

Project Title:

Predictive Shelter Demand Analysis for Disaster Preparedness using Historical Event Data

Problem Statement:

Natural disasters such as floods, cyclones, droughts, and earthquakes cause large-scale human displacement every year. One of the major challenges during these events is the absence of predictive systems to estimate shelter needs and evacuation requirements. This often results in delayed responses, inadequate facilities, and increased vulnerability of affected populations.

Description:

This project utilizes the Natural Disasters Emergency Events Database to analyze historical disaster patterns and apply machine learning techniques to predict shelter demand and identify high-risk regions. The outcomes will support policymakers and disaster management agencies in evacuation planning, infrastructure readiness, and sustainable disaster risk reduction strategies.


```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder, MinMaxScaler
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.tree import DecisionTreeRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.cluster import KMeans, DBSCAN
from sklearn.decomposition import PCA
import pickle
```

Load the dataset

```
df = pd.read_csv("natural_disasters.csv", sep=";")
```

Display first 5 rows

```
df.head()
```



	Year	Country	ISO	Disaster Group	Disaster Subroup	Disaster Type	Disaster Subtype	Total Events	Total Affected	Total Deaths	Total Damage (USD, original)	Total Damage (USD, adjusted)	CPI, ..
0	1900	Cabo Verde	CPV	Natural	Climatological	Drought	Drought	1	NaN	11000.0	NaN	NaN	2,8.49084E+12,,
1	1900	India	IND	Natural	Climatological	Drought	Drought	1	NaN	1250000.0	NaN	NaN	2,8.49084E+12,,
2	1900	Jamaica	JAM	Natural	Hydrological	Flood	NaN	1	NaN	300.0	NaN	NaN	2,8.49084E+12,,
3	1900	Japan	JPN	Natural	Geophysical	Volcanic activity	Ash fall	1	NaN	30.0	NaN	NaN	2,8.49084E+12,,

Next steps:

[Generate code with df](#)

[View recommended plots](#)

[New interactive sheet](#)

Explore and understand the dataset

```
# Check structure
df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10431 entries, 0 to 10430
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Year                  10431 non-null  int64
1   Country               10431 non-null  object
2   ISO                   10431 non-null  object
3   Disaster Group        10431 non-null  object
4   Disaster Subroup      10431 non-null  object
5   Disaster Type         10431 non-null  object
6   Disaster Subtype      8298 non-null   object
7   Total Events          10431 non-null  int64
8   Total Affected        7586 non-null   float64
9   Total Deaths          7375 non-null   float64
```

```

10 Total Damage (USD, original) 3834 non-null float64
11 Total Damage (USD, adjusted) 3830 non-null float64
12 CPI,, 10431 non-null object
dtypes: float64(4), int64(2), object(7)
memory usage: 1.0+ MB

```

```

# Check missing values
df.isnull().sum()

```

```

0
Year 0
Country 0
ISO 0
Disaster Group 0
Disaster Subroup 0
Disaster Type 0
Disaster Subtype 2133
Total Events 0
Total Affected 2845
Total Deaths 3056
Total Damage (USD, original) 6597
Total Damage (USD, adjusted) 6601
CPI,, 0

dtype: int64

```

```
df.describe()
```

```

Year Total Events Total Affected Total Deaths Total Damage (USD, original) Total Damage (USD, adjusted)
count 10431.000000 10431.000000 7.586000e+03 7.375000e+03 3.834000e+03 3.830000e+03
mean 1995.609625 1.446649 1.125969e+06 3.107711e+03 1.122262e+09 1.748704e+09
std 22.001186 1.246589 9.760891e+06 7.255589e+04 6.792339e+09 9.115319e+09
min 1900.000000 1.000000 1.000000e+00 1.000000e+00 2.000000e+03 2.469000e+03
25% 1986.000000 1.000000 1.200000e+03 6.000000e+00 1.000000e+07 2.020927e+07
50% 2001.000000 1.000000 1.141400e+04 2.300000e+01 6.800000e+07 1.469247e+08
75% 2011.000000 1.000000 1.193045e+05 9.000000e+01 4.000000e+08 7.847767e+08
max 2023.000000 20.000000 3.300000e+08 3.700000e+06 2.100000e+11 2.732184e+11

```

```
print(df.columns.tolist())
```

```
['Year', 'Country', 'ISO', 'Disaster Group', 'Disaster Subroup', 'Disaster Type', 'Disaster Subtype', 'Total Events', 'Total Affected', 'Total Deaths', 'Total Damage (USD, original)', 'Total Damage (USD, adjusted)']
```

```
print(df['Disaster Type'].unique())
```

```

['Drought' 'Flood' 'Volcanic activity' 'Earthquake' 'Storm'
'Mass movement (dry)' 'Landslide' 'Wildfire' 'Insect infestation'
'Extreme temperature ' 'Fog' 'Animal accident' 'Glacial lake outburst']

```

```

# Distribution of affected population
df['Total Affected'].describe()

```



Total Affected	
count	7.586000e+03
mean	1.125969e+06
std	9.760891e+06
min	1.000000e+00
25%	1.200000e+03
50%	1.141400e+04
75%	1.193045e+05
max	3.300000e+08

dtype: float64

```
# Correlation check for numeric columns
df.corr(numeric_only=True)
```



	Year	Total Events	Total Affected	Total Deaths	Total Damage (USD, original)	Total Damage (USD, adjusted)
Year	1.000000	0.109110	-0.005482	-0.093444	0.103596	0.043928
Total Events	0.109110	1.000000	0.102799	-0.011392	0.175127	0.161398
Total Affected	-0.005482	0.102799	1.000000	0.129899	0.109523	0.129427
Total Deaths	-0.093444	-0.011392	0.129899	1.000000	0.011775	0.053985
Total Damage (USD, original)	0.103596	0.175127	0.109523	0.011775	1.000000	0.973481

