4222-SURYA GROUP OF INSTITUTIONS

VIKARAVANDI -605 652

PROJECT NAME:

EARTHQUAKE-PREDICTION-USING-PYTHON

PHASE 3: DEVELOPMENT PART 1

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ECE DEPARTMENT

AI_PHASE 3 :

INTRODUCTION FOR PREPROCESSING:

An earthquake preprocessing dataset is a meticulously curated collection of raw seismic data gathered from various sensors and sources before undergoing any analysis or interpretation. This process involves removing noise, correcting inconsistencies, and standardizing formats, ensuring that the dataset is reliable and ready for in-depth analysis

STEPS FOR EARTHQUAKE PREPROCESSING:

1. Data Collection:

Gather raw seismic data from various seismometers and networks.

2. Data Conversion:

Convert data from different formats into a standard format for consistency.

3. Noise Removal:

Remove noise from the data to enhance the signal-to-noise ratio. This can involve using filters or statistical methods to identify and remove unwanted noise.

4. Instrument Response Removal:

Correct for the instrument's response to seismic waves. Seismic instruments often have a specific frequency response that needs to be removed to obtain accurate earthquake signals.

5. Data Segmentation:

Divide the continuous data into smaller segments for analysis. Common segments include hours or days.

6. Event Detection:

Use algorithms to detect earthquake events within the segmented data. These algorithms can identify patterns associated with seismic events.

7. Event Association:

Identify which seismic signals belong to the same earthquake event. This can involve clustering nearby seismic events in both time and space.

8. Phase Picking:

Identify the arrival times of seismic waves (P, S, etc.) for each event. This is crucial for locating the epicenter and determining the magnitude.

9. Hypocenter Location:

Calculate the earthquake's hypocenter (latitude, longitude, and depth) using the phase arrival times from different seismometers. Various methods, like triangulation, are used for this purpose.

10. Magnitude Estimation:

Determine the earthquake's magnitude using the amplitude of seismic waves. Common magnitude scales include Richter scale and moment magnitude scale.

11. Data Integration:

Integrate the earthquake location, magnitude, and other relevant information into a database or a suitable format for further analysis and visualization.

12. Quality Control:

Perform quality checks at various stages of the preprocessing to ensure the accuracy and reliability of the results.

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

from sklearn.decomposition **import** PCA
from sklearn.preprocessing **import** OneHotEncoder
from sklearn.discriminant_analysis **import** LinearDiscriminantAnalysis **as** LDA
from mpl_toolkits.mplot3d **import** Axes3D

df = pd**.**read_csv("data/train_values.csv")

SI NO	building_id	geo_level_1_id	geo_level_2_id	geo_level_3_id	count_floors_pre_eq	age	area_percentage	height_percentage
0	802906	6	487	12198	2	30	6	5
1	28830	8	900	2812	2	10	8	7
2	94947	21	363	8973	2	10	5	5
3	590882	22	418	10694	2	10	6	5
4	201944	11	131	1488	3	30	8	9

Df**.**columns

```
Index(['building_id', 'geo_level_1_id', 'geo_level_2_id', 'geo_level_3_id',
       'count_floors_pre_eq', 'age', 'area_percentage', 'height_percentage',
       'land_surface_condition', 'foundation_type', 'roof_type',
       'ground_floor_type', 'other_floor_type', 'position',
       'plan_configuration', 'has_superstructure_adobe_mud',
       'has_superstructure_mud_mortar_stone', 'has_superstructure_stone_flag',
       'has_superstructure_cement_mortar_stone',
       'has_superstructure_mud_mortar_brick',
       'has_superstructure_cement_mortar_brick', 'has_superstructure_timber',
       'has_superstructure_bamboo', 'has_superstructure_rc_non_engineered',
       'has_superstructure_rc_engineered', 'has_superstructure_other',
       'legal_ownership_status', 'count_families', 'has_secondary_use',
       'has_secondary_use_agriculture', 'has_secondary_use_hotel',
       'has_secondary_use_rental', 'has_secondary_use_institution',
       'has_secondary_use_school', 'has_secondary_use_industry',
       'has_secondary_use_health_post', 'has_secondary_use_gov_office',
       'has_secondary_use_use_police', 'has_secondary_use_other'],
      dtype='object')
```

labels = pd**.**read_csv("data/train_labels.csv") labels.head()

SINO	building_id	damage_grade
1	802906	3
2	28830	2
3	94947	3
4	590882	2
5	201944	3

```
df = df.sort_values("building_id")
labels = labels.sort_values("building_id")
```

df.head()

SINO	building_id	geo_level_1_id	geo_level_2_id	geo_level_3_id	count_floors_pre_eq	age	area_percentage	height_percentage
47748	4	30	266	1224	1	25	5	2
212102	8	17	409	12182	2	0	13	7
60133	12	17	716	7056	2	5	12	6
34181	16	4	651	105	2	80	5	4
25045	17	3	1387	3909	5	40	5	10

labels.head()

SINO	building_id	damage_grade
1	**47748**	2
2	**212102**	3
3	**60133**	3
4	**34181**	2
5	**25045**	2

df["damage_grade"] = labels["damage_grade"]

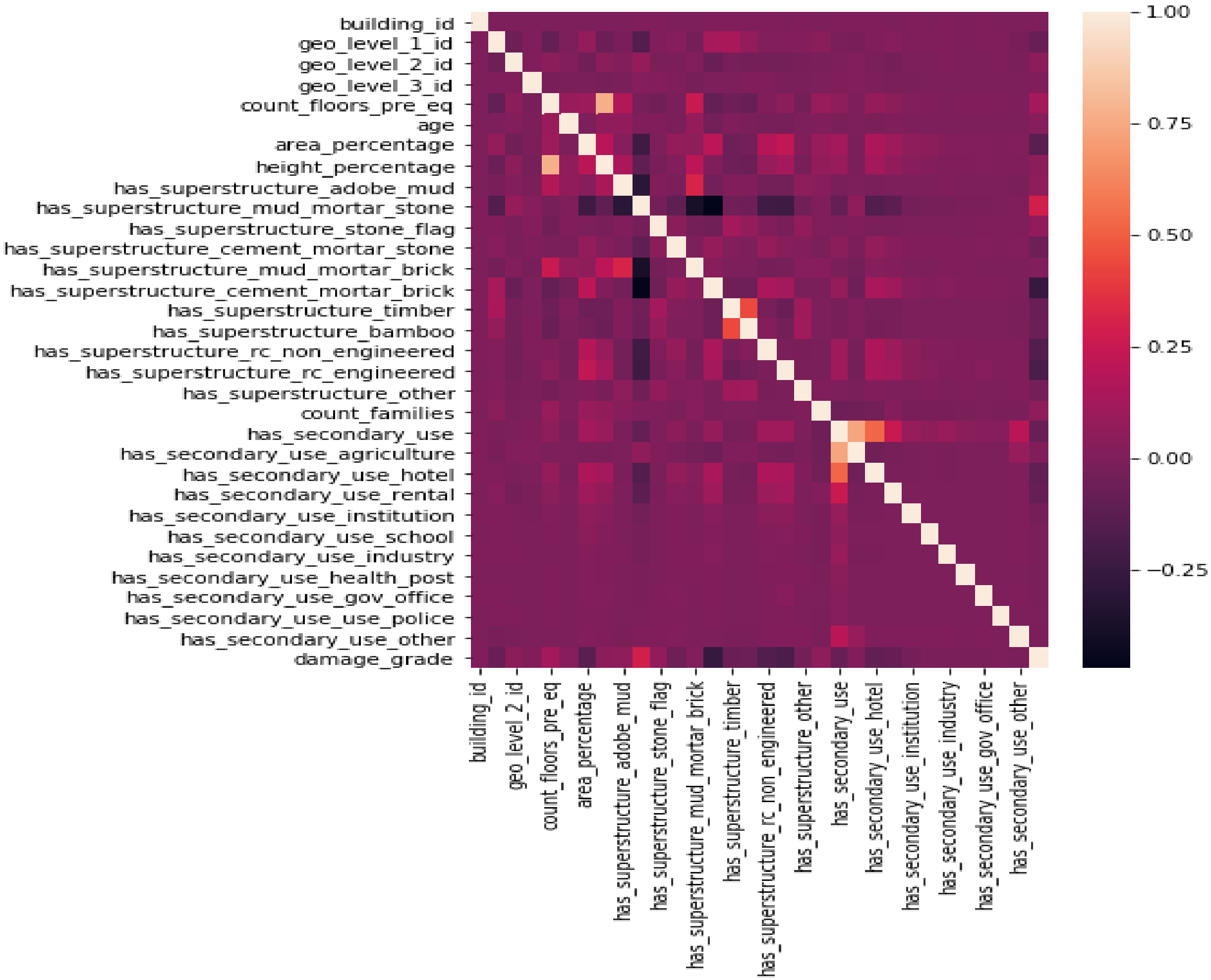
df.head()

SINO	building_id	building_id	geo_level_2_id	geo_level_3_id	count_floors_pre_eq	age	area_percentage	height_percentage
47748	4	30	266	1224	1	25	15	2
212102	8	17	409	12182	2	0	13	7
60133	12	17	716	7056	2	5	12	6
34181	16	4	651	105	2	80	5	4
25045	17	3	1387	3909	5	40	5	10

```
df.to_csv("data/labeled_train.csv")
```

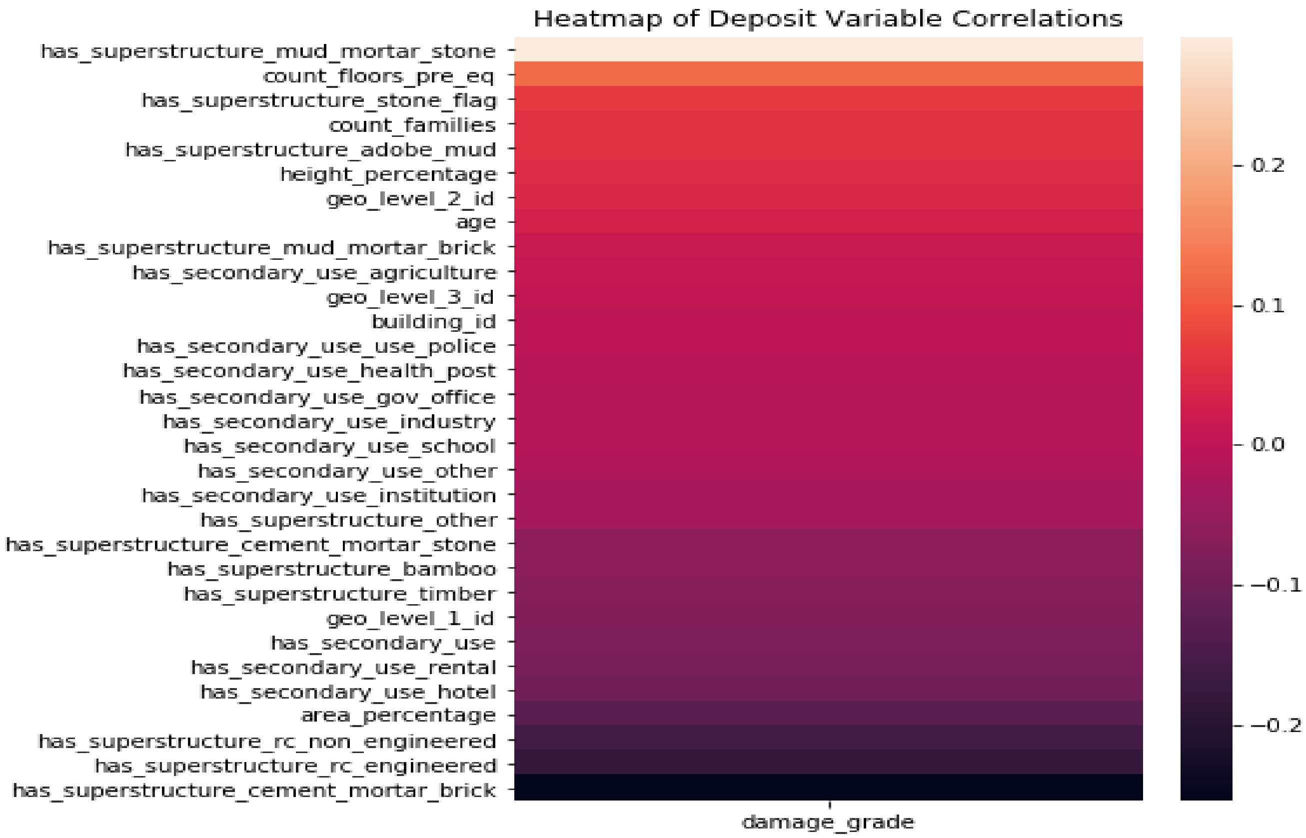
```
plt.rcParams["figure.figsize"] = (6,8)
sns.heatmap(df.corr())
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f6ff8d5ec18>
```




```
DEPOSIT_COLUMN = 'damage_grade'
correlation_matrix = df.corr()
def plot_deposit_correlations(data):
    '''
    Isolates the deposit columns of the correlation matrix and visualize it.
    '''
    deposit_correlation_column = pd.DataFrame(correlation_matrix[DEPOSIT_COLUMN].drop(DEPOSIT_COLUMN))
    deposit_correlation_column = deposit_correlation_column.sort_values(by=DEPOSIT_COLUMN, ascending=False)
    sns.heatmap(deposit_correlation_column)
    plt.title('Heatmap of Deposit Variable Correlations')

plot_deposit_correlations(df)
```



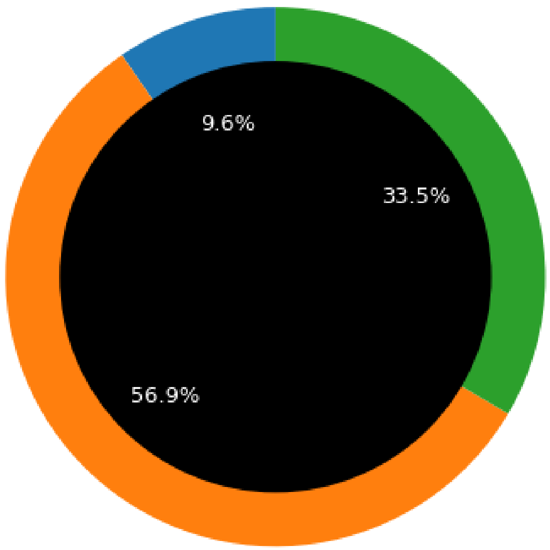

```
categorical_vars = ["land_surface_condition", "roof_type", "ground_floor_type",
"other_floor_type", "position", "plan_configuration", "legal_ownership_status"]
for var in categorical_vars:
    df = fuck_naman(df, var)
```

```
df.to_csv('data/labeled_train.csv')
```

```
df["damage_grade"].value_counts()
```

```
2    148259
3     87218
1     25124
Name: damage_grade, dtype: int64

# Pie chart
labels = ['Damage 1', 'Damage 2', 'Damage 3']
sizes = [25124, 148259, 87218,]
# only "explode" the 2nd slice (i.e. 'Hogs')
explode = (0, 0, 0)
fig1, ax1 = plt.subplots()
patches, texts, autotexts = ax1.pie(sizes, labels=labels, autopct='%1.1f%%',
startangle=90)
for text in texts:
    text.set_color('white')
    text.set_size(13)
for autotext in autotexts:
    autotext.set_color('white')
    autotext.set_size(13)
#draw circle
centre_circle = plt.Circle((0,0),0.80,fc='black')
fig = plt.gcf()
fig.gca().add_artist(centre_circle)
# Equal aspect ratio ensures that pie is drawn as a circle
ax1.axis('equal')
plt.tight_layout()
plt.show()
```



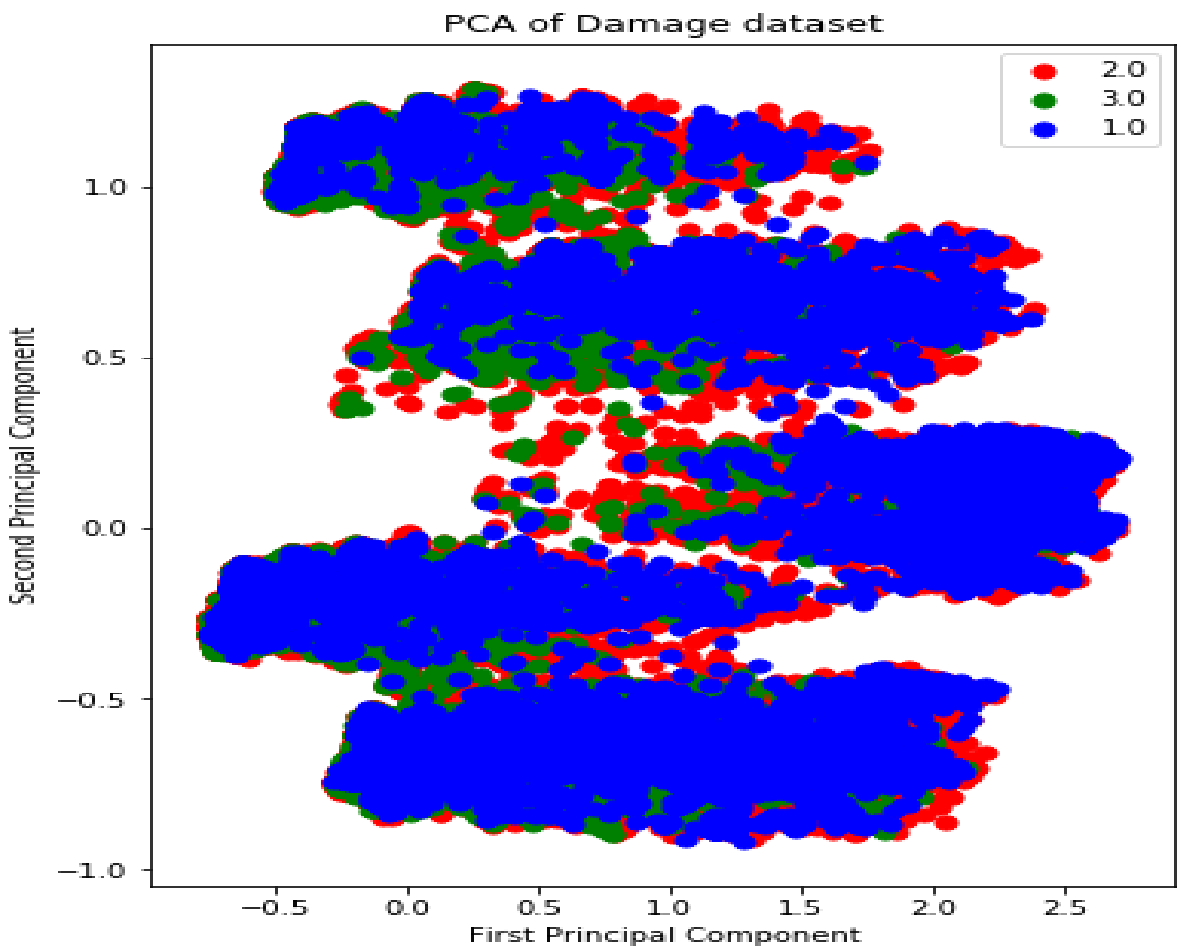

```
normalized_df=(df-df.min())/(df.max()-df.min())
df = normalized_df


X = df.drop("damage_grade", axis=1)
y = df["damage_grade"]
targets = df["damage_grade"].unique()
print(targets)
pca = PCA(n_components=2)
X_r = pca.fit(X).transform(X)
print(X_r.shape)
PCA_Df = pd.DataFrame(data = X_r
            , columns = ['principal component 1', 'principal component 2'])
print(PCA_Df.head())
colors = ['r', 'g', 'b']
for target, color in zip(targets,colors):
    indicesToKeep = df['damage_grade'] == target
    plt.scatter(PCA_Df.loc[indicesToKeep, 'principal component 1']
            , PCA_Df.loc[indicesToKeep, 'principal component 2'], c = color, s = 50)
plt.legend((targets + .5) * 2)
plt.title('PCA of Damage dataset')
```

```
plt.xlabel("First Principal Component")
plt.ylabel('Second Principal Component')
```

```
[0.5 1.  0. ]
(260601, 2)
   principal component 1  principal component 2
0               0.029283              -0.653984
1              -0.605595              -0.171097
2              -0.417904               1.041256
3              -0.719406              -0.306778
4              -0.102610              -0.187304
```

```
Text(0, 0.5, 'Second Principal Component')
```

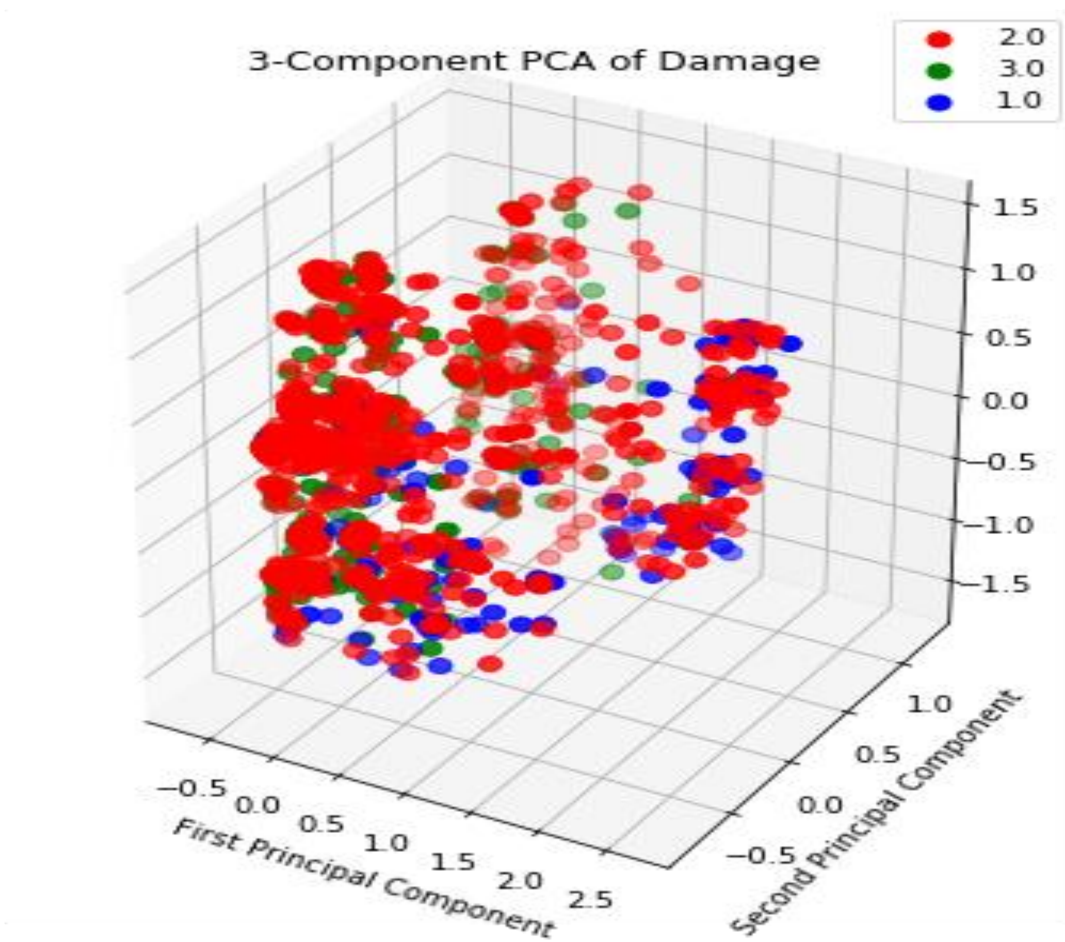



```
X = df.drop("damage_grade", axis=1)
y = df["damage_grade"]
targets = df["damage_grade"].unique()
print(targets)
pca = PCA(n_components=3)
X_r = pca.fit(X).transform(X)
print(X_r.shape)
```

```
PCA_Df = pd.DataFrame(data = X_r[0:2000]
             , columns = ['principal component 1', 'principal component 2', 'principal
component 3'])
colors = ['r', 'g', 'b']
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
for target, color in zip(targets,colors):
    indicesToKeep = df['damage_grade'] == target
    ax.scatter(PCA_Df.loc[indicesToKeep, 'principal component 1']
               , PCA_Df.loc[indicesToKeep, 'principal component 2'],
PCA_Df.loc[indicesToKeep, 'principal component 3'], c = color, s = 50)
plt.legend((targets + .5) * 2)
plt.title('3-Component PCA of Damage ')
plt.xlabel("First Principal Component")
plt.ylabel('Second Principal Component')
```

```
[0.5 1.  0. ]
(260601, 3)

Text(0.5, 0, 'Second Principal Component')
```



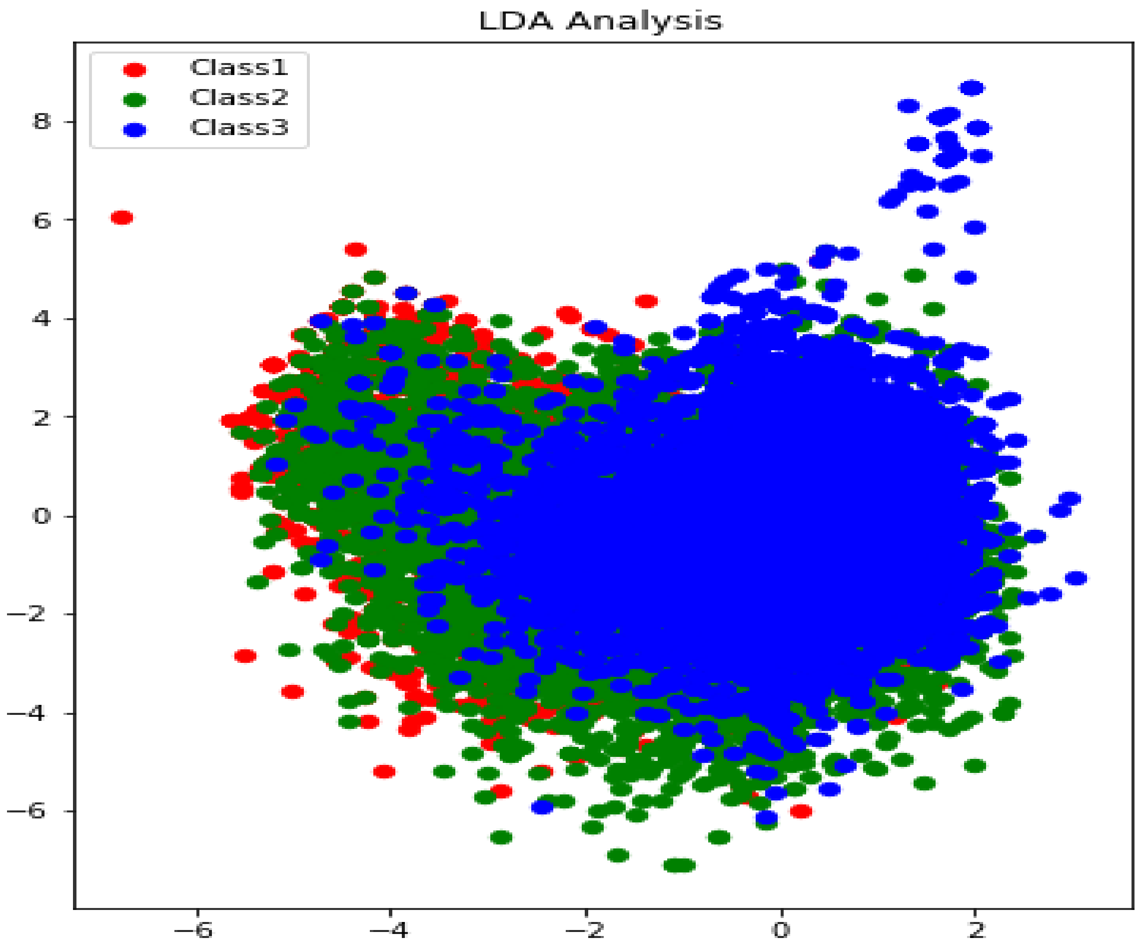
```
X = df.drop("damage_grade", axis=1).astype('int')
y = ((df["damage_grade"] + 0.5) * 2).astype('int')
lda = LDA(n_components=2)
dmg_lda = lda.fit_transform(X, y)
print(dmg_lda)
l_x = dmg_lda[:,0]
l_y = dmg_lda[:,1]
cdict={1:'red',2:'green',3:'blue'}
labl={1:'Class1',2:'Class2',3:'Class3'}
for l in np.unique(y):
    ix=np.where(y==l)
    ax = plt.scatter(l_x[ix],l_y[ix],c=cdict[l],s=40,
           label=labl[l])
plt.title("LDA Analysis")
plt.legend()
```

```
/home/jordanrodrigues/anaconda3/lib/python3.7/site-packages/sklearn/discriminant_analysis.py:388: UserWarning: Variables are collinear.
  warnings.warn("Variables are collinear.")

[[-0.39785383 -1.70783617]
 [ 0.42992898 -0.02751219]
 [ 0.87874376  0.49585697]
 ...
 [ 0.61089644  0.2825365 ]
 [ 0.75307395  0.58296292]
 [ 1.70574956  7.67655413]]



<matplotlib.legend.Legend at 0x7f6fe9e9d908>
```

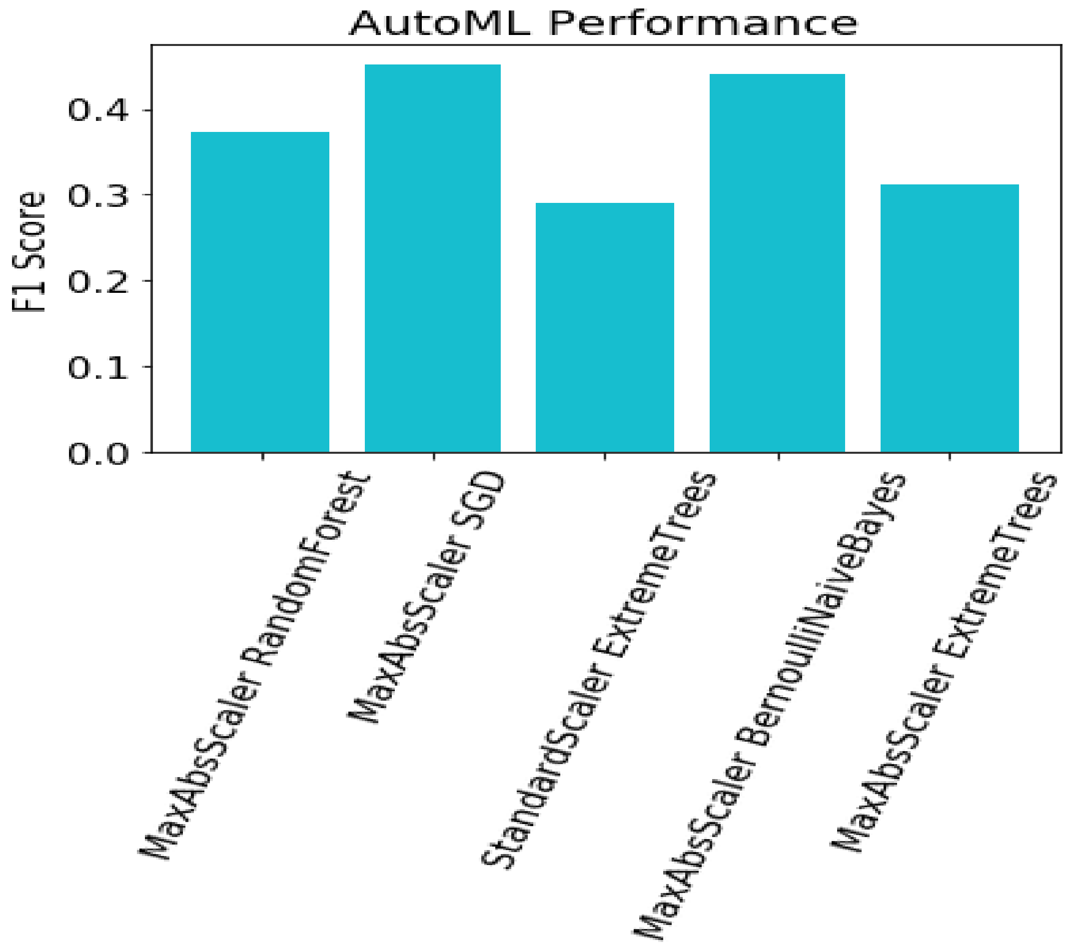



```
labels = ["MaxAbsScaler RandomForest", "MaxAbsScaler SGD", "StandardScaler ExtremeTrees", "MaxAbsScaler BernoulliNaiveBayes", "MaxAbsScaler ExtremeTrees"]

values = [.3720, .4521, .2893, .4397,  .3116]

plt.bar(labels, values, color='tab:cyan')
plt.xticks(rotation=70)
plt.rcParams.update({'font.size': 15})
plt.title("AutoML Performance")
plt.ylabel("F1 Score")
```

Text(0, 0.5, 'F1 Score')



CONCLUSION:

Earthquake preprocessing plays a vital role in enhancing our understanding of seismic events and improving early warning systems. By employing advanced techniques such as data filtering, noise reduction, and signal analysis, researchers can extract valuable information from seismic data, leading to more accurate predictions and effective disaster management strategies.