000      1.096675   1425.476744   
std        1.899822     12.585558      2.474173      0.473911   1132.462122   
min        0.499900      1.000000      0.846154      0.333333      3.000000   
25%        2.563400     18.000000      4.440716      1.006079    787.000000   
50%        3.534800     29.000000      5.229129      1.048780   1166.000000   
75%        4.743250     37.000000      6.052381      1.099526   1725.000000   
max       15.000100     52.000000    141.909091     34.066667  35682.000000   

           AveOccup      Latitude     Longitude   MedHouseVal  
count  20640.000000  20640.000000  20640.000000  20640.000000  
mean       3.070655     35.631861   -119.569704      2.068558  
std       10.386050      2.135952      2.003532      1.153956  
min        0.692308     32.540000   -124.350000      0.149990  
25%        2.429741     33.930000   -121.800000      1.196000  
50%        2.818116     34.260000   -118.490000      1.797000  
75%        3.282261     37.710000   -118.010000      2.647250  
max     1243.333333     41.950000   -114.310000      5.000010  
------------------------------------------------------------
```

In [10]:

```python
#duplicate row removing
print_section(f"Total Row Befor removing duplicated row: \033[1m{len(ch)}\033[0m")
ch = ch.drop_duplicates()
print_section(f"Total Row After removing duplicated row: \033[1m{len(ch)}\033[0m\nSice B
```

```
------------------------------------------------------------
Total Row Befor removing duplicated row: 20640
------------------------------------------------------------
------------------------------------------------------------
```

```
Total Row After removing duplicated row: 20640
Sice Bhoth values are same the duplicates rows not avilable
------------------------------------------------------------
```

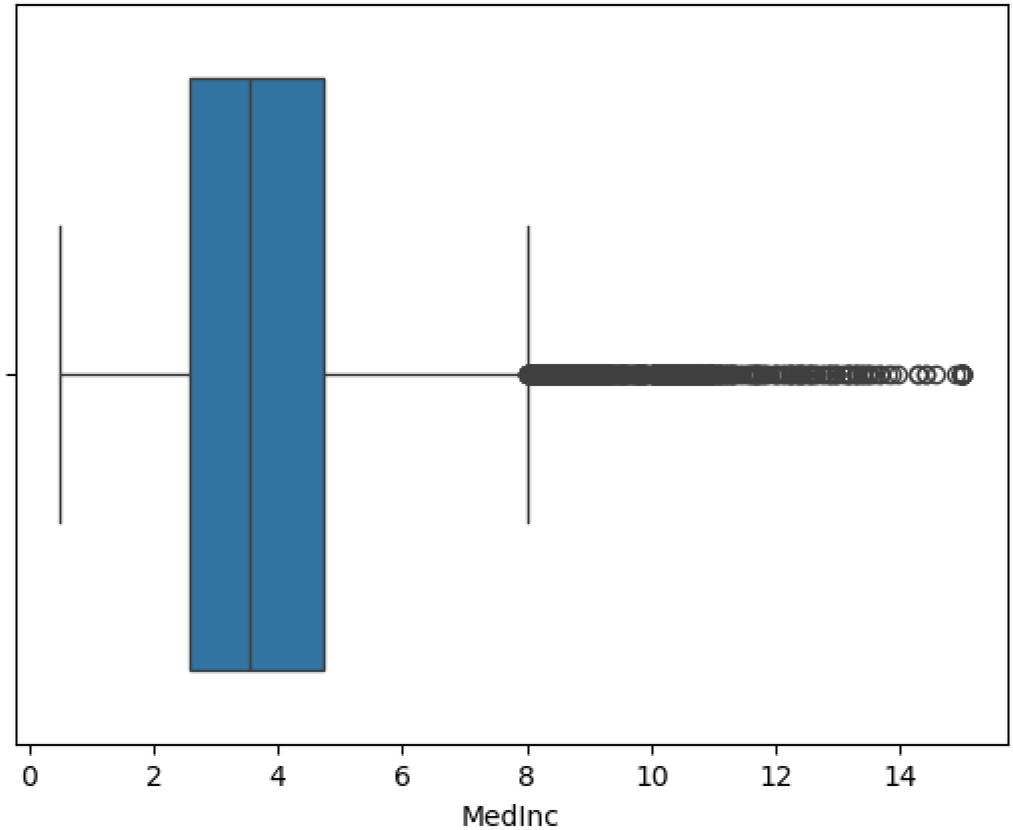
In [11]:
```python
# mean and standerd deviation of given dataframe
ch_mean = ch.mean(axis = 0,numeric_only=True)
print_section("\033[1mMean of DataFrame\033[0m")
print_section(ch_mean)
ch_mean = ch.std(axis = 0,numeric_only=True)
print_section("\033[1mStanderd deviation of DataFrame\033[0m")
print_section(ch_mean)
```

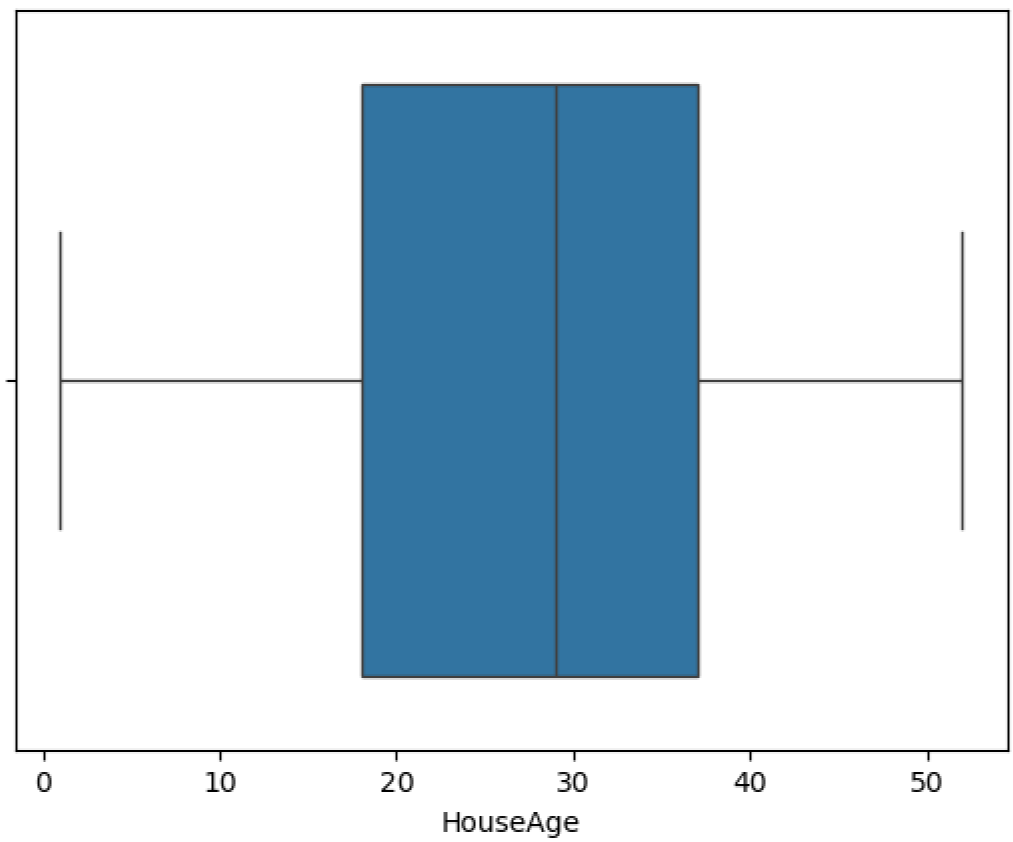
```
------------------------------------------------------------
Mean of DataFrame
------------------------------------------------------------
------------------------------------------------------------
MedInc            3.870671
HouseAge         28.639486
AveRooms          5.429000
AveBedrms         1.096675
Population     1425.476744
AveOccup          3.070655
Latitude         35.631861
Longitude      -119.569704
MedHouseVal       2.068558
dtype: float64
------------------------------------------------------------
------------------------------------------------------------
Standerd deviation of DataFrame
------------------------------------------------------------
------------------------------------------------------------
MedInc            1.899822
HouseAge         12.585558
AveRooms          2.474173
AveBedrms         0.473911
Population     1132.462122
AveOccup         10.386050
Latitude          2.135952
Longitude         2.003532
MedHouseVal       1.153956
dtype: float64
------------------------------------------------------------
```

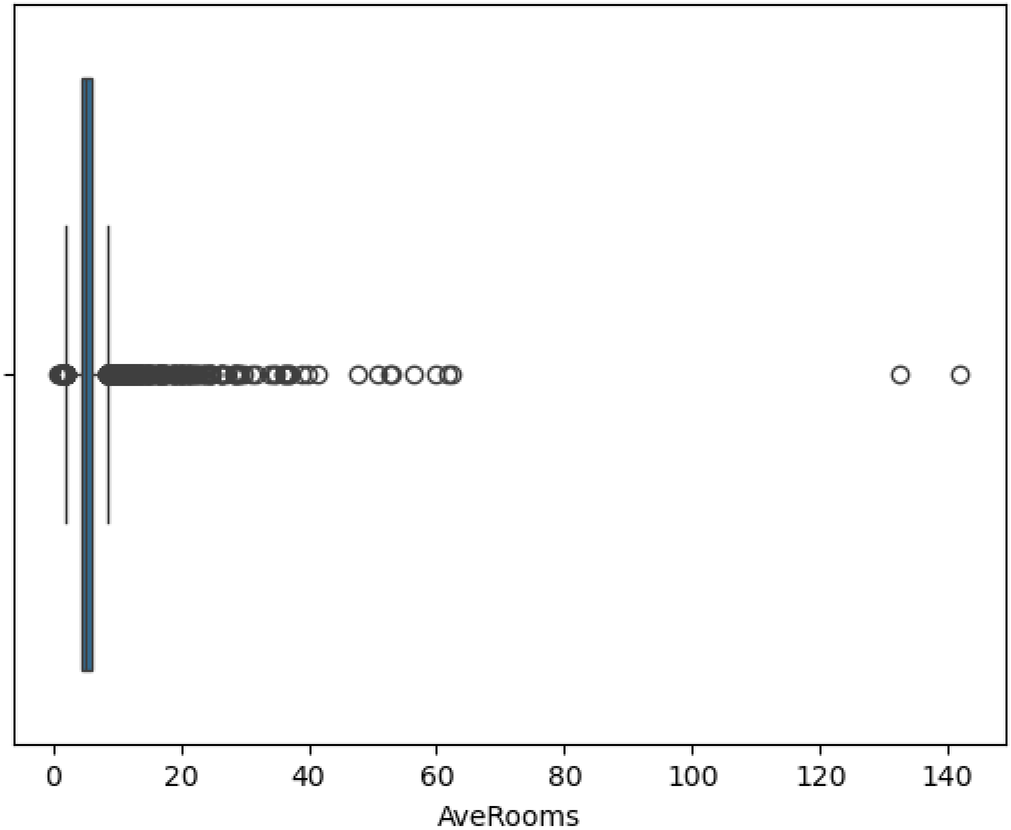
In [12]:
```python
### Creating new datafame for outlier visualisation
ch_col = ch.select_dtypes(include='number')
print(ch_col.info())
### syntex to visualise the df to detect outliers for each columns
for i in ch_col.columns:
    sns.boxplot(data=ch,x=i)
    plt.show()
```

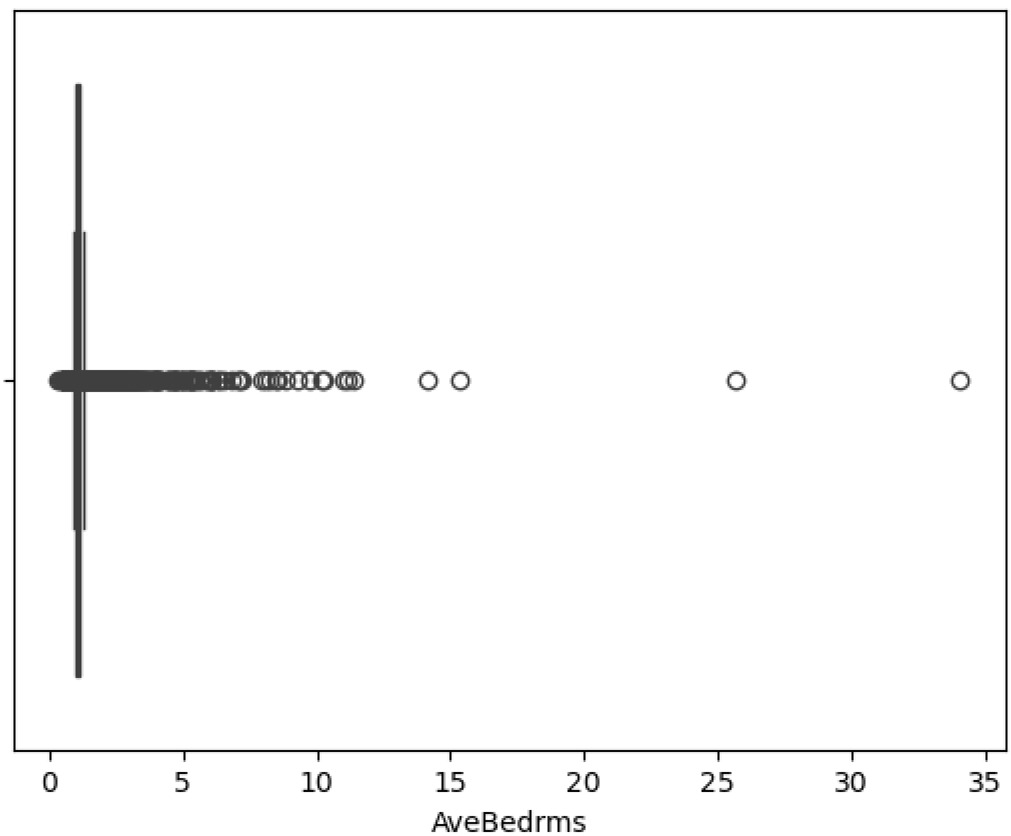
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
```

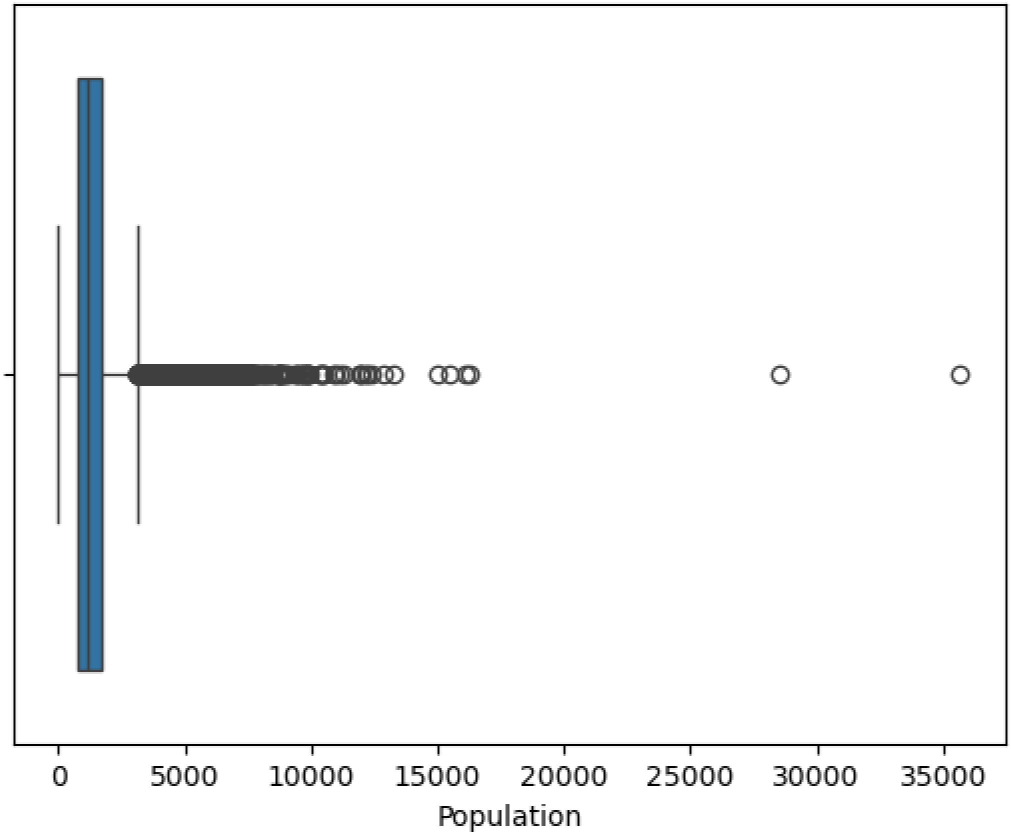
```
memory usage: 1.4 MB
None
```

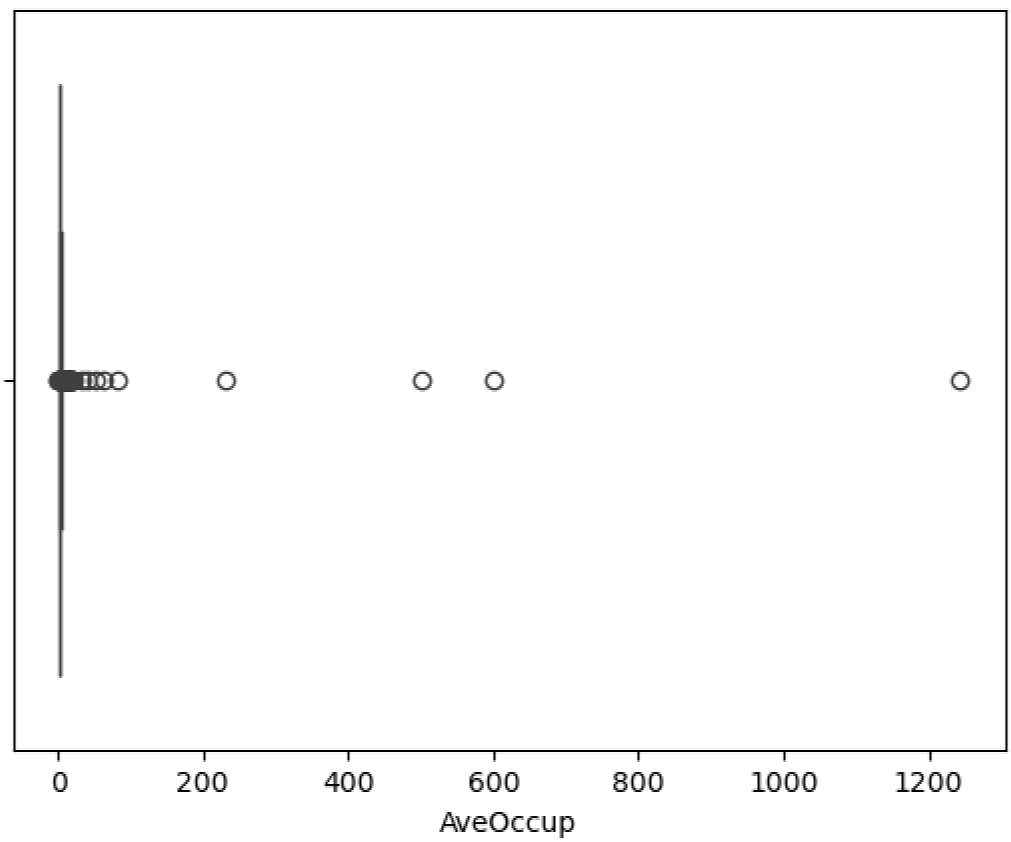


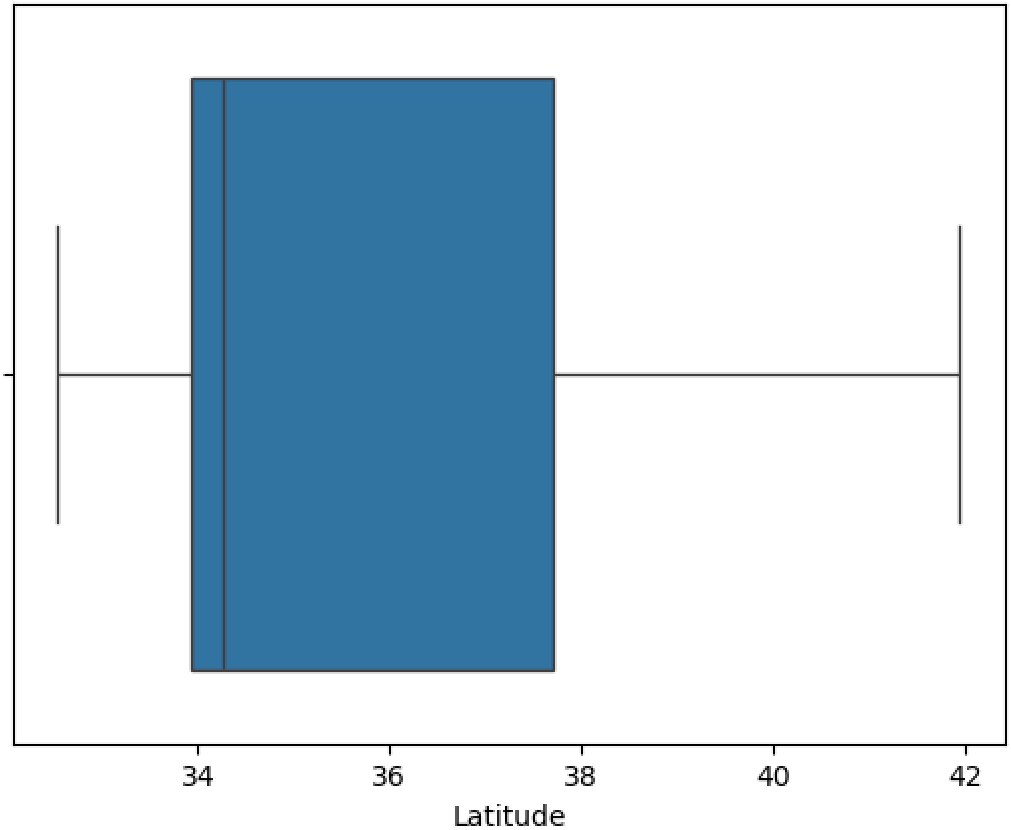


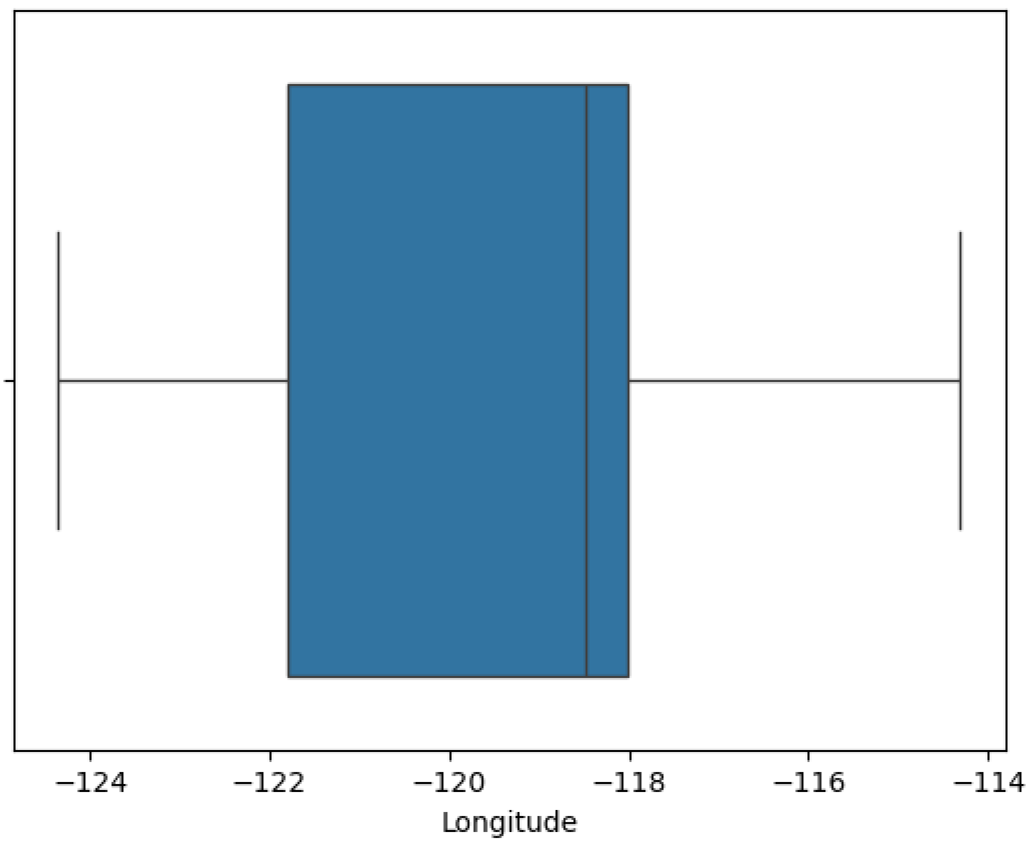

0
20
40
60
80
100
120
140
AveRooms

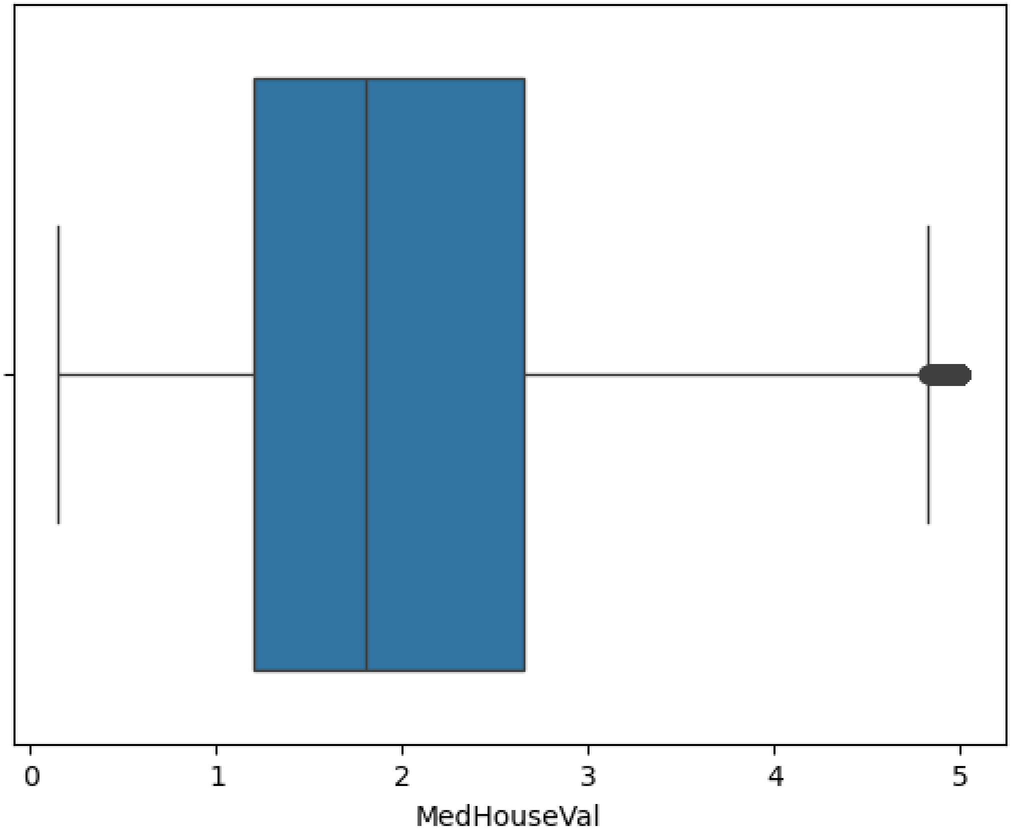

0
5
10
15
20
25
30
35
AveBedrms


0
5000
10000
15000
20000
25000
30000
35000
Population


0
200
400
600
800
1000
1200
AveOccup


34
36
38
40
42
Latitude


−124
−122
−120
−118
−116
−114
Longitude



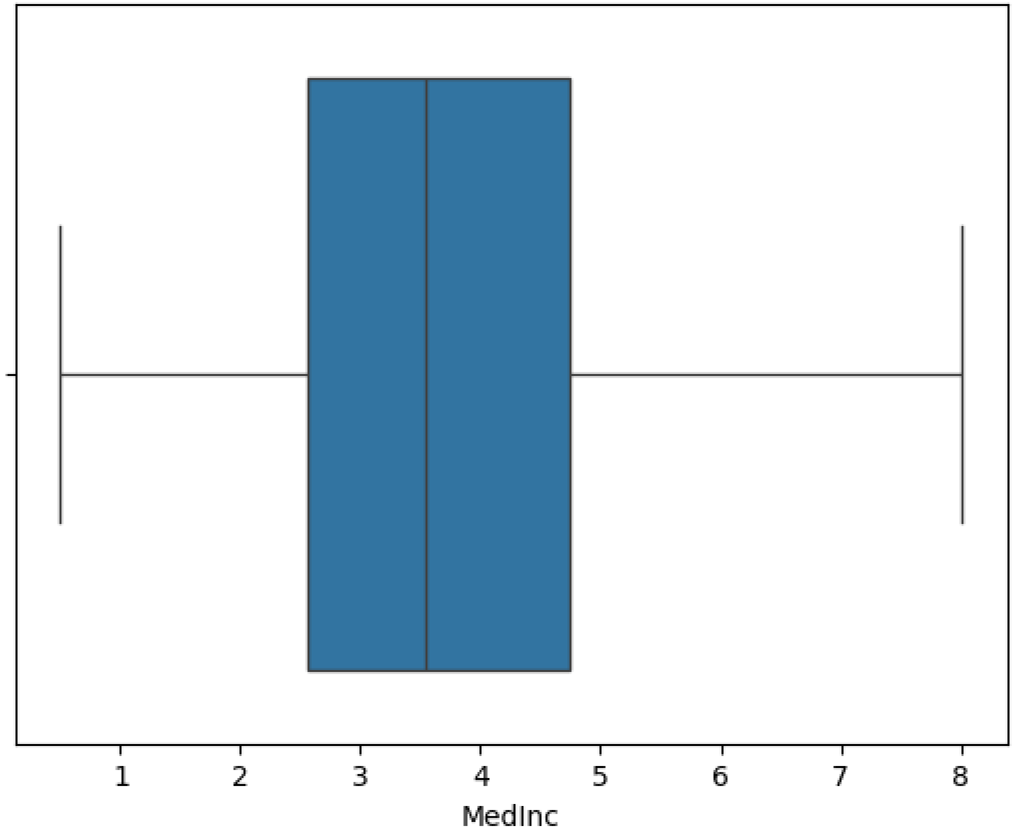
In [13]:
```
# creating custom definition to remove outliers using IQR method
def outliers(df):
    for col in df.select_dtypes(include=['int64','float64']).columns:
        Q1 = df[col].quantile(0.25)
        Q3 = df[col].quantile(0.75)
        IQR = Q3 - Q1

        lower = Q1 - (1.5*IQR)
        upper = Q3 + (1.5*IQR)

        # Capping
        df[col] = df[col].apply(lambda x: lower if x < lower else upper if x > upper els

    return df
```

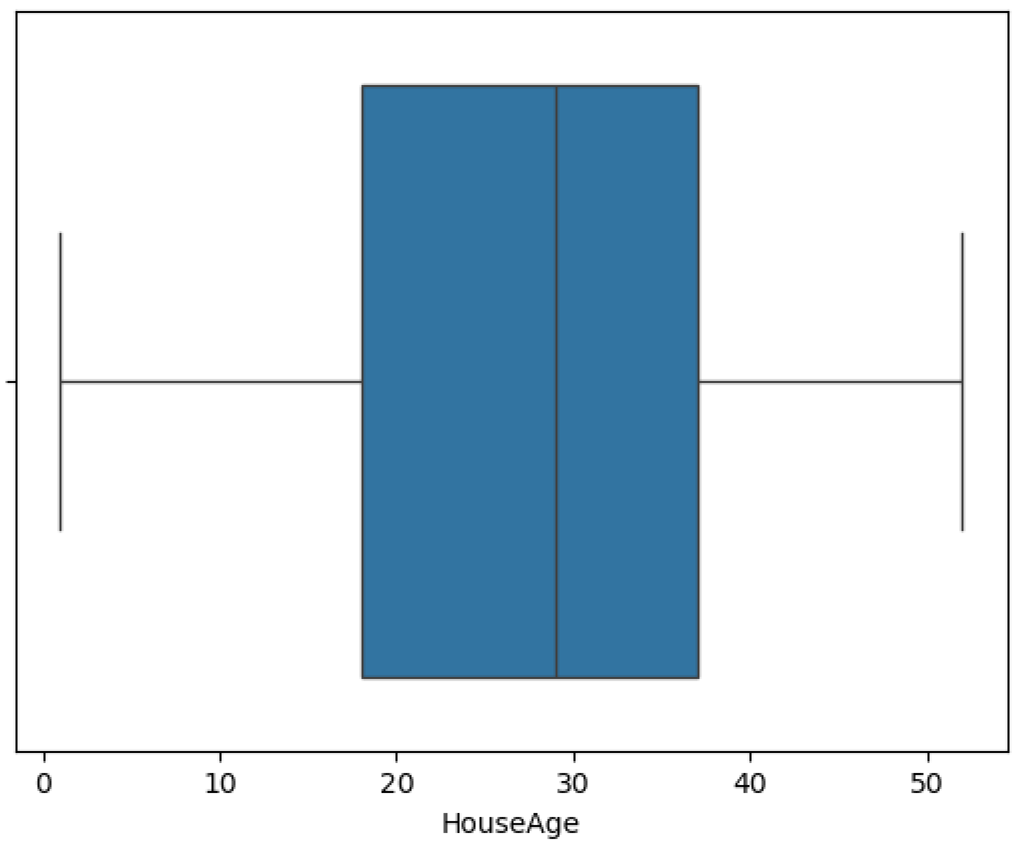
In [14]:
```
#calling custom definition to remove outliers of dataframe 'ch'
new_ch = outliers(ch)
new_ch.info()
```

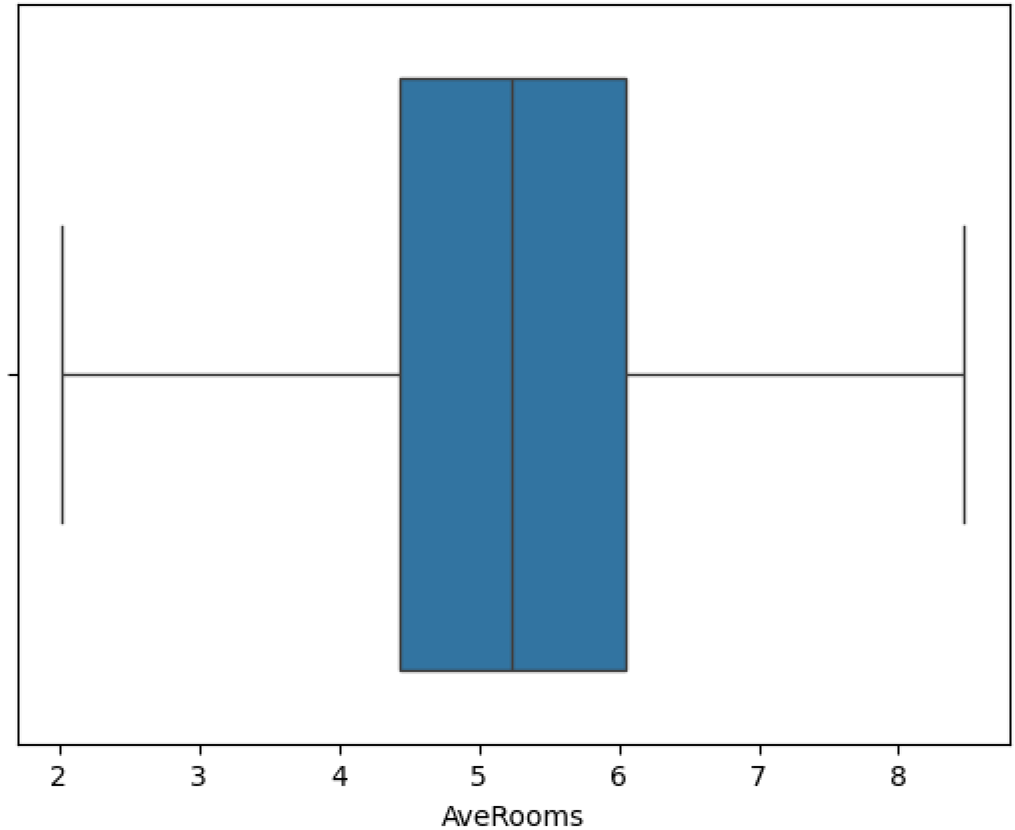
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   MedInc       20640 non-null  float64
 1   HouseAge     20640 non-null  float64
 2   AveRooms     20640 non-null  float64
 3   AveBedrms    20640 non-null  float64
 4   Population   20640 non-null  float64
 5   AveOccup     20640 non-null  float64
 6   Latitude     20640 non-null  float64
 7   Longitude    20640 non-null  float64
 8   MedHouseVal  20640 non-null  float64
dtypes: float64(9)
memory usage: 1.4 MB
```

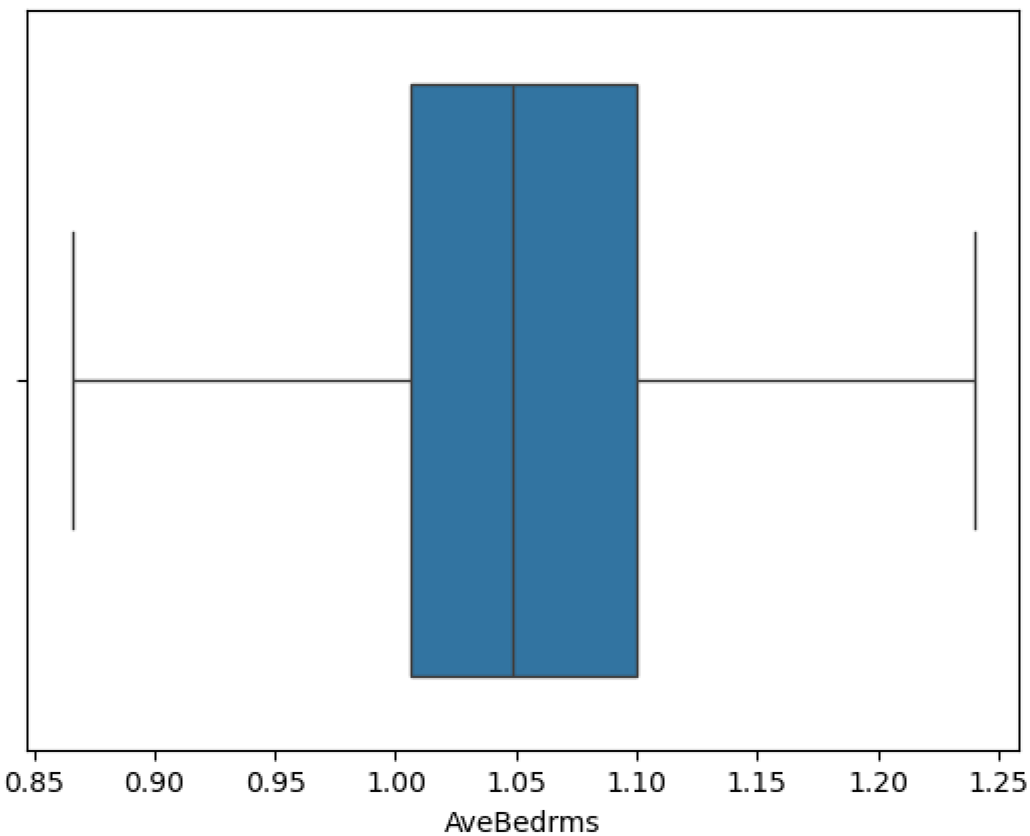
In [15]:
```
### syntex to visualise the df to detect outliers for each columns after removing outlie
```

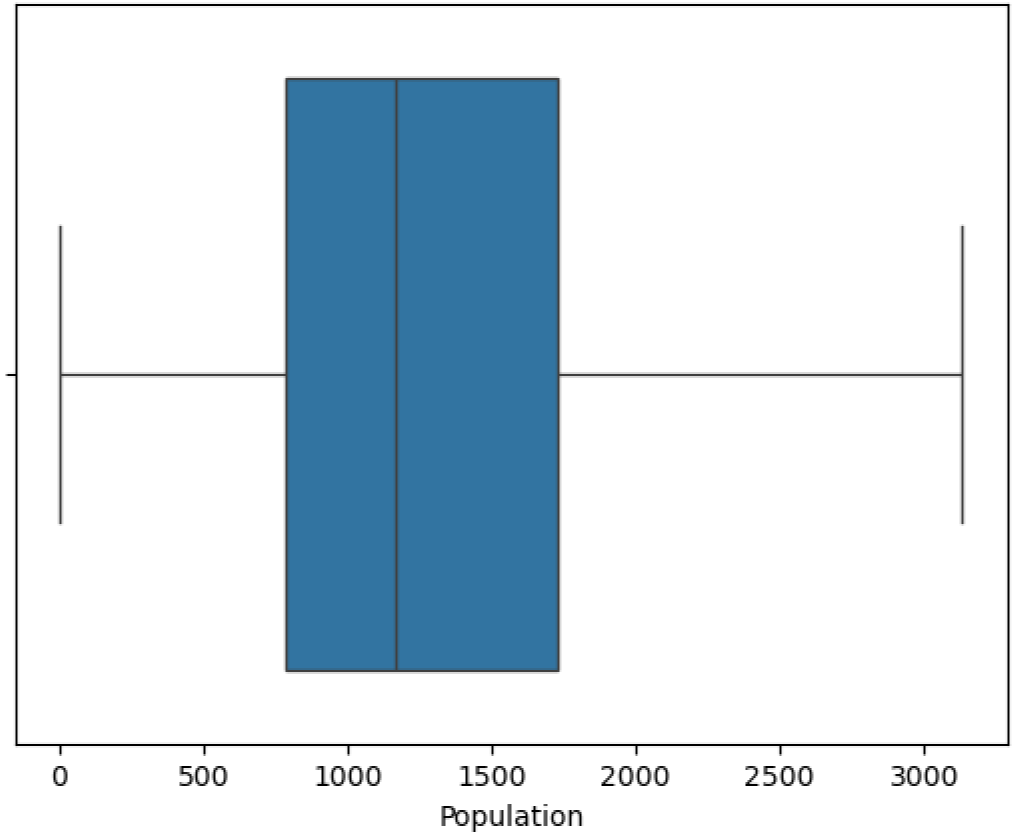
```
for i in new_ch.columns:
    sns.boxplot(data=new_ch,x=i)
    plt.show()
```

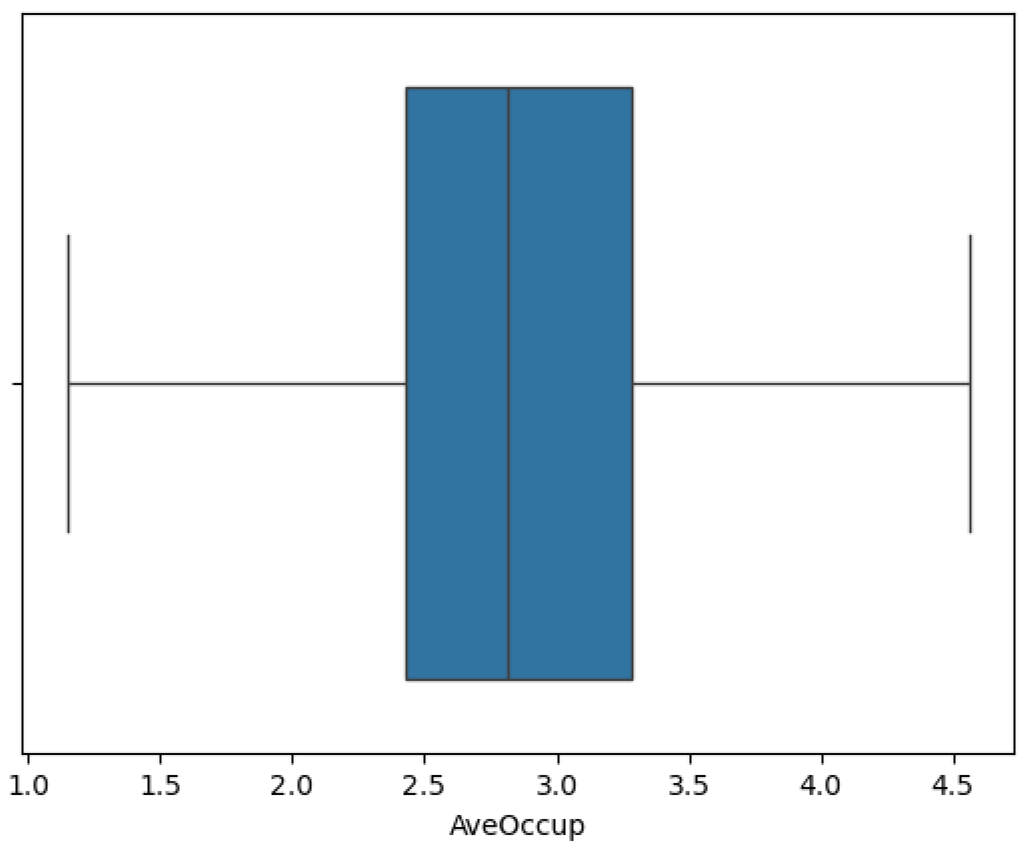


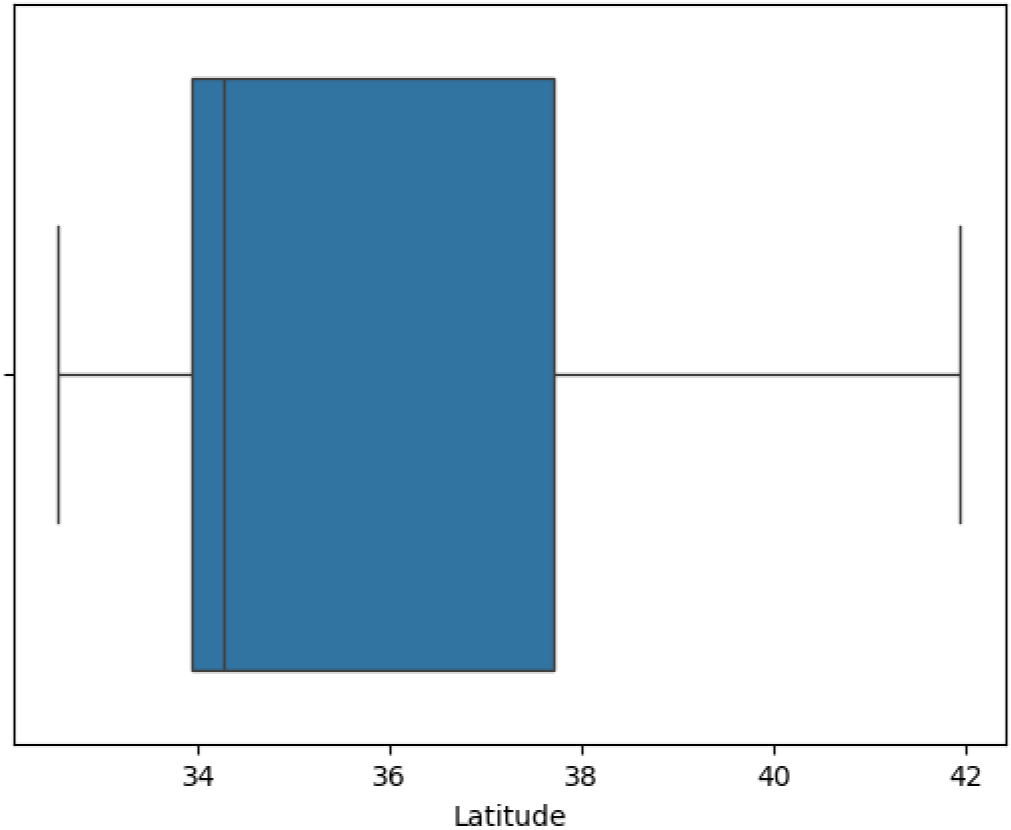


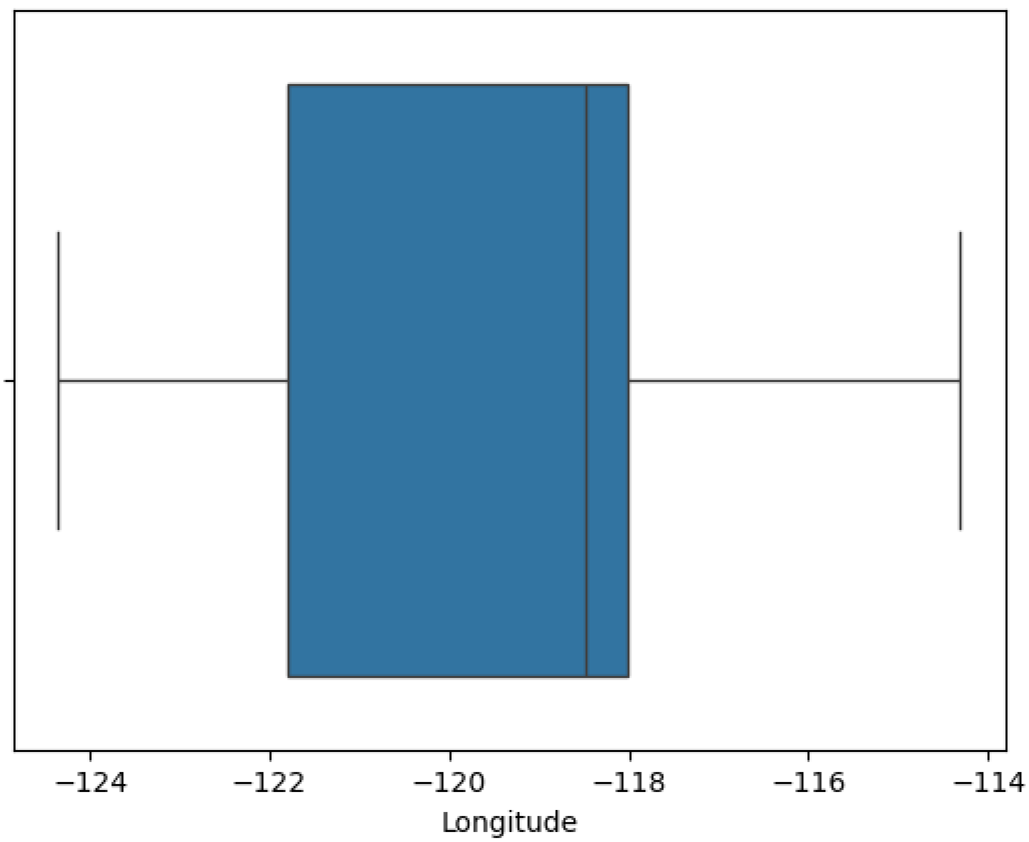

2
3
4
5
6
7
8
AveRooms

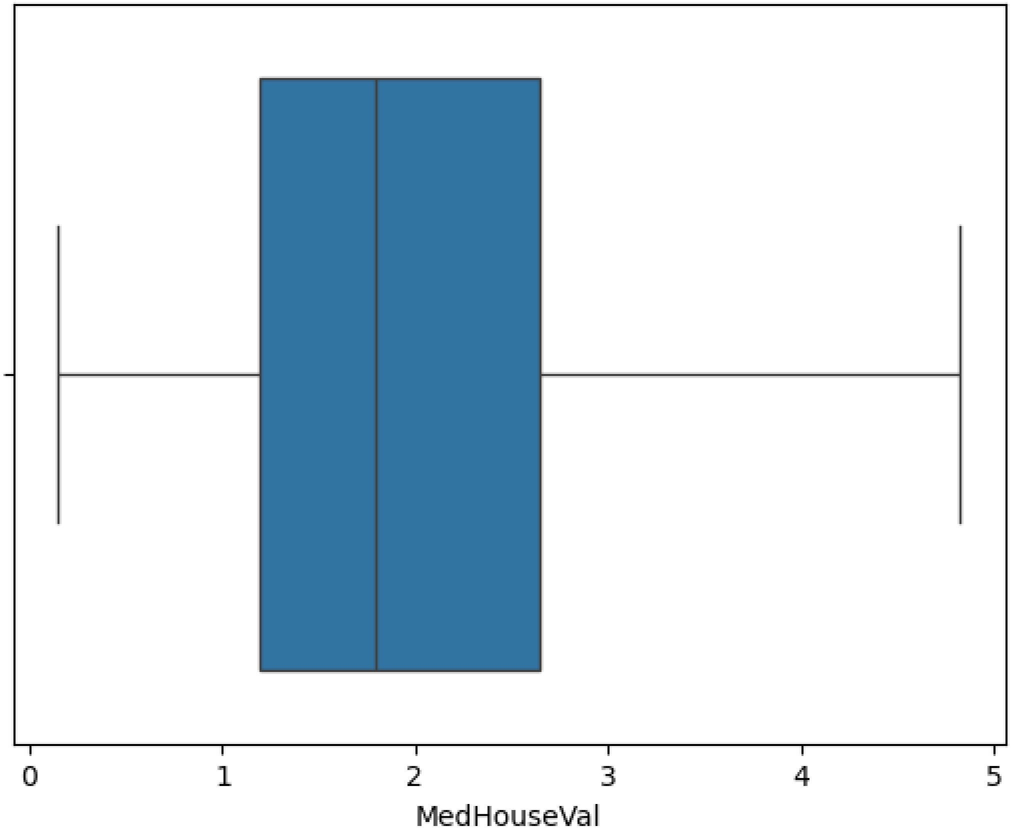

0.85
0.90
0.95
1.00
1.05
1.10
1.15
1.20
1.25
AveBedrms


0
500
1000
1500
2000
2500
3000
Population


1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
AveOccup


34
36
38
40
42
Latitude


−124
−122
−120
−118
−116
−114
Longitude



In [16]:

```
#minmax scaling
numerical_col = new_ch.select_dtypes(include=['number'])
scl_Minmax = MinMaxScaler()
scl_dta_mimax = scl_Minmax.fit_transform(numerical_col)
ch_scl_minmax = pd.DataFrame(scl_dta_mimax, columns=numerical_col.columns, index=new_ch.
New_ch_minmax = pd.concat([new_ch.drop(columns=numerical_col.columns), ch_scl_minmax], a
print_title("New df after MinMax Scaling")
print_section(f'\n{New_ch_minmax}')
```

```
------------------------------------------------------------
New df after MinMax Scaling
------------------------------------------------------------

         MedInc  HouseAge  AveRooms  AveBedrms  Population  AveOccup  \
0      1.000000  0.784314  0.769532   0.422435    0.101950  0.411895
1      1.000000  0.392157  0.653814   0.283508    0.766379  0.281190
2      0.899426  1.000000  0.971808   0.555229    0.157558  0.484240
3      0.684562  1.000000  0.588542   0.554193    0.177373  0.409663
4      0.445394  1.000000  0.660596   0.575654    0.179610  0.302194
...         ...       ...       ...        ...         ...       ...
20635  0.141140  0.470588  0.468806   0.715445    0.269096  0.413376
20636  0.273774  0.333333  0.634564   1.000000    0.112816  0.578240
20637  0.159734  0.313725  0.493639   0.680021    0.320869  0.344471
20638  0.181988  0.333333  0.512869   0.818676    0.235858  0.285110
20639  0.251387  0.294118  0.501267   0.792844    0.442314  0.429908

       Latitude  Longitude  MedHouseVal
0      0.567481   0.211155     0.936218
1      0.565356   0.212151     0.734897
2      0.564293   0.210159     0.721205
3      0.564293   0.209163     0.698099
4      0.564293   0.209163     0.700025
...         ...        ...          ...
20635  0.737513   0.324701     0.135000
20636  0.738576   0.312749     0.132861
20637  0.732200   0.311753     0.165380
20638  0.732200   0.301793     0.149121
20639  0.725824   0.309761     0.159176
```

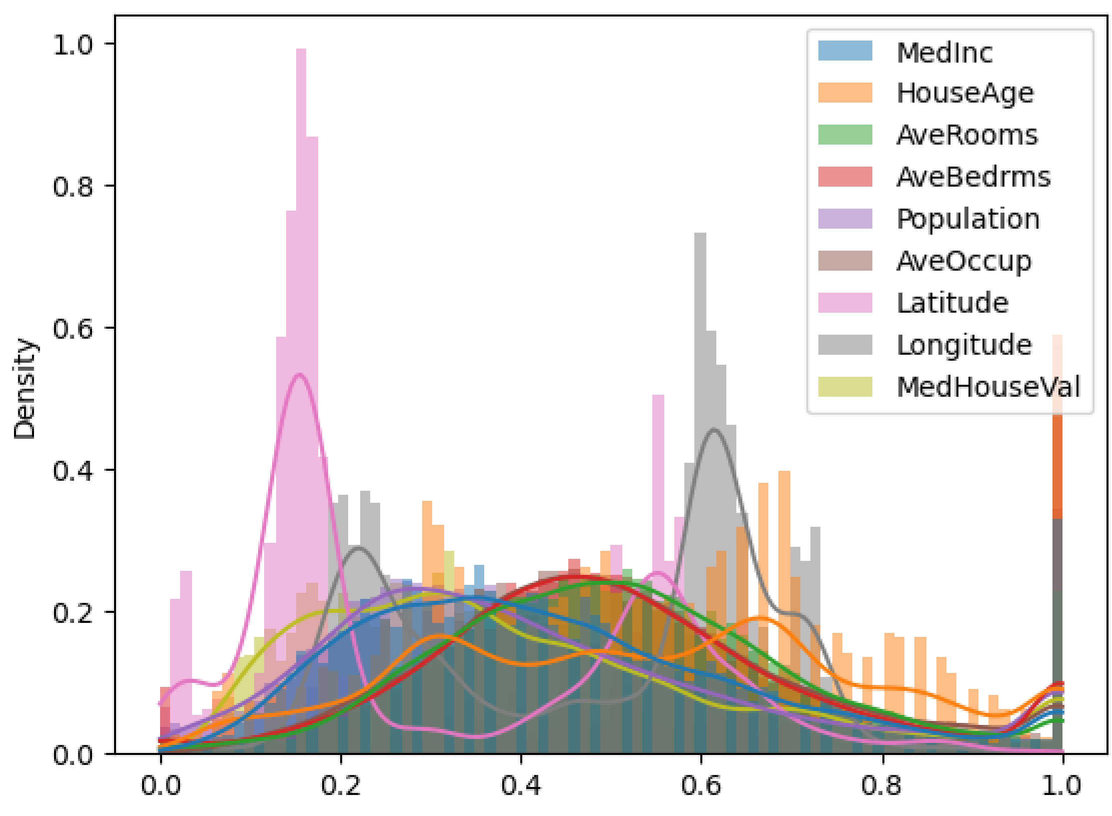
```
[20640 rows x 9 columns]
-------------------------------------------------------------
```

In [17]:
```
skewness = New_ch_minmax.skew()
print_section("\033[1mSkewness of Features in dataframe after Scaling\033[0m")
print_section(skewness)
```

```
-------------------------------------------------------------
Skewness of Features in dataframe after Scaling
-------------------------------------------------------------
-------------------------------------------------------------
MedInc         0.735618
HouseAge       0.060331
AveRooms       0.348567
AveBedrms      0.462645
Population     0.842247
AveOccup       0.510453
Latitude       0.465953
Longitude     -0.297801
MedHouseVal    0.912330
dtype: float64
-------------------------------------------------------------
```

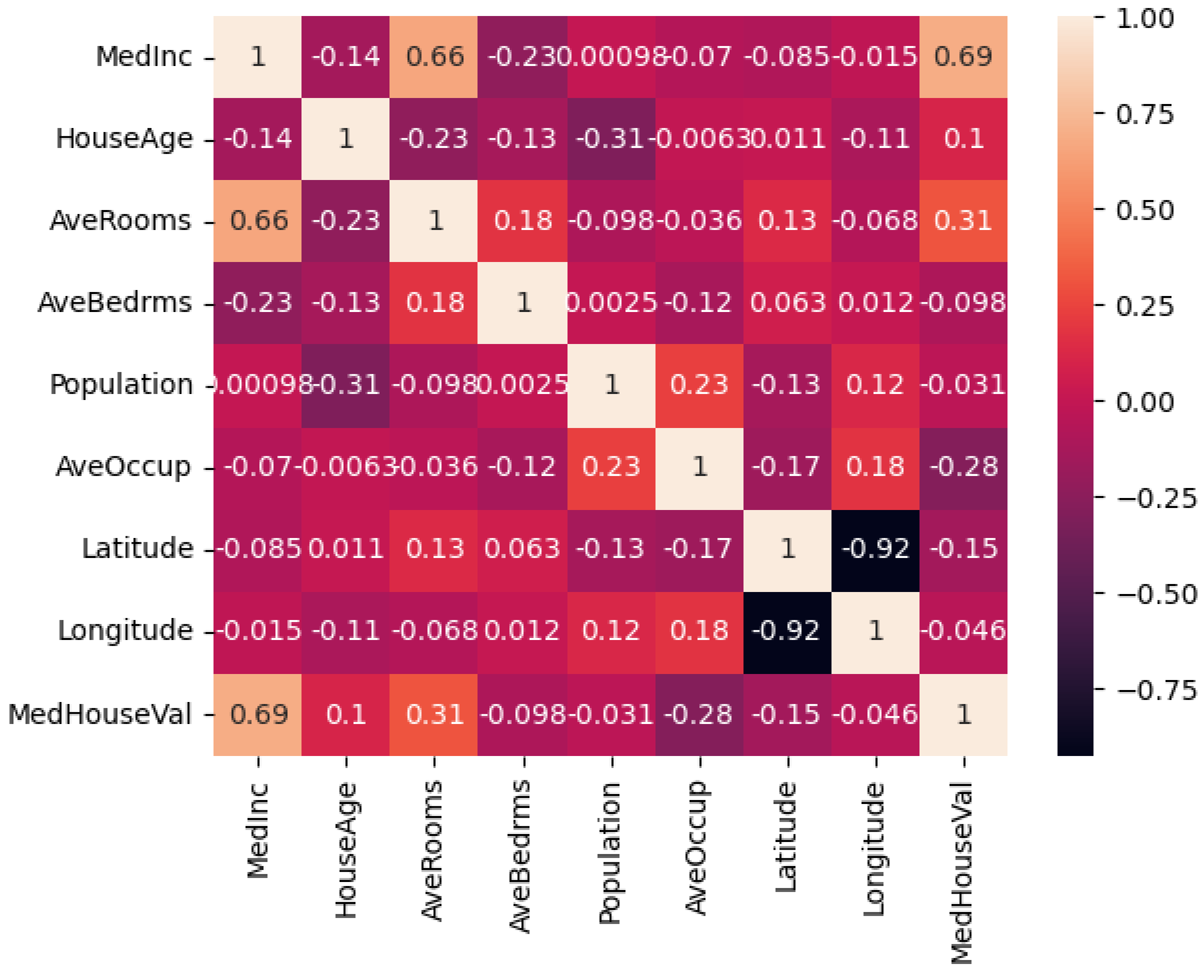
In [18]:
```
sns.histplot(New_ch_minmax,kde=True,stat='density',linewidth=0)
print_section("\033[1mHistplot of dataframe after Scaling\033[0m")
plt.show()
```

```
-------------------------------------------------------------
Histplot of dataframe after Scaling
-------------------------------------------------------------
```



In [19]:
```
corr_ch = New_ch_minmax.corr()
```

In [20]:
```
sns.heatmap(corr_ch,annot=True)
plt.show()
skewness = New_ch_minmax.skew()
print_section("\033[1mSkewness of Features in dataframe after Scaling\033[0m")
print_section(skewness)
```




```
------------------------------------------------------------
Skewness of Features in dataframe after Scaling
------------------------------------------------------------
------------------------------------------------------------
MedInc         0.735618
HouseAge       0.060331
AveRooms       0.348567
AveBedrms      0.462645
Population     0.842247
AveOccup       0.510453
Latitude       0.465953
Longitude     -0.297801
MedHouseVal    0.912330
dtype: float64
------------------------------------------------------------
```

The Histplot of after scaling and before scaling gives a clear visual of above steps of data preprocessing is necessary for the dataset and Highly skewd features have good co-relation with the targen variable 'MedHouseVal' and less co-related features has good skewness. Therefore, the dataset 'New_ch_minmax' can be concluded to be fit for the next process

(2) Regression Algoritham Implementaion

In [23]:

```
Cal_H=New_ch_minmax #renaming for futher Analysis
# Feature selection
X=Cal_H[['MedInc','HouseAge','AveRooms','AveBedrms','Population','AveOccup','Latitude','
Y=Cal_H['MedHouseVal']
```

In [24]:

```
#depentent veriable
Y
```

```
0         0.936218
```

```
Out[24]: 1        0.734897
2        0.721205
3        0.698099
4        0.700025
           ...
20635    0.135000
20636    0.132861
20637    0.165380
20638    0.149121
20639    0.159176
Name: MedHouseVal, Length: 20640, dtype: float64
```

Linear Regression

```
In [26]: #syntex for traning and testing for linear regression
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=42
```

```
In [27]: #syntes for linear regression modeling
model = LinearRegression()
model.fit(X_train, y_train)
```

```
Out[27]: ▾ LinearRegression
LinearRegression()
```

```
In [28]: #syntex for model prediction
y_pred = model.predict(X_test)
print(y_pred)
```

```
[0.02279585 0.38853306 0.69908632 ... 0.83300977 0.23446578 0.32665012]
```

```
In [29]: #sytex for model score
Score_LinearRegression = model.score(X_test,y_test)
```

Decidion Tree Regressor

```
In [31]: #syntex for traning and testing for Decidion Tree Regressor
X1_train, X1_test, y1_train, y1_test = train_test_split(X, Y, test_size=0.2, random_stat
```

```
In [32]: #syntes for Decidion Tree Regressor modeling
model1 = DecisionTreeRegressor(random_state=42)
model1.fit(X1_train, y1_train)
```

```
Out[32]: ▾ DecisionTreeRegressor
DecisionTreeRegressor(random_state=42)
```

```
In [33]: #syntex for model prediction
y1_pred = model1.predict(X1_test)
print(y1_pred)
```

```
[0.08729102 0.22528446 1.         ... 1.         0.10911324 0.27042651]
```

```
In [34]: #sytex for model score
Score_DecisionTreeRegressor = model1.score(X1_test,y1_test)
```

Random Forest Regressor

```
In [36]: #syntex for traning and testing for Random Forest Regressor
```

```
X2_train, X2_test, y2_train, y2_test = train_test_split(X, Y, test_size=0.2, random_stat
```

In [37]:
```
#syntes for Random Forest Regressor modeling
model2 = RandomForestRegressor(random_state=42)
model2.fit(X2_train, y2_train)
```

Out[37]:
```
RandomForestRegressor
RandomForestRegressor(random_state=42)
```

In [38]:
```
#syntex for model prediction
y2_pred = model2.predict(X2_test)
print(y2_pred)
```

```
[0.0779203  0.12537293 0.98714789 ... 0.92966881 0.12087156 0.32966741]
```

In [39]:
```
#sytex for model score
Score_RandomForestRegressor = model1.score(X2_test,y2_test)
```

Gradient Boosting Regressor

In [41]:
```
#syntex for traning and testing for Gradient Boosting Regressor
X3_train, X3_test, y3_train, y3_test = train_test_split(X, Y, test_size=0.2, random_stat
```

In [42]:
```
#syntes for Gradient Boosting Regressor modeling
model3 = GradientBoostingRegressor(random_state=42)
model3.fit(X3_train, y3_train)
```

Out[42]:
```
GradientBoostingRegressor
GradientBoostingRegressor(random_state=42)
```

In [43]:
```
#syntex for model prediction
y3_pred = model3.predict(X3_test)
print(y2_pred)
```

```
[0.0779203  0.12537293 0.98714789 ... 0.92966881 0.12087156 0.32966741]
```

In [44]:
```
#sytex for model score
Score_GradientBootingRegressor = model1.score(X3_test,y3_test)
```

Support Vector Regressor (SVR)

In [46]:
```
scaler_x = StandardScaler()
x_scaled = scaler_x.fit_transform(X)
scaler_y = StandardScaler()
y_scaled = scaler_y.fit_transform(Y.values.reshape(-1, 1))
```

In [47]:
```
#syntex for traning and testing for Support Vector Regressor
X4_train, X4_test, y4_train, y4_test = train_test_split(x_scaled, y_scaled, test_size=0.
```

In [48]:
```
#syntes for Support Vector Regressor modeling
model4 = SVR(kernel='rbf', C=1.0, epsilon=0.1)
model4.fit(X4_train, y4_train.ravel())
```

Out[48]:
```
SVR
SVR()
```

In [49]:
```
#syntex for model prediction
y4_pred = model4.predict(X4_test)
print(y4_pred)
```

```
[-1.40585189 -0.53264762  2.2693782  ...  2.14964491 -1.29540304
 -0.27994881]
```

In [50]:
```
#sytex for model score
Score_SVR = model4.score(X4_test,y4_test)
```

In [51]:
```
print(f'Accuracy of Linear Regression is \033[1m{int(100*(Score_LinearRegression))}%\033
print(f'The SVR Accuracy rate is \033[1m{int(100*(Score_SVR))}%\033[0m, it is higher tha
```

Accuracy of Linear Regression is **65%**
Accuracy of DecisionTree Regression is **62%**
Accuracy of RandomForest Regression is **62%**
Accuracy of GradientBoosting Regression is **62%**
and Accuracy of SVR Regression is **76%**
The SVR Accuracy rate is **76%**, it is higher than other methond

(3) Model Evelution Comparison

Evaluateing the performance of Mean Squared Error(MSE), Mean Absolute error(MAE) and R-Squared Score

Evaluating Linear Regression model using following metrics

In [55]:
```
mae_LR = mean_absolute_error(y_test,y_pred)
mse_LR = mean_squared_error(y_test,y_pred)
r2_LR = r2_score(y_test,y_pred)
print_title(f'The Evaluated performace of MSE, MAE and R-Squred Score\nfor Linear Regres
print_section(f'Mean Squared Error: {mse_LR}\nMean Absolute Error: {mae_LR}\nR-Squared S
```

```
------------------------------------------------------------
The Evaluated performace of MSE, MAE and R-Squred Score
for Linear Regression model
------------------------------------------------------------
Mean Squared Error: 0.020249838675798007
Mean Absolute Error: 0.10583073170383961
R-Squared Score: 0.6500913755505537
------------------------------------------------------------
```

Evaluating Decidion Tree Regressor model using following metrics

In [57]:
```
mae_DTR = mean_absolute_error(y1_test,y1_pred)
mse_DTR = mean_squared_error(y1_test,y1_pred)
r2_DTR = r2_score(y1_test,y1_pred)
print_title(f'The Evaluated performace of MSE, MAE and R-Squred Score\nfor Decidion Tree
print_section(f'Mean Squared Error: {mse_DTR}\nMean Absolute Error: {mae_DTR}\nR-Squared
```

```
------------------------------------------------------------
The Evaluated performace of MSE, MAE and R-Squred Score
for Decidion Tree Regresso model
------------------------------------------------------------
Mean Squared Error: 0.02195135377872779
Mean Absolute Error: 0.09570921090834345
R-Squared Score: 0.6206899161770678
------------------------------------------------------------
```

Evaluating Random Forest Regressor model using following metrics

In [59]:
```
mae_RFR = mean_absolute_error(y2_test,y2_pred)
mse_RFR = mean_squared_error(y2_test,y2_pred)
r2_RFR = r2_score(y2_test,y2_pred)
print_title(f'The Evaluated performace of MSE, MAE and R-Squred Score\nfor Random Forest
print_section(f'Mean Squared Error: {mse_RFR}\nMean Absolute Error: {mae_RFR}\nR-Squared
```

```
------------------------------------------------------------
The Evaluated performace of MSE, MAE and R-Squred Score
for Random Forest Regressor model
------------------------------------------------------------
Mean Squared Error: 0.01114867521661751
Mean Absolute Error: 0.06943318886675323
R-Squared Score: 0.8073556203614282
------------------------------------------------------------
```

Evaluating Gradient Boosting Regressor model using following metrics

In [61]:
```
mae_GBR = mean_absolute_error(y3_test,y3_pred)
mse_GBR = mean_squared_error(y3_test,y3_pred)
r2_GBR = r2_score(y3_test,y3_pred)
print_title(f'The Evaluated performace of MSE, MAE and R-Squred Score\nfor Gradient Boos
print_section(f'Mean Squared Error: {mse_GBR}\nMean Absolute Error: {mae_GBR}\nR-Squared
```

```
------------------------------------------------------------
The Evaluated performace of MSE, MAE and R-Squred Score
for Gradient Boosting Regressor model
------------------------------------------------------------
Mean Squared Error: 0.012799214573888404
Mean Absolute Error: 0.07796846596239415
R-Squared Score: 0.7788350002543363
------------------------------------------------------------
```

Evaluating Support Vector Regressor model using following metrics

In [63]:
```
mae_SVR = mean_absolute_error(y4_test,y4_pred)
mse_SVR = mean_squared_error(y4_test,y4_pred)
r2_SVR = r2_score(y4_test,y4_pred)
print_title(f'The Evaluated performace of MSE, MAE and R-Squred Score\nfor Support Vecto
print_section(f'Mean Squared Error: {mse_SVR}\nMean Absolute Error: {mae_SVR}\nR-Squared
```

```
------------------------------------------------------------
The Evaluated performace of MSE, MAE and R-Squred Score
for Support Vector Regressor model
------------------------------------------------------------
Mean Squared Error: 0.23314051024564758
Mean Absolute Error: 0.3249791281149936
R-Squared Score: 0.7636512832262522
------------------------------------------------------------
```

In [ ]:

Comparing and identifying the results of all models

In [69]:
```
R_score = {'model':['Linear Regression','Decidion Tree Regressor','Random Forest Regress
                    'Gradient Boosting Regressor','Support Vector Regressor'],
           'R2_Score %':[100*r2_LR,100*r2_DTR,100*r2_RFR,100*r2_GBR,100*r2_SVR]}
R_score = pd.DataFrame(R_score)
higih= R_score['R2_Score %'].max()
low= R_score['R2_Score %'].min()
Iden_model = R_score.loc[R_score['R2_Score %'] == higih, 'model'].item()
wrost_model = R_score.loc[R_score['R2_Score %'] == low, 'model'].item()
print_title('         '"Result Comparison using R-Squared Score")
print_section(f'Compared and Identifyed model using R2_Score metric\nof \033[1m{Iden_mod
```

Result Comparison using R-Squared Score

Compared and Identifyed model using R2_Score metric
of **Random Forest Regressor** its R-Squared Score
is **80%** and it has best-performing algoritham
wtih justification. And the Wrost model
is **Decidion Tree Regressor** its R-Squred score is **62%**
