IBM NaanMudhalvan

ARTIFICIAL INTELLIGENCE

Project Title : Earthquake Prediction Using Python

Phase 2 : Importing the Dataset and Perform data Cleaning & Data Analysis.

Workbook Link :
https://colab.research.google.com/drive/1Rg6nBZBsCQJnRI8JJOL5vKWeRT-MnWbk?usp=sharing

INTRODUCTION:

In the realm of Earthquake Prediction using Machine Learning, the initial steps of importing the dataset and conducting meticulous data cleaning are pivotal. This project begins by acquiring seismic data, a critical precursor to predictive modeling. Rigorous data cleaning techniques are then employed to ensure the dataset's integrity and reliability. Subsequently, through advanced data analysis, we aim to unveil patterns and insights crucial for developing a robust ML model capable of predicting seismic activities. This introduction sets the stage for a comprehensive exploration of earthquake prediction, emphasizing the foundational role of data import and cleaning in the ML-driven analytical process.

WORKSPACE:

We've worked on Google Colab for the intricate task of data cleaning and analysis in Earthquake Prediction using Python. Google Colab served as a powerful and accessible platform. Leveraging the collaborative and cloud-based features of Google Colab facilitated seamless collaboration and efficient processing of seismic datasets. The platform's integration with popular Python libraries streamlined coding and analysis workflows, enhancing productivity. For a detailed walkthrough of the data cleaning and analysis process, refer to the Notebook on Google Colab.

IMPORTING THE DATASET:

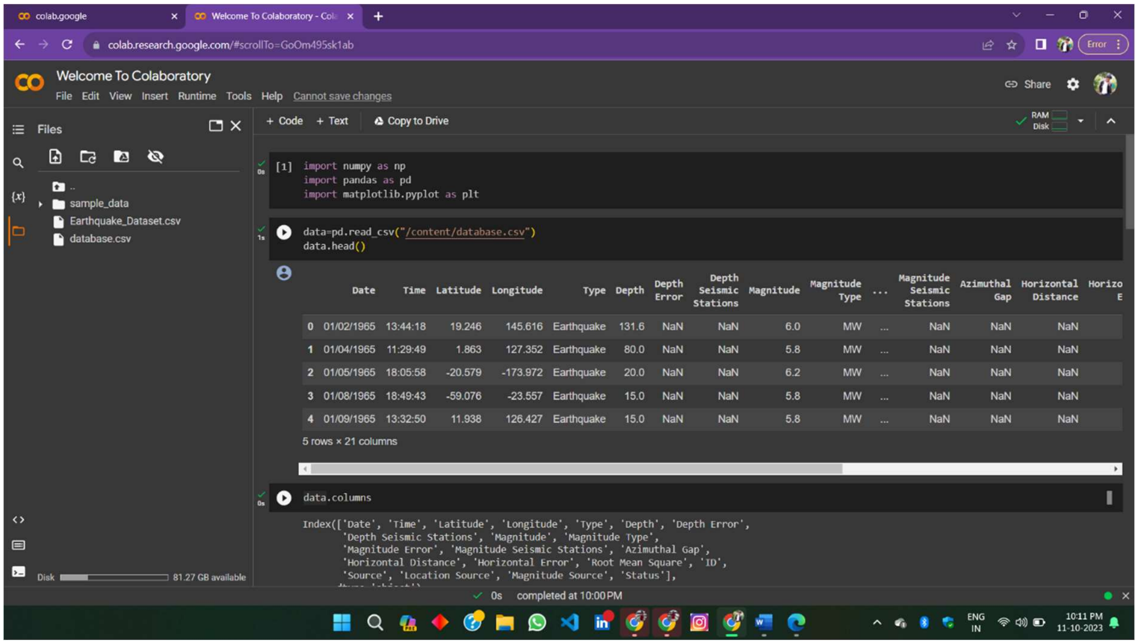
Importing the dataset is the foundational step in our Earthquake Prediction using ML project. We seamlessly fetched seismic data from reliable sources, ensuring its accuracy and relevance. Leveraging the versatility of Python, we employed libraries like Pandas to efficiently read and organize the dataset for subsequent analysis. The chosen dataset encompasses essential seismic parameters, forming the basis for training and validating our machine learning model. The streamlined import process lays the groundwork for a comprehensive exploration into earthquake prediction methodologies.

PROGRAM :

Original file is located at

```
# Importing the Libraries
import pandas as pd
import numpy as np

# Loading the Dataset
data  = pd.read_csv('database.csv')
data.head()
```

OUTPUT :



DATA ANALYSIS:

Data analysis in our Earthquake Prediction using ML project involves a meticulous exploration of seismic patterns and trends. Employing Python-based tools like NumPy and Pandas, we conducted descriptive statistics, revealing key insights into the dataset's characteristics. Visualization techniques, implemented with libraries such as Matplotlib and Seaborn, aided in uncovering spatial and temporal aspects of seismic activity. Correlation analysis provided a deeper understanding of feature relationships, guiding the model development process. The comprehensive data analysis phase contributes crucial inputs for building a robust machine learning model for earthquake prediction.

PROGRAM :

```
# Checking the Shape of the Dataset
data.shape
# Checking the Number of Entities
data.columns
# Checking Descriptive Structure of the data
data.describe()
```

```
# Checking Duplicated Rows.
data.duplicated()
# Checking the Data Information
data.info()
df = pd.DataFrame(data)
# Checking Categorical and Numerical Columns
# Categorical columns
cat_col = [col for col in df.columns if df[col].dtype == 'object']
print('Categorical columns :',cat_col)
# Numerical columns
num_col = [col for col in df.columns if df[col].dtype != 'object']
print('Numerical columns :',num_col)
# Checking total number of Values in Categorical Columns
df[cat_col].nunique()
# Checking total number of Values in Numerical Columns
df[num_col].nunique()
# Checking the Missing Values Percentage
round((df.isnull().sum()/df.shape[0])*100,2)
```

OUTPUT :

```
# Checking the Shape of the Dataset
data.shape
```

```
(23412, 21)
```

```
[4] # Checking the Number of Entities
data.columns
```

```
Index(['Date', 'Time', 'Latitude', 'Longitude', 'Type', 'Depth', 'Depth Error',
       'Depth Seismic Stations', 'Magnitude', 'Magnitude Type',
       'Magnitude Error', 'Magnitude Seismic Stations', 'Azimuthal Gap',
       'Horizontal Distance', 'Horizontal Error', 'Root Mean Square', 'ID',
       'Source', 'Location Source', 'Magnitude Source', 'Status'],
      dtype='object')
```

```
[5] # Checking Descriptive Structure of the data
data.describe()
```

	Latitude	Longitude	Depth	Depth Error	Depth Seismic Stations	Magnitude	Magnitude Error	Magnitude Seismic Stations	Azimuthal Gap	Horizontal Distance	Horizontal Error	Root Mean Square
count	23412.000000	23412.000000	23412.000000	4461.000000	7097.000000	23412.000000	327.000000	2564.000000	7299.000000	1604.000000	1156.000000	17352.000000
mean	1.679033	39.639961	70.767911	4.993115	275.364098	5.882531	0.071820	48.944618	44.163532	3.992660	7.662759	1.022784
std	30.113183	125.511959	122.651898	4.875184	162.141631	0.423066	0.051466	62.943106	32.141486	5.377262	10.430396	0.188545
min	-77.080000	-179.997000	-1.100000	0.000000	0.000000	5.500000	0.000000	0.000000	0.000000	0.004505	0.085000	0.000000
25%	-18.653000	-76.349750	14.522500	1.800000	146.000000	5.600000	0.046000	10.000000	24.100000	0.968750	5.300000	0.900000
50%	-3.568500	103.982000	33.000000	3.500000	255.000000	5.700000	0.059000	28.000000	36.000000	2.319500	6.700000	1.000000
75%	26.190750	145.026250	54.000000	6.300000	384.000000	6.000000	0.075500	66.000000	54.000000	4.724500	8.100000	1.130000
max	86.005000	179.998000	700.000000	91.295000	934.000000	9.100000	0.410000	821.000000	360.000000	37.874000	99.000000	3.440000

```
[6] # Checking Duplicated Rows.
    data.duplicated()
```

```
0        False
1        False
2        False
3        False
4        False
         ...
23407    False
23408    False
23409    False
23410    False
23411    False
Length: 23412, dtype: bool
```

```
# Checking the Data Information
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 23412 entries, 0 to 23411
Data columns (total 21 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   Date                        23412 non-null  object
 1   Time                        23412 non-null  object
 2   Latitude                    23412 non-null  float64
 3   Longitude                   23412 non-null  float64
 4   Type                        23412 non-null  object
 5   Depth                       23412 non-null  float64
 6   Depth Error                 4461 non-null   float64
 7   Depth Seismic Stations      7097 non-null   float64
 8   Magnitude                   23412 non-null  float64
 9   Magnitude Type              23409 non-null  object
 10  Magnitude Error             327 non-null    float64
 11  Magnitude Seismic Stations  2564 non-null   float64
 12  Azimuthal Gap               7299 non-null   float64
 13  Horizontal Distance         1604 non-null   float64
 14  Horizontal Error            1156 non-null   float64
 15  Root Mean Square            17352 non-null  float64
 16  ID                          23412 non-null  object
 17  Source                      23412 non-null  object
 18  Location Source             23412 non-null  object
 19  Magnitude Source            23412 non-null  object
 20  Status                      23412 non-null  object
dtypes: float64(12), object(9)
memory usage: 3.8+ MB
```

```
[8] df = pd.DataFrame(data)
```

```
[9] # Checking Categorical and Numerical Columns
    # Categorical columns
    cat_col = [col for col in df.columns if df[col].dtype == 'object']
    print('Categorical columns :',cat_col)
    # Numerical columns
    num_col = [col for col in df.columns if df[col].dtype != 'object']
    print('Numerical columns :',num_col)
```

```
Categorical columns : ['Date', 'Time', 'Type', 'Magnitude Type', 'ID', 'Source', 'Location Source', 'Magnitude Source', 'Status']
Numerical columns : ['Latitude', 'Longitude', 'Depth', 'Depth Error', 'Depth Seismic Stations', 'Magnitude', 'Magnitude Error', 'Magnit
```

```
# Checking total number of Values in Categorical Columns
df[cat_col].nunique()
```

```
Date                 12401
Time                 20472
Type                     4
Magnitude Type          10
ID                   23412
Source                  13
Location Source         48
Magnitude Source        24
Status                   2
dtype: int64
```

```
[11] # Checking total number of Values in Numerical Columns
     df[num_col].nunique()
```

```
Latitude                      20676
Longitude                     21474
Depth                          3485
Depth Error                     297
Depth Seismic Stations          736
Magnitude                        64
Magnitude Error                 100
Magnitude Seismic Stations      246
Azimuthal Gap                  1109
Horizontal Distance            1448
Horizontal Error                186
Root Mean Square                190
dtype: int64
```

FEATURE ENGINEERING :

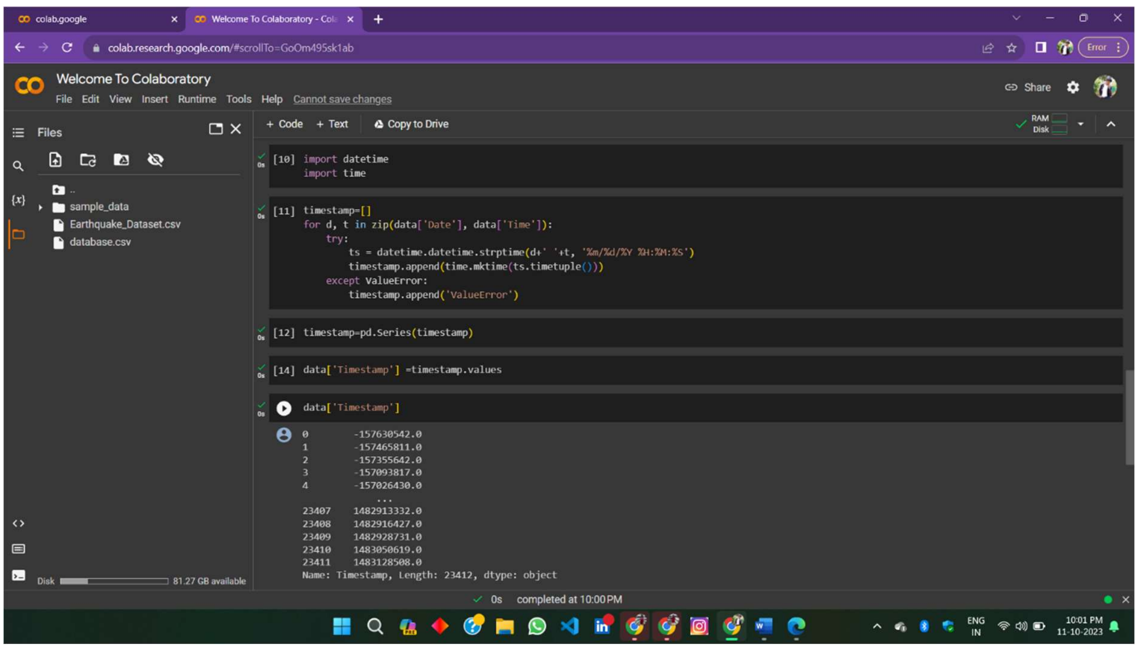
Feature engineering is a critical aspect of machine learning where raw data is transformed or new features are created to enhance model performance. It involves techniques like polynomial expansion, interaction terms, and domain-specific transformations to extract meaningful information. Dimensionality reduction methods, such as PCA, help manage high-dimensional data, preventing overfitting and improving model efficiency. Handling categorical variables through encoding methods ensures effective utilization of non-numeric data. Feature engineering is an iterative process, guided by continuous evaluation and refinement to build models that accurately capture underlying patterns in the data.

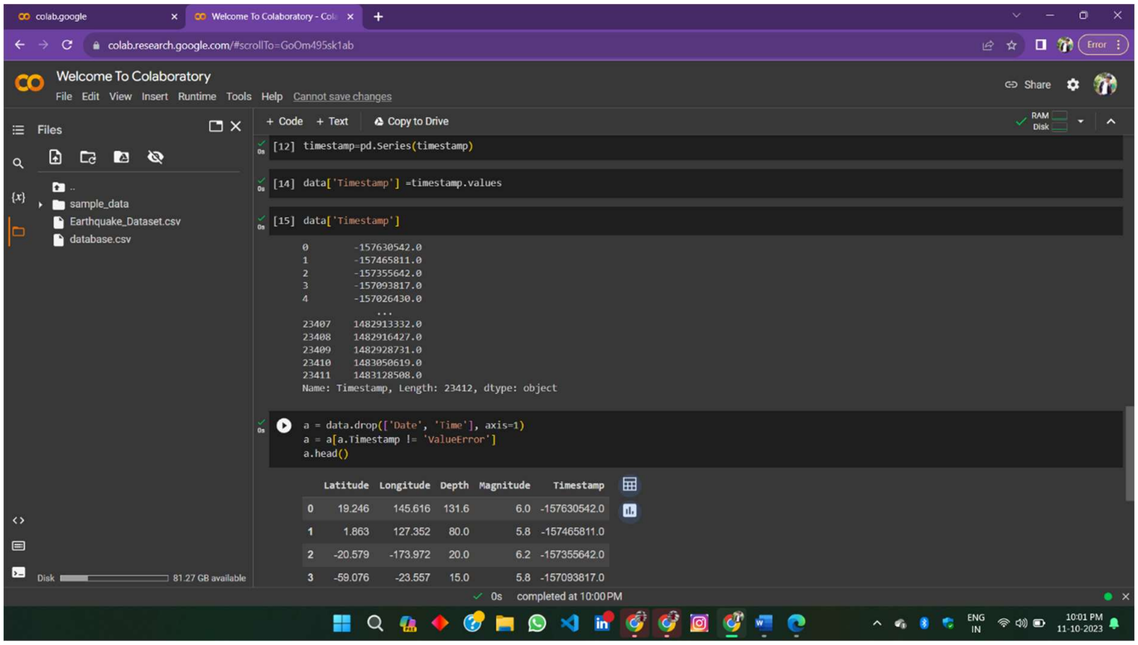
PROGRAM :

```
# Creating Timestamp Column from Data and Time Column
import datetime
import time


timestamp = []
for d, t in zip(data['Date'], data['Time']):
   try:
      ts = datetime.datetime.strptime(d+' '+t, '%m/%d/%Y %H:%M:%S')
      timestamp.append(time.mktime(ts.timetuple()))
   except ValueError:
      # print('ValueError')
      timestamp.append('ValueError')


# Converting the Tuple values into Series Values
timeStamp = pd.Series(timestamp)
data['Timestamp'] = timeStamp.values
```

```
# Droping the Date and Time Columns.
a = df.drop(['Date', 'Time'], axis=1)
a= a[a.Timestamp != 'ValueError']
a.head()
```

OUTPUT :





DATA CLEANING:

PROGRAM:

 # Removal Of Unwanted Columns

Data=data[['Date','Time','Latitude','Longitude','Depth','Magnitude']]

 # Checking the Shape of Dataset after Removing the Columns

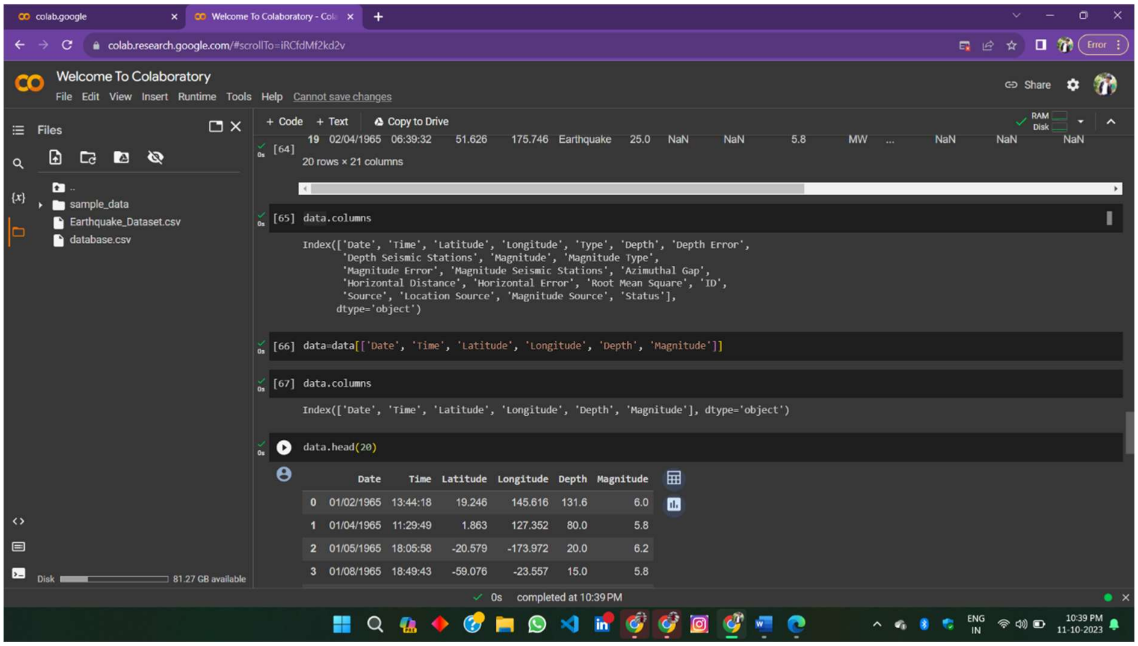
```
df1.shape
```

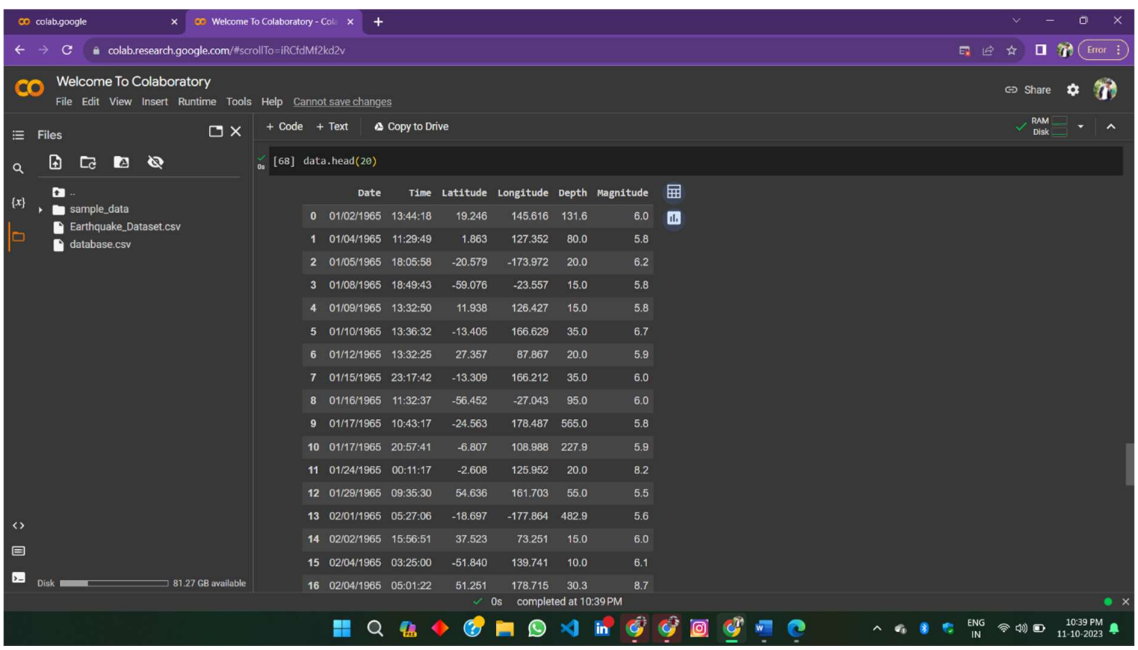
```
df1.head(10)
```

 # Checking Columns

```
df1.columns
```

OUTPUT:


colab.google
Welcome To Colaboratory - Col
colab.research.google.com/#scrollTo=iRCfdMf2kd2v
Welcome To Colaboratory
File Edit View Insert Runtime Tools Help Cannot save changes
Share
Files
+ Code + Text Copy to Drive
sample_data
Earthquake_Dataset.csv
database.csv
[64]
19 02/04/1965 06:39:32 51.626 175.746 Earthquake 25.0 NaN NaN 5.8 MW ... NaN NaN NaN
20 rows × 21 columns
[65] data.columns
Index(['Date', 'Time', 'Latitude', 'Longitude', 'Type', 'Depth', 'Depth Error',
'Depth Seismic Stations', 'Magnitude', 'Magnitude Type',
'Magnitude Error', 'Magnitude Seismic Stations', 'Azimuthal Gap',
'Horizontal Distance', 'Horizontal Error', 'Root Mean Square', 'ID',
'Source', 'Location Source', 'Magnitude Source', 'Status'],
dtype='object')
[66] data=data[['Date', 'Time', 'Latitude', 'Longitude', 'Depth', 'Magnitude']]
[67] data.columns
Index(['Date', 'Time', 'Latitude', 'Longitude', 'Depth', 'Magnitude'], dtype='object')
data.head(20)
Date Time Latitude Longitude Depth Magnitude
0 01/02/1965 13:44:18 19.246 145.616 131.6 6.0
1 01/04/1965 11:29:49 1.863 127.352 80.0 5.8
2 01/05/1965 18:05:58 -20.579 -173.972 20.0 6.2
3 01/08/1965 18:49:43 -59.076 -23.557 15.0 5.8
Disk 81.27 GB available
0s completed at 10:39 PM
10:39 PM
11-10-2023


colab.google
Welcome To Colaboratory - Col
colab.research.google.com/#scrollTo=iRCfdMf2kd2v
Welcome To Colaboratory
File Edit View Insert Runtime Tools Help Cannot save changes
Share
Files
+ Code + Text Copy to Drive
sample_data
Earthquake_Dataset.csv
database.csv
[68] data.head(20)
Date Time Latitude Longitude Depth Magnitude
0 01/02/1965 13:44:18 19.246 145.616 131.6 6.0
1 01/04/1965 11:29:49 1.863 127.352 80.0 5.8
2 01/05/1965 18:05:58 -20.579 -173.972 20.0 6.2
3 01/08/1965 18:49:43 -59.076 -23.557 15.0 5.8
4 01/09/1965 13:32:50 11.938 126.427 15.0 5.8
5 01/10/1965 13:36:32 -13.405 166.629 35.0 6.7
6 01/12/1965 13:32:25 27.357 87.867 20.0 5.9
7 01/15/1965 23:17:42 -13.309 166.212 35.0 6.0
8 01/16/1965 11:32:37 -56.452 -27.043 95.0 6.0
9 01/17/1965 10:43:17 -24.563 178.487 565.0 5.8
10 01/17/1965 20:57:41 -6.807 108.988 227.9 5.9
11 01/24/1965 00:11:17 -2.608 125.952 20.0 8.2
12 01/29/1965 09:35:30 54.636 161.703 55.0 5.5
13 02/01/1965 05:27:06 -18.697 -177.864 482.9 5.6
14 02/02/1965 15:56:51 37.523 73.251 15.0 6.0
15 02/04/1965 03:25:00 -51.840 139.741 10.0 6.1
16 02/04/1965 05:01:22 51.251 178.715 30.3 8.7
Disk 81.27 GB available
0s completed at 10:39 PM
10:39 PM
11-10-2023

HYPERPARAMETER TUNING:

Hyperparameter tuning allows data scientists to tweak model performance for optimal results. This process is an essential part of machine learning, and choosing appropriate hyperparameter values is crucial for success.

1. GridSearchCV
2. RandomizedSearchCV

ENSEMBLE TECHNIQUE:

Ensemble learning is a general meta approach to machine learning that seeks better predictive performance by combining the predictions from multiple models.
Although there are a seemingly unlimited number of ensembles that you can develop for your predictive modeling problem, there are three methods that dominate the field of ensemble learning. So much so, that rather than algorithms per se, each is a field of study that has spawned many more specialized methods.

The three main classes of ensemble learning methods are **bagging**, **stacking**, and **boosting**, and it is important to both have a detailed understanding of each method and to consider them on your predictive modeling project.

CONCLUSION:

The process of earthquake prediction using machine learning involves meticulous data cleaning to ensure dataset reliability. Data importing combines seismic, geological, and environmental data for a comprehensive analysis. Feature engineering enhances the dataset, optimizing models for pattern recognition. Iterative refinement based on model performance fosters nuanced earthquake prediction insights. Overall, this approach, encompassing data cleaning, importing, and analysis, advances our ability to develop accurate machine learning models for mitigating the impact of seismic events.