

Regression with a Flood Prediction Dataset

(Playground Series - Season 4, Episode 5)

Using Stacking Regressor

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Descriptions

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The dataset for this competition (both train and test) was generated from a deep learning model trained on the Flood Prediction Factors dataset. Feature distributions are close to, but not exactly the same, as the original.

Files train.csv - the training dataset; FloodProbability is the target

test.csv - the test dataset; your objective is to predict the FloodProbability for each row

sample_submission.csv - a sample submission file in the correct format

Objectives

The goal of this competition is to predict the probability of a region flooding based on various factors.

About Author

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1. Importing Libraries and Data sets

1.1 Libraries

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import plotly.express as px
import warnings
```

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1.2 Data Sets

```
In [2]: df_train = pd.read_csv(r"C:\Users\shuve\Desktop\ML((GFG)\Kaggle Comp\Fload\train.csv")
df_test = pd.read_csv(r"C:\Users\shuve\Desktop\ML((GFG)\Kaggle Comp\Fload\test.csv")
```

```
In [3]: df_train.head(3)
```

```
Out[3]:
```

	id	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	AgriculturalPractic
0	0	5	8	5	8	6	4	4	3	
1	1	6	7	4	4	8	8	3	5	
2	2	6	5	6	7	3	7	1	5	

3 rows × 22 columns

```
In [4]: df_test.head(3)
```

```
Out[4]:
```

	id	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	Agricultural
0	1117957	4	6	3	5	6	7	8	7	
1	1117958	4	4	2	9	5	5	4	7	
2	1117959	1	3	6	5	7	2	4	6	

3 rows × 21 columns

```
In [5]: df_train.columns
```

```
Out[5]: Index(['id', 'MonsoonIntensity', 'TopographyDrainage', 'RiverManagement',
            'Deforestation', 'Urbanization', 'ClimateChange', 'DamsQuality',
            'Siltation', 'AgriculturalPractices', 'Encroachments',
            'IneffectiveDisasterPreparedness', 'DrainageSystems',
            'CoastalVulnerability', 'Landslides', 'Watersheds',
            'DeterioratingInfrastructure', 'PopulationScore', 'WetlandLoss',
            'InadequatePlanning', 'PoliticalFactors', 'FloodProbability'],
            dtype='object')
```

```
In [6]: df_test.columns
```

```
Out[6]: Index(['id', 'MonsoonIntensity', 'TopographyDrainage', 'RiverManagement',
            'Deforestation', 'Urbanization', 'ClimateChange', 'DamsQuality',
            'Siltation', 'AgriculturalPractices', 'Encroachments',
            'IneffectiveDisasterPreparedness', 'DrainageSystems',
            'CoastalVulnerability', 'Landslides', 'Watersheds',
            'DeterioratingInfrastructure', 'PopulationScore', 'WetlandLoss',
            'InadequatePlanning', 'PoliticalFactors'],
            dtype='object')
```

1.3 Defining Features and Targets

Features:

1. 'id'
2. 'MonsoonIntensity'
3. 'TopographyDrainage'
4. 'RiverManagement'
5. 'Deforestation'
6. 'Urbanization'
7. 'ClimateChange'
8. 'DamsQuality'
9. 'Siltation'
10. 'AgriculturalPractices'
11. 'Encroachments'
12. 'IneffectiveDisasterPreparedness'
13. 'DrainageSystems'

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15. 'Landslides'
16. 'Watersheds'
17. 'DeterioratingInfrastructure'
18. 'PopulationScore'
19. 'WetlandLoss'
20. 'InadequatePlanning'
21. 'PoliticalFactors'
- #### **Target:**
22. 'FloodProbability'

2.Data Exploration

2.1 Dimensions

```
In [7]: # df_train.shape, df_test.shape
```

2.2 Statistical Summary

```
In [8]: # df_train.info()
```

2.3 Dropping Id Column

```
In [9]: df_train.drop(columns= ["id"], inplace=True)  
df_train.head(2)
```

Out[9]:

	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	AgriculturalPractices
0	5	8	5	8	6	4	4	3	3
1	6	7	4	4	8	8	3	5	4

2 rows × 10 columns

2.4 Check for Duplicacy

In [10]: `df_train.duplicated().sum()`

Out[10]: 0

Remark: No duplicacy found

2.5 Check for Null values

In [11]: `df_train.isnull().sum()`

```
Out[11]: MonsoonIntensity      0
          TopographyDrainage    0
          RiverManagement      0
          Deforestation         0
          Urbanization          0
          ClimateChange         0
          DamsQuality           0
          Siltation             0
          AgriculturalPractices 0
          Encroachments        0
          IneffectiveDisasterPreparedness 0
          DrainageSystems       0
          CoastalVulnerability  0
          Landslides            0
          Watersheds            0
          DeterioratingInfrastructure 0
          PopulationScore       0
          WetlandLoss           0
          InadequatePlanning     0
          PoliticalFactors       0
          FloodProbability       0
          dtype: int64
```

Remark: No Null value Found

2.6 Descriptive Analytics

```
In [12]: df_train.describe()
```


Out[12]:

	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	Agricultural
count	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06	1.117957e+06
mean	4.921450e+00	4.926671e+00	4.955322e+00	4.942240e+00	4.942517e+00	4.934093e+00	4.955878e+00	4.927791e+00	4.942240e+00
std	2.056387e+00	2.093879e+00	2.072186e+00	2.051689e+00	2.083391e+00	2.057742e+00	2.083063e+00	2.065992e+00	2.065992e+00
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	3.000000e+00	3.000000e+00	4.000000e+00	4.000000e+00	3.000000e+00	3.000000e+00	4.000000e+00	3.000000e+00	3.000000e+00
50%	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00	5.000000e+00
75%	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00	6.000000e+00
max	1.600000e+01	1.800000e+01	1.600000e+01	1.700000e+01	1.700000e+01	1.700000e+01	1.600000e+01	1.600000e+01	1.600000e+01

8 rows × 21 columns

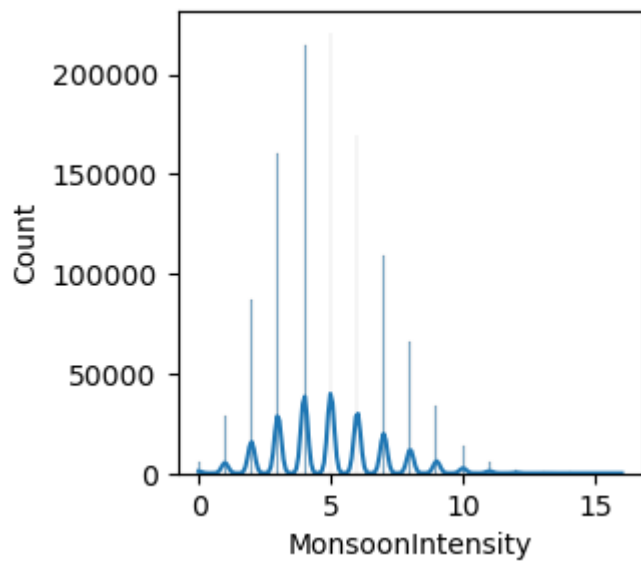
3. EDA

3.1 Univariate Analysis

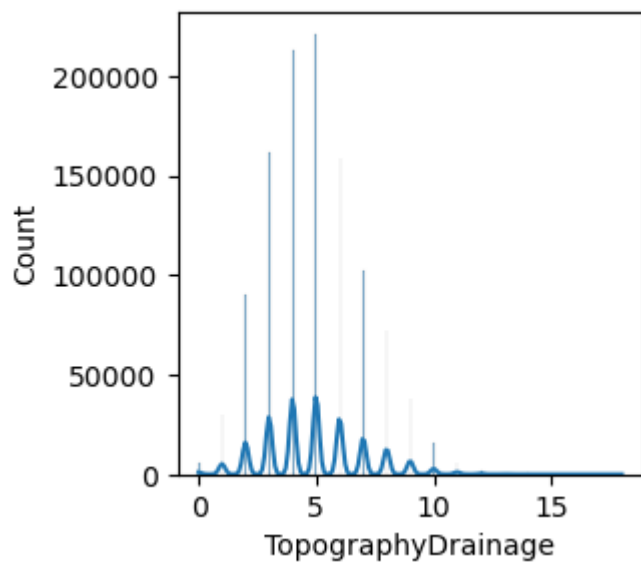
3.1.1 Distributions

```
In [13]: for i in df_train.columns:
plt.figure(figsize = (3,3))
print(sns.histplot(df_train[i],kde = True))
plt.show()
```

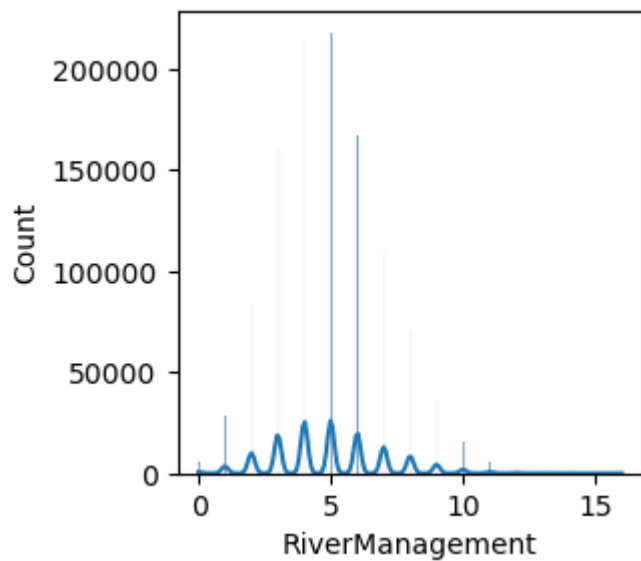
Axes(0.125,0.11;0.775x0.77)



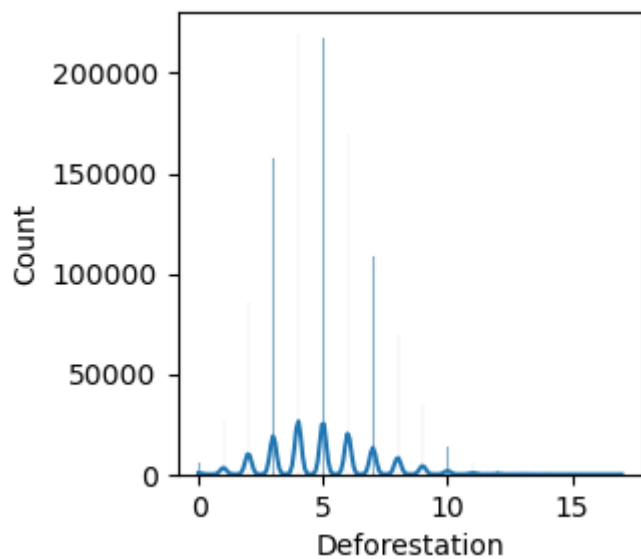
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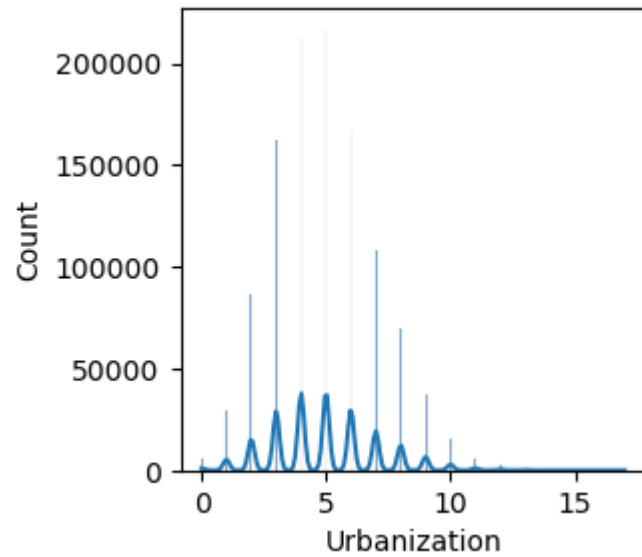
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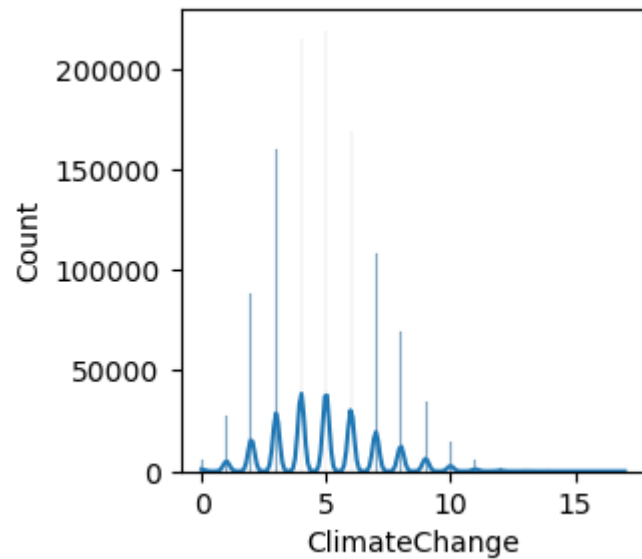
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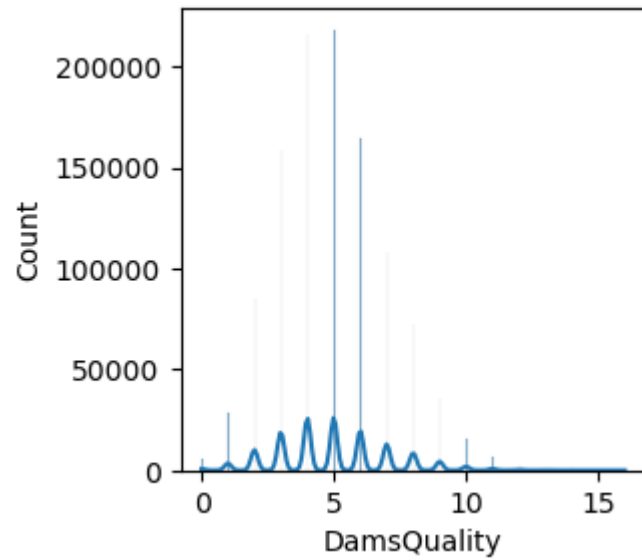
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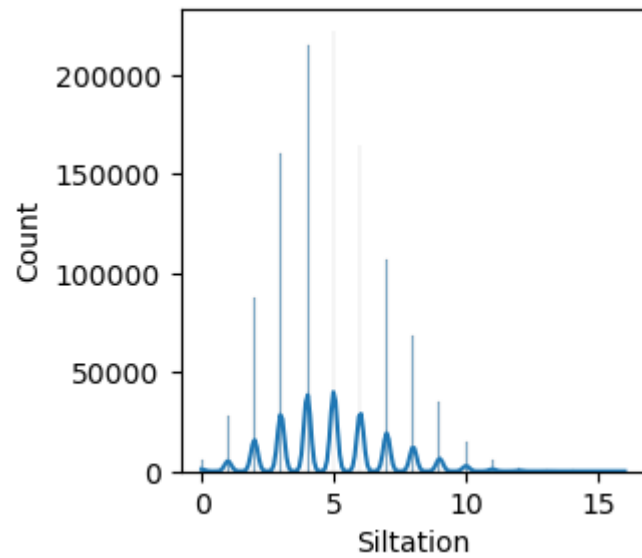
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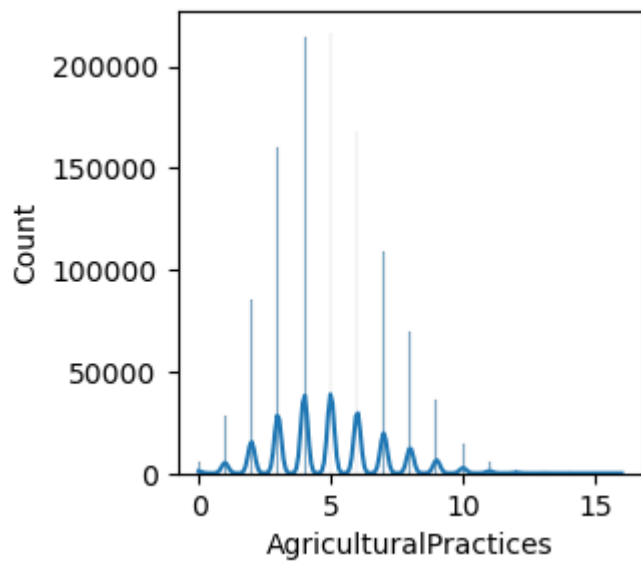
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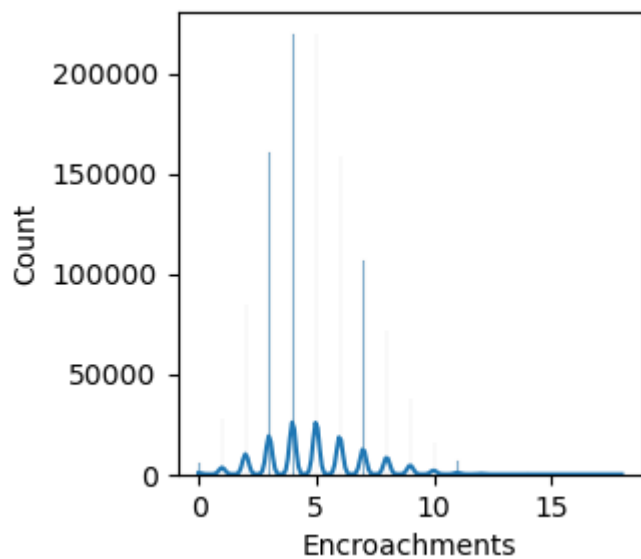
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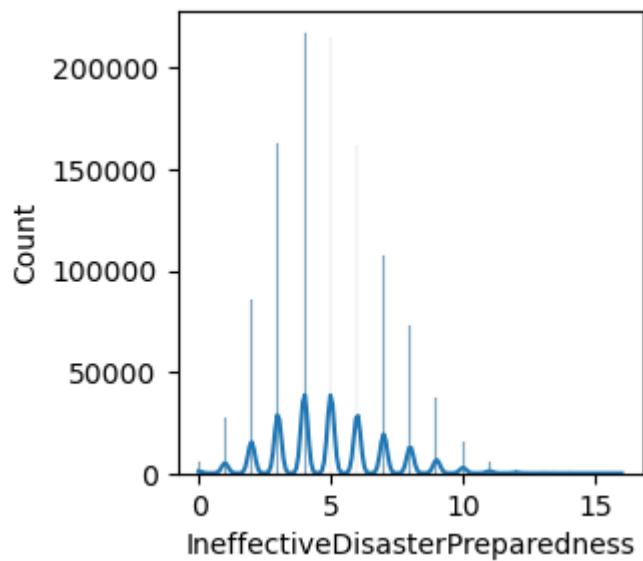
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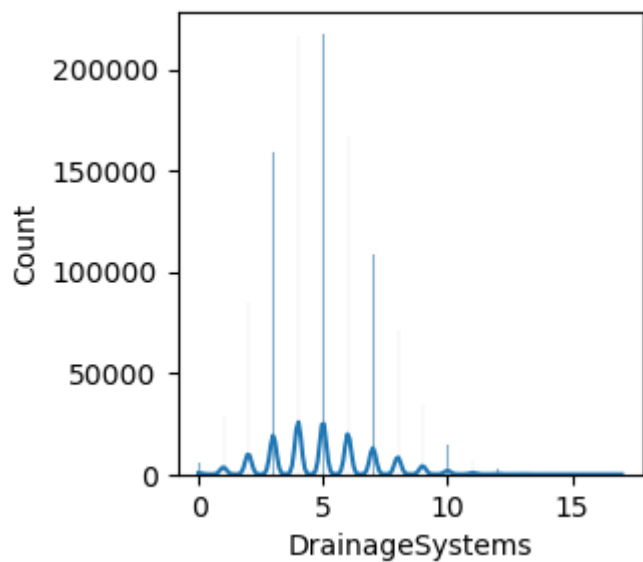
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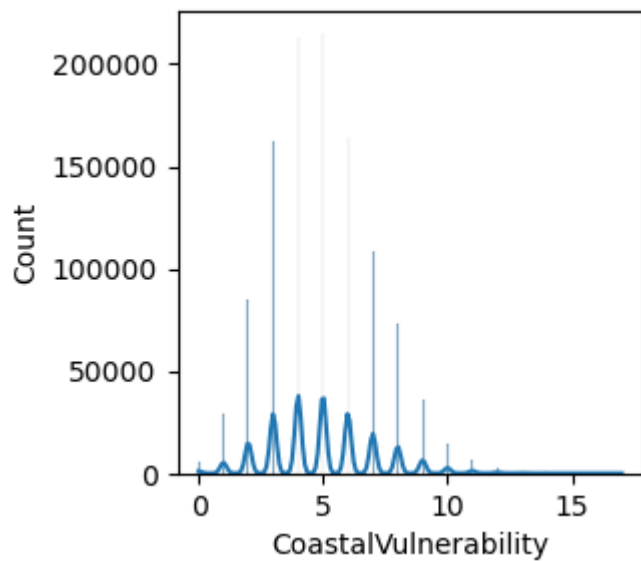
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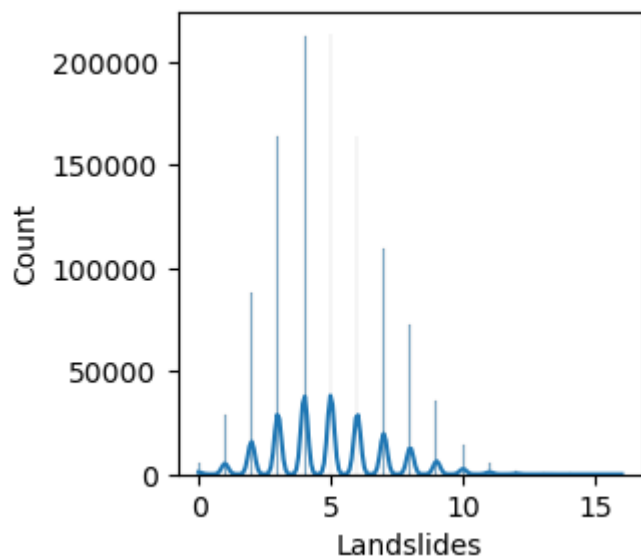
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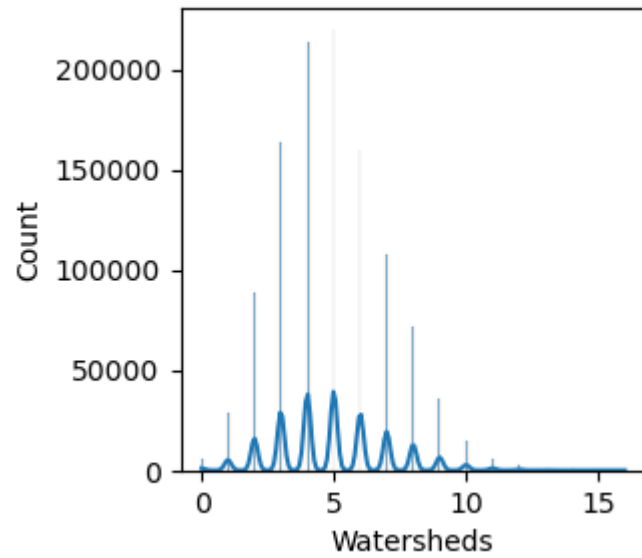
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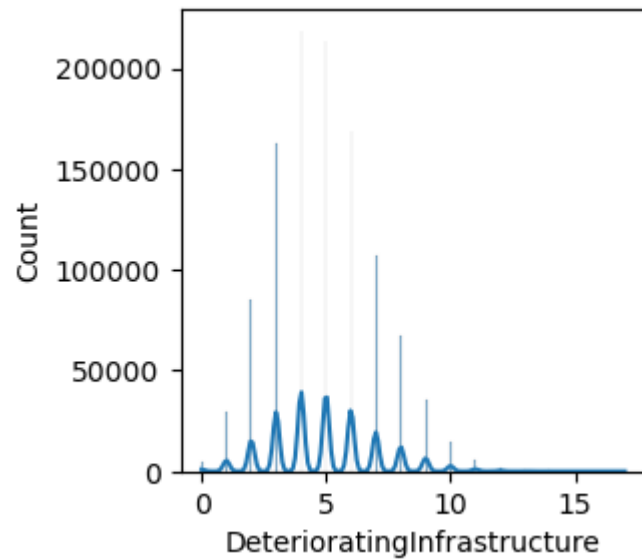
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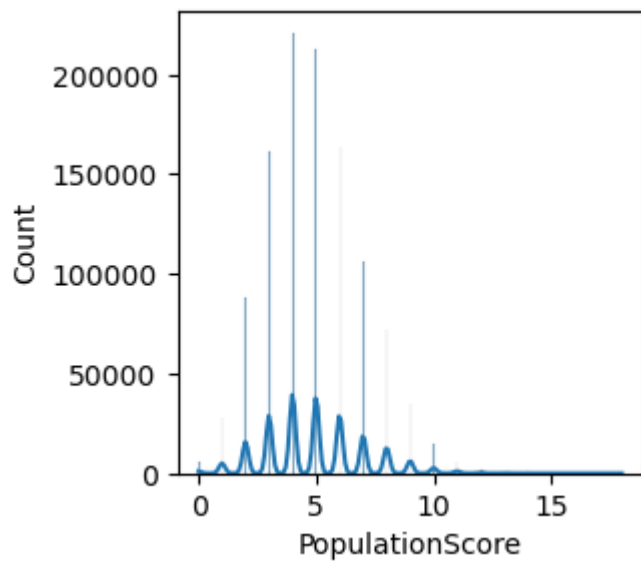
Axes(0.125,0.11;0.775x0.77)



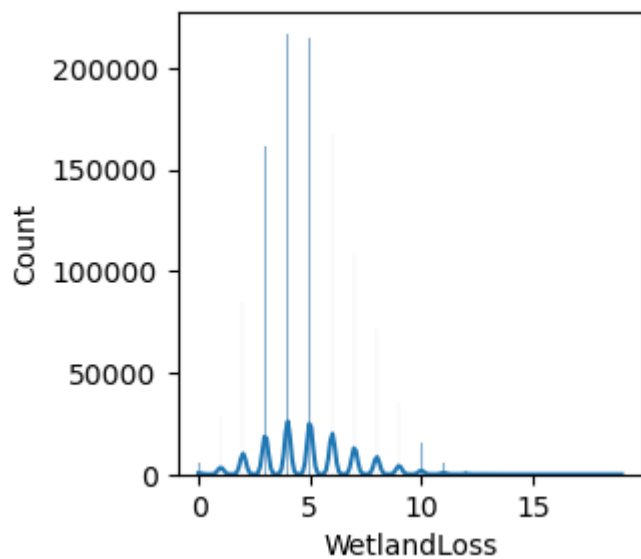
Axes(0.125,0.11;0.775x0.77)



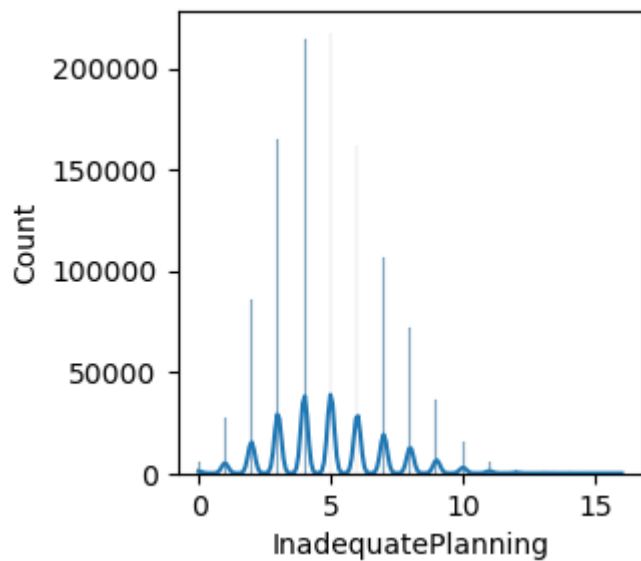
Axes(0.125,0.11;0.775x0.77)



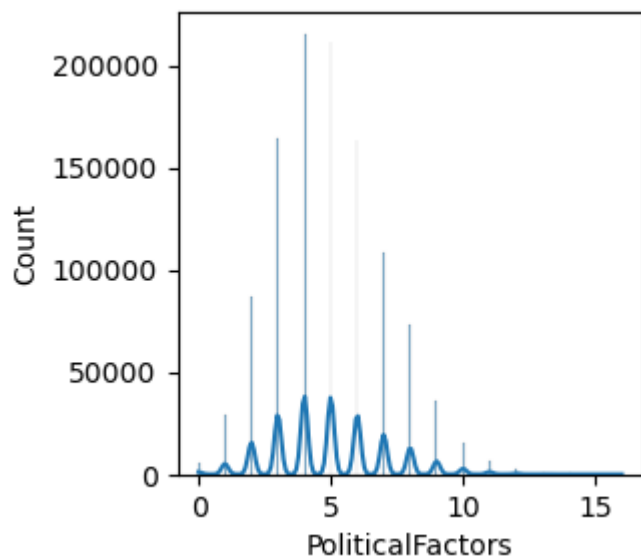
Axes(0.125,0.11;0.775x0.77)



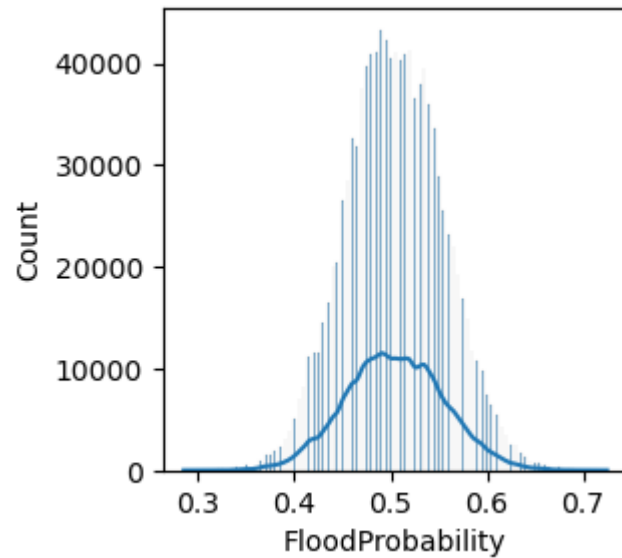
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Axes(0.125,0.11;0.775x0.77)



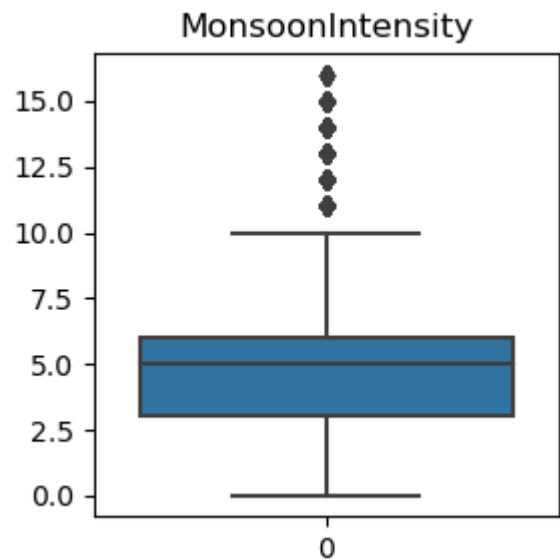
Axes(0.125,0.11;0.775x0.77)



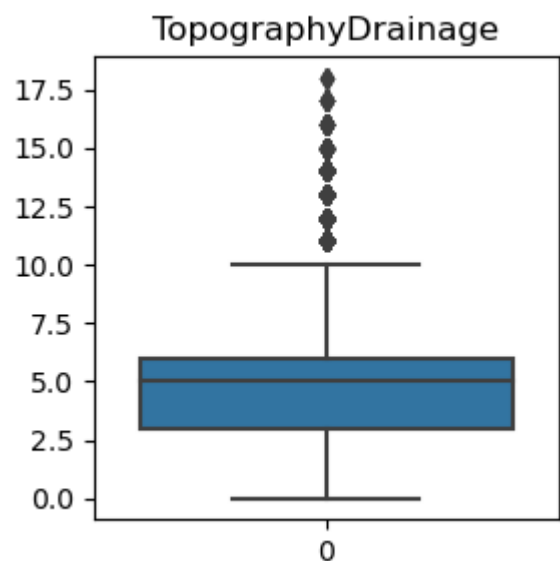
3.1.2 Box-Plot

```
In [14]: for i in df_train.columns:
plt.figure(figsize = (3,3))
print(sns.boxplot(df_train[i]), end = " ")
plt.title(i)
plt.show()
```

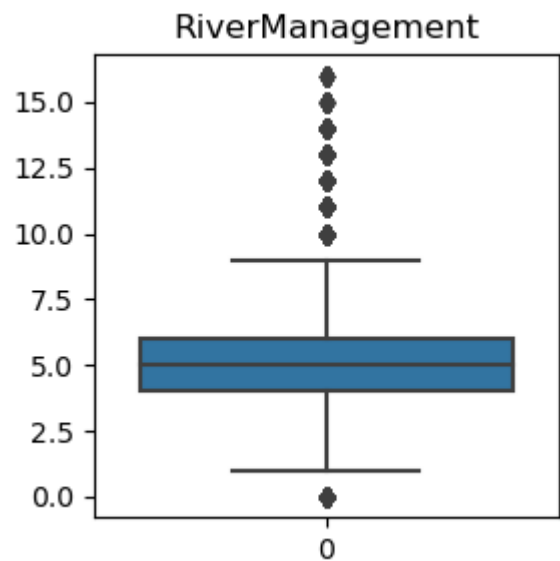
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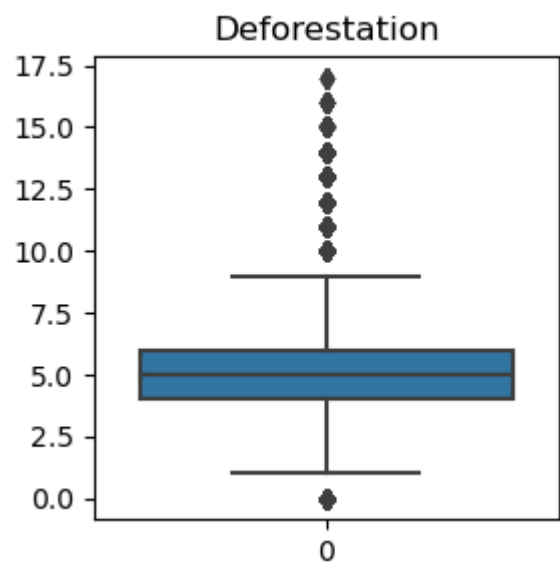
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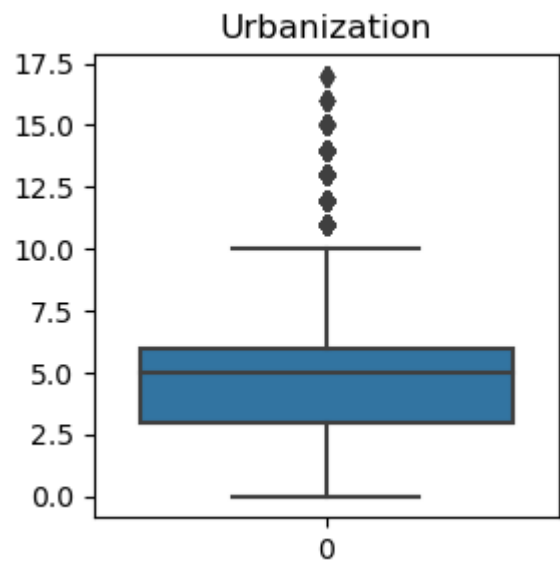
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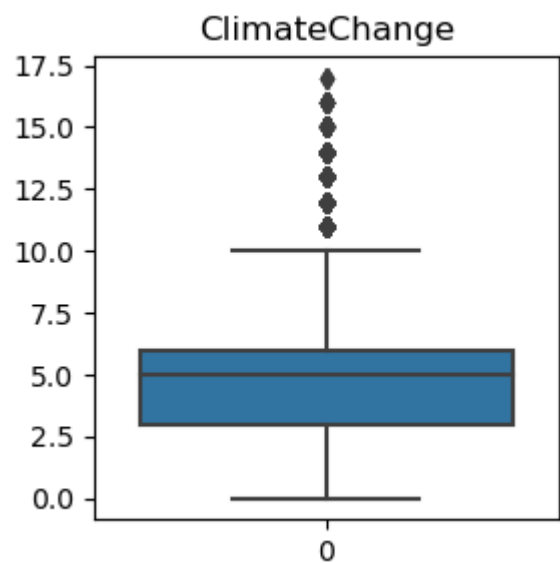
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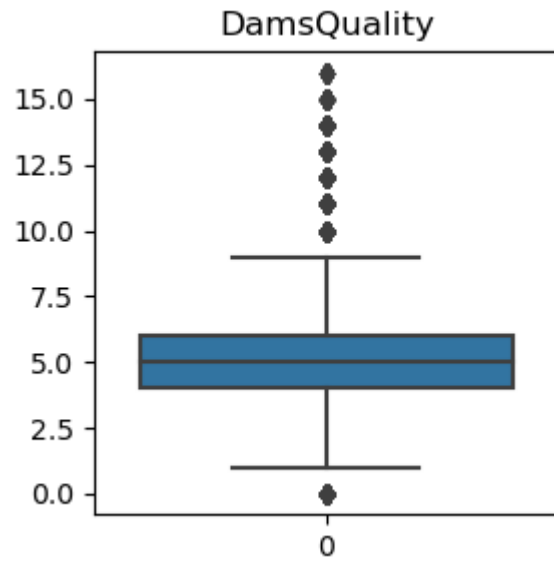
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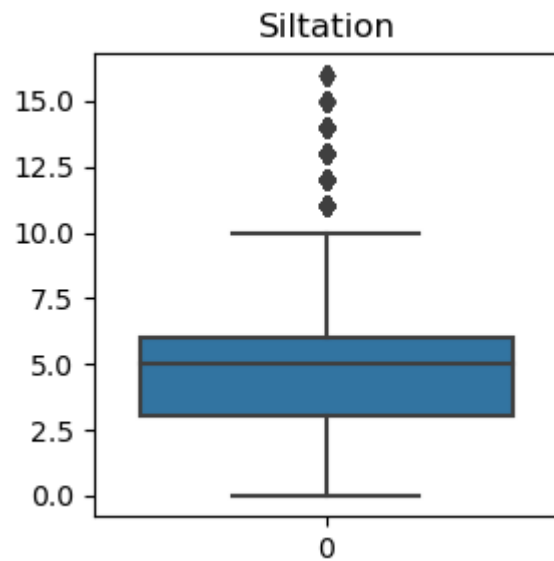
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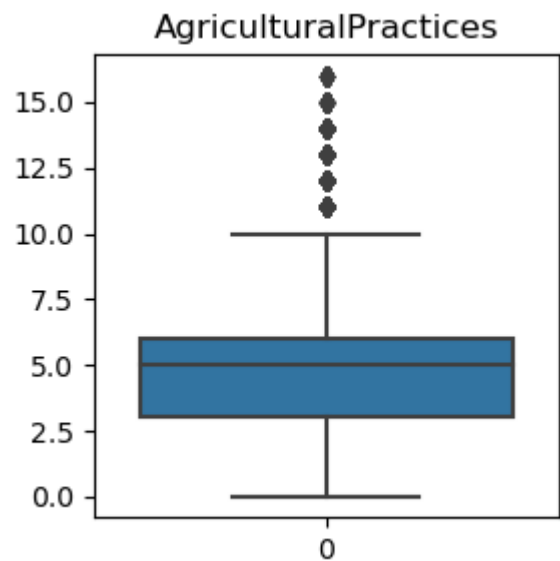
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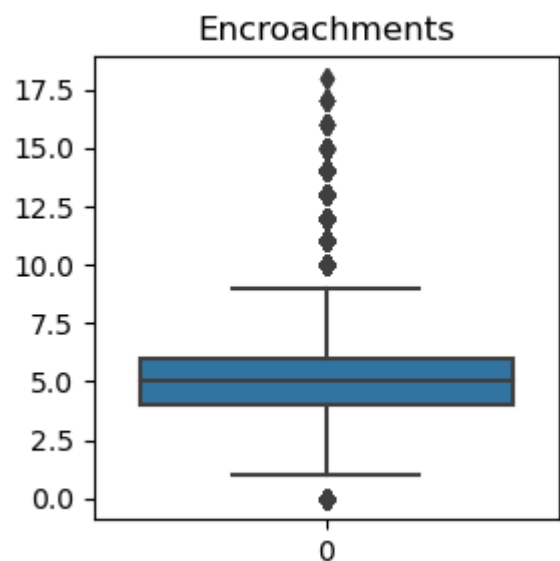
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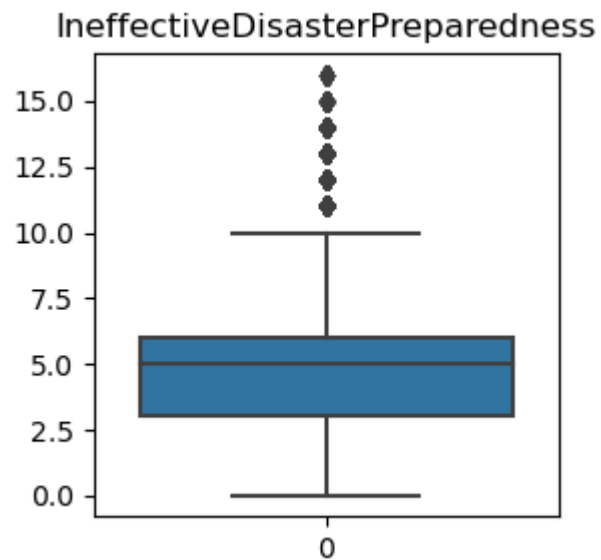
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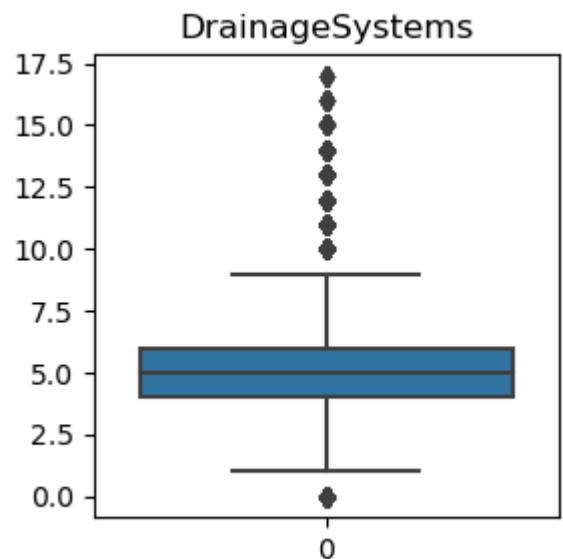
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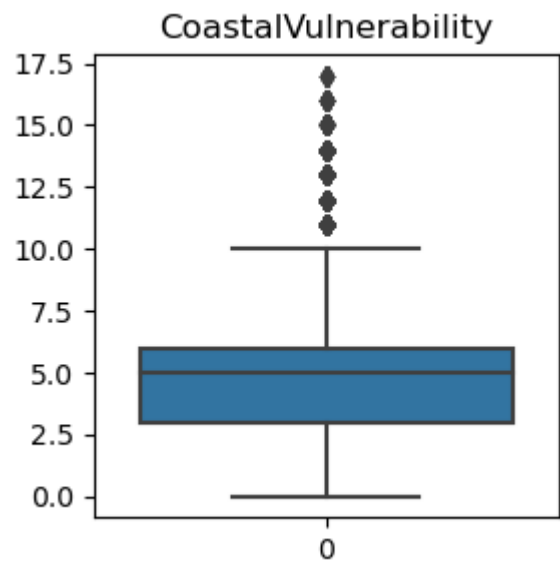
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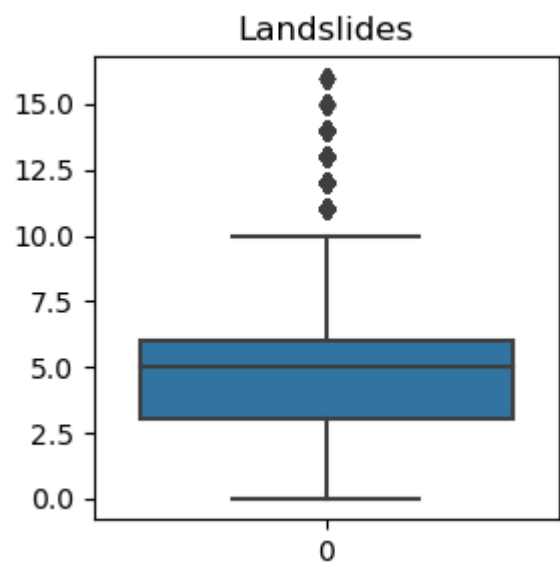
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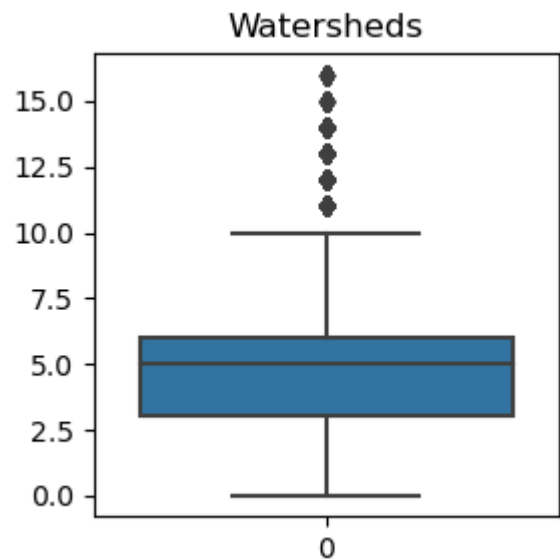
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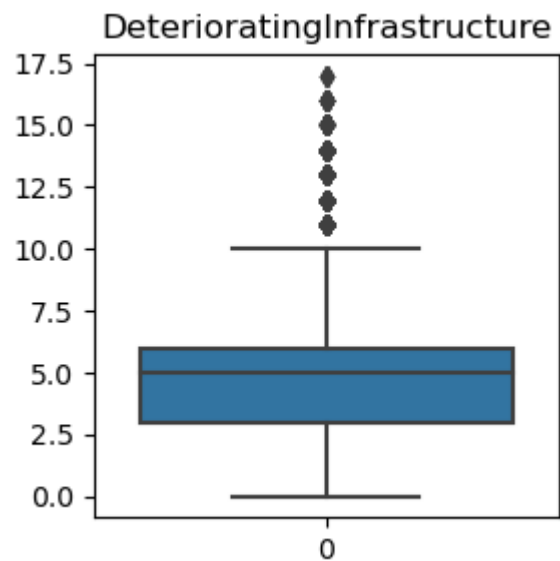
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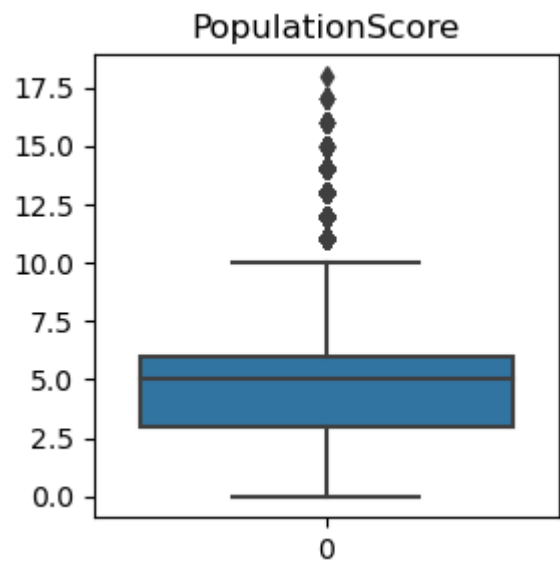
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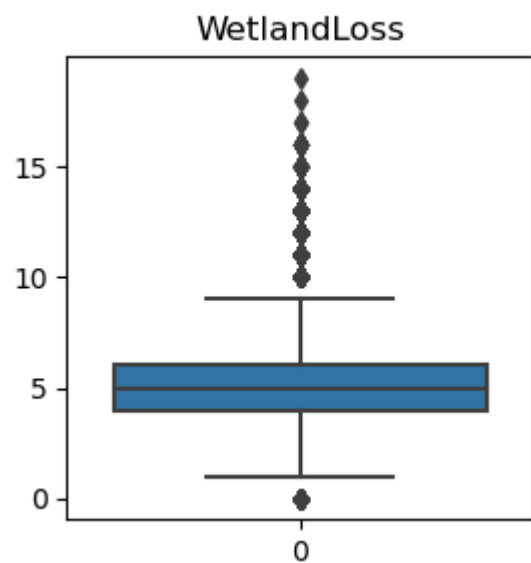
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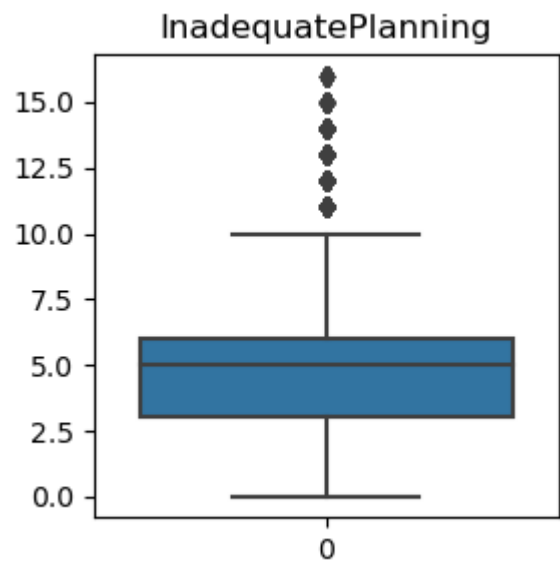
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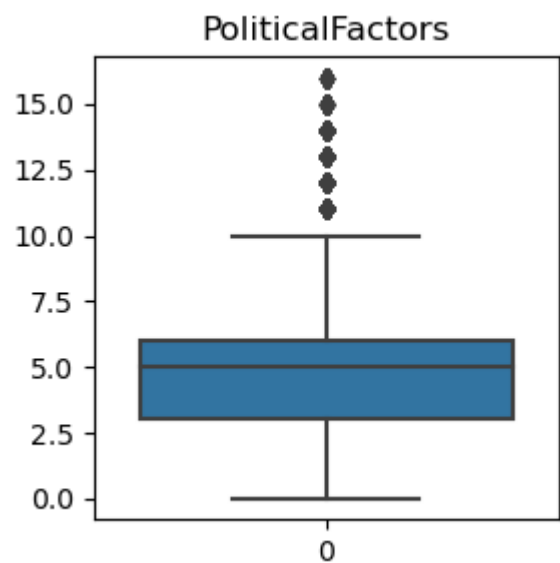
Axes(0.125,0.11;0.775x0.77)



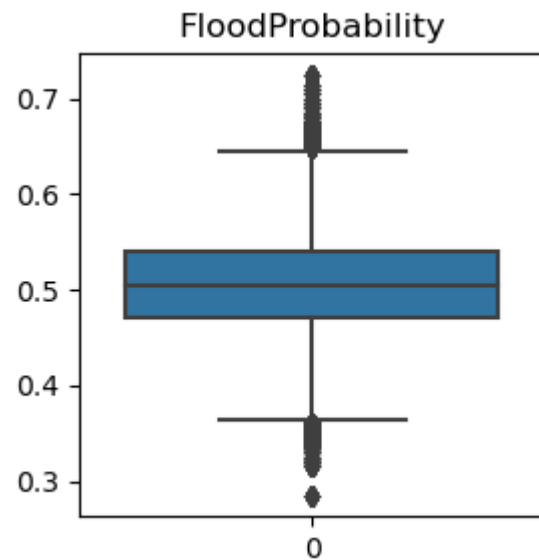
Axes(0.125,0.11;0.775x0.77)



Axes(0.125,0.11;0.775x0.77)



Axes(0.125,0.11;0.775x0.77)



3.2 Multivariate Analysis

3.2.2 Correlation Matrix

```
In [15]: df_train.corr()
```

Out[15]:

	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	S
MonsoonIntensity	1.000000	-0.007362	-0.008070	-0.007251	-0.009309	-0.008031	-0.007787	-0
TopographyDrainage	-0.007362	1.000000	-0.009924	-0.008548	-0.010532	-0.009619	-0.007607	-0
RiverManagement	-0.008070	-0.009924	1.000000	-0.008574	-0.012292	-0.009237	-0.008711	-0
Deforestation	-0.007251	-0.008548	-0.008574	1.000000	-0.012248	-0.008266	-0.009356	-0
Urbanization	-0.009309	-0.010532	-0.012292	-0.012248	1.000000	-0.011199	-0.011128	-0
ClimateChange	-0.008031	-0.009619	-0.009237	-0.008266	-0.011199	1.000000	-0.008427	-0
DamsQuality	-0.007787	-0.007607	-0.008711	-0.009356	-0.011128	-0.008427	1.000000	-0
Siltation	-0.007836	-0.009824	-0.010058	-0.011536	-0.010153	-0.009457	-0.009401	1
AgriculturalPractices	-0.008232	-0.009496	-0.010783	-0.010039	-0.010559	-0.011517	-0.009033	-0
Encroachments	-0.010309	-0.012887	-0.011615	-0.013175	-0.010784	-0.012533	-0.010890	-0
IneffectiveDisasterPreparedness	-0.008032	-0.010746	-0.010675	-0.009512	-0.012685	-0.011346	-0.009515	-0
DrainageSystems	-0.009716	-0.010056	-0.011277	-0.010490	-0.012572	-0.009650	-0.010439	-0
CoastalVulnerability	-0.010659	-0.012526	-0.011680	-0.012388	-0.014497	-0.013005	-0.012096	-0
Landslides	-0.009121	-0.010240	-0.008994	-0.009257	-0.010582	-0.009352	-0.009924	-0
Watersheds	-0.008900	-0.011067	-0.011412	-0.010671	-0.012107	-0.009882	-0.009085	-0
DeterioratingInfrastructure	-0.008486	-0.006628	-0.005827	-0.008862	-0.010656	-0.006324	-0.009831	-0
PopulationScore	-0.008679	-0.010815	-0.006727	-0.011777	-0.011485	-0.010332	-0.009599	-0
WetlandLoss	-0.006811	-0.010267	-0.010069	-0.011004	-0.011023	-0.009376	-0.009372	-0
InadequatePlanning	-0.008155	-0.011617	-0.009673	-0.010424	-0.011584	-0.010772	-0.011374	-0
PoliticalFactors	-0.008474	-0.012350	-0.011550	-0.009661	-0.013005	-0.011379	-0.013081	-0
FloodProbability	0.189098	0.187635	0.187131	0.184001	0.180861	0.184761	0.187996	0

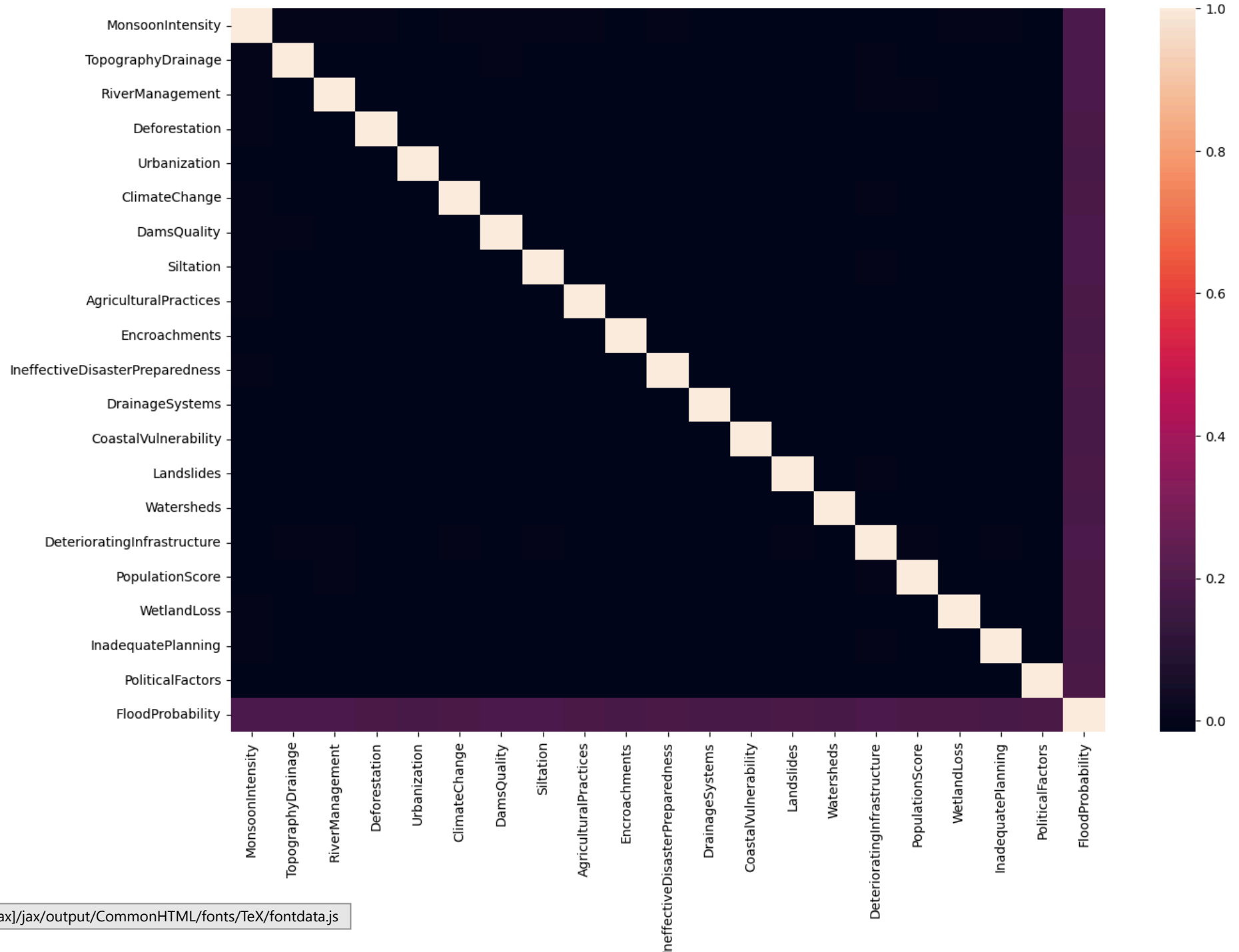
21 rows × 21 columns

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Remark: As correlation coefficients are tends to 0 , no dependent feature exists

3.2.3 Correlation Heatmap

```
In [16]: plt.figure(figsize =(15,10))  
sns.heatmap(df_train.corr())  
plt.show()
```



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4. Feature Engineering

4.1 Feature Transformation

4.1.2 Scaling

4.1.2.1 Standardization

```
In [17]: x_train = df_train.iloc[:, :20]
y_train = df_train.iloc[:, -1]
x_test = df_test.iloc[:, 1:]
```

```
In [18]: x_train = (x_train - x_train.mean())/x_train.std()
x_test = (x_test - x_test.mean())/x_test.std()
```

```
In [19]: x_train.head(2)
```

```
Out[19]:
```

	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	AgriculturalPractices
0	0.038198	1.467768	0.021561	1.490362	0.507578	-0.453941	-0.458881	-0.933107	-0.939124
1	0.524488	0.990186	-0.461021	-0.459251	1.467551	1.489938	-0.938943	0.034951	-0.455692

4.2 Feature Extraction

4.2.1 Principal Component Analysis

```
In [20]: from sklearn.decomposition import PCA
```

```
In [21]: x_trn = x_train
```

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```
explained_variance = pca.explained_variance_ratio_
print(explained_variance)
```

```
[0.05098534 0.05087619 0.0508146  0.05078321 0.0506943  0.05066361
 0.05063026 0.05061952 0.05058528 0.05051905 0.05045643 0.05041462
 0.05038968 0.05034189 0.0503254  0.05029073 0.05025888 0.05023953
 0.05011    0.04000149]
```

Remark : As it can be observed that for 95% proportion of variance explained, the number of principal components are 20 . So, it is not suggested to go for PCA , as it will not reduce a significant dimension.

4.3 Feature Selection

4.3.1 Filter Method (Pearson Correlation Coefficient)

```
In [22]: for i in x_train.columns:
          if np.corrcoef(x_train[i],y_train)[1][0] > 0.56:
              print(i,"is poorly related to `Target Variable`", "Corr_coeff :", np.corrcoef(x_train[i],y_train)[1][0])
          else:
              print("All are considered to be significant for now.")
```

All are considered to be significant for now.

Remark: As, no independent variable is highly related to dependent variable, all are taken into consideration.

5. Model Building

5.1 Splitting Training data into Model Training and Hold data (For Model Training)

```
In [23]: from sklearn.model_selection import train_test_split
          x_trn,x_tst,y_trn,y_tst=train_test_split(x_train,y_train,test_size=0.25)
```

5.1.1 Shape of Training and Test Data for Models

```
In [24]: x_trn.shape,x_tst.shape,y_trn.shape,y_tst.shape
```

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Out[24]: ((838467, 20), (279490, 20), (838467,), (279490,))

5.2 Model Building

5.2.1 Importing Libraries

```
In [25]: import xgboost as xgb
import lightgbm as lgb
import catboost as cb
from sklearn.svm import SVR
```

5.2.2 Baseline Models

```
In [26]: base_model_xgb = xgb.XGBRegressor(random_state=42)
base_model_cb = cb.CatBoostRegressor(random_state=42, verbose=False)
base_model_SVR = SVR()
```

5.2.3 Model Accuracy of each Base models

```
In [27]: from sklearn.metrics import mean_squared_error, r2_score
```

5.2.3.1 Model Accuracy of XGBoostingRegressor

```
In [28]: base_model_xgb.fit(x_trn, y_trn)
y_prd_2 = base_model_xgb.predict(x_tst)
mse_trn_2 = mean_squared_error(y_tst, y_prd_2)
r2_score_trn_2 = r2_score(y_tst, y_prd_2)
print("XG Boosting MSE:", mse_trn_2)
print("XG r2_score:", r2_score_trn_2)
```

XG Boosting MSE: 0.000497271555534172

XG r2_score: 0.8096917261595232

5.2.3.2 Model Accuracy of CatBoostRegressor

```
In [29]: base_model_cb.fit(x_trn, y_trn)
y_prd_4 = base_model_cb.predict(x_tst)
r2_score_trn_4 = r2_score(y_tst, y_prd_4)
```

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```
print("cat Boosting MSE:", mse_trn_4)
print("cat r2_score:", r2_score_trn_4)
```

```
cat Boosting MSE: 0.0004011605310292122
cat r2_score: 0.8464738886762002
```

5.2.3.3 Model Accuracy of SVR

```
In [30]: base_model_SVR.fit(x_trn, y_trn)
y_prd_5 = base_model_SVR.predict(x_tst)
mse_trn_5 = mean_squared_error(y_tst, y_prd_5)
r2_score_trn_5 = r2_score(y_tst, y_prd_5)
print("Hist Gradient Boosting MSE:", mse_trn_5)
print("Hist Gradient r2_score:", r2_score_trn_5)
```

```
Hist Gradient Boosting MSE: 0.0010134904735254254
Hist Gradient r2_score: 0.6121322033728573
```

5.2.4 Stacking Regressor

```
In [31]: from sklearn.ensemble import StackingRegressor
from sklearn.neural_network import MLPRegressor
```

5.2.5 Final Estimator

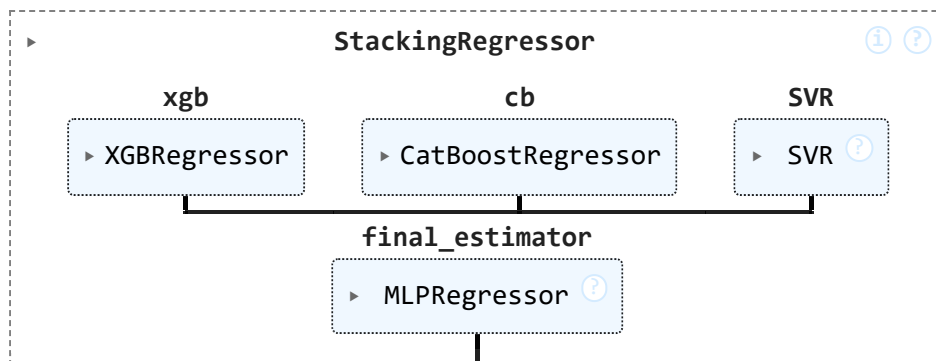
```
In [32]: final_estimator = MLPRegressor()
```

```
In [33]: stacking_regressor = StackingRegressor(estimators=[
    ('xgb', base_model_xgb),
    ('cb', base_model_cb),
    ('SVR', base_model_SVR)
], final_estimator = final_estimator)
```

5.2.6 Final Model

```
In [34]: stacking_regressor.fit(x_trn, y_trn)
```

Out[34]:



6. Model Accuracy

6.1 Model Accuracy on Hold data (Model Training Data)

```

In [35]: y_prd = stacking_regressor.predict(x_tst)
mse_trn = mean_squared_error(y_tst, y_prd)
r2_score_trn = r2_score(y_tst, y_prd)
print("Final model MSE:", mse_trn)
print("Final model r2_score:", r2_score_trn)

```

```

Final model MSE: 0.0003787025582490078
Final model r2_score: 0.8550686654861588

```

7. Model Prediction

7.1 Model Prediction on Test data (Model Testing Data)

```

In [36]: y_test = stacking_regressor.predict(x_test)

```

```

In [37]: y_test

```

```

Out[37]: array([0.57330199, 0.44394068, 0.44221133, ..., 0.62352514, 0.55090508,
0.50850966])

```

7.2.1 Addition of Id in final submission

In [38]: `df_test.head()`

Out[38]:

	id	MonsoonIntensity	TopographyDrainage	RiverManagement	Deforestation	Urbanization	ClimateChange	DamsQuality	Siltation	Agricultural
0	1117957	4	6	3	5	6	7	8	7	
1	1117958	4	4	2	9	5	5	4	7	
2	1117959	1	3	6	5	7	2	4	6	
3	1117960	2	4	4	6	4	5	4	3	
4	1117961	6	3	2	4	6	4	5	5	

5 rows × 21 columns

In [39]:

```
submission_df = pd.DataFrame({
    'id': df_test['id'],
    'FoodPrediction': y_test
})
```

In [40]: `submission_df.head()`

Out[40]:

	id	FoodPrediction
0	1117957	0.573302
1	1117958	0.443941
2	1117959	0.442211
3	1117960	0.458675
4	1117961	0.457712

In [41]:

```
submission_df.to_csv('submission_stacking.csv', index=False)
print("Submission file created successfully.")
```

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Submission file created successfully.

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