In [2]:
```
#In this project we are predicting POSSIBILITY(in the form of 0 or 1) & the
#our model will give 1 as the outcome for earthquake will ouccur and 0 as th
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.linear_model import LinearRegression,LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import mean_squared_error,r2_score,accuracy_score,clas
```

In [3]:
```
data=pd.read_csv("C://Users//ridhi//Downloads//query (1) (1).csv",encoding=
```

In [5]:
```
data
```

Out[5]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms
0	2024-03-18T00:18:03.554Z	-6.2159	146.9556	86.441	5.10	mb	96.0	67.0	3.175	0.5
1	2024-03-18T00:45:47.063Z	64.6558	-17.7271	10.000	4.70	mb	157.0	59.0	1.549	1.0
2	2024-03-18T01:25:01.175Z	33.6817	93.1840	10.000	4.00	mb	25.0	90.0	4.336	0.7
3	2024-03-18T01:39:31.936Z	-22.2034	-176.6137	150.411	4.50	mb	39.0	90.0	1.667	0.6
4	2024-03-18T02:10:38.894Z	38.5875	70.4189	12.980	4.10	mb	46.0	114.0	1.395	0.7
...	...	...	...	...	...	...	...	...	...	..
9709	2024-08-18T15:58:57.520Z	18.7645	-64.9665	53.710	3.41	md	11.0	242.0	0.410	0.2
9710	2024-08-18T18:05:38.347Z	-31.2599	117.6740	7.210	4.60	mb	35.0	79.0	1.703	0.8
9711	2024-08-18T18:33:40.498Z	-31.1853	117.6124	10.069	4.40	mb	25.0	92.0	1.766	0.7
9712	2024-08-18T18:44:00.241Z	2.1882	126.6833	44.615	4.50	mb	44.0	112.0	1.564	0.8
9713	2024-08-18T19:28:20.845Z	16.0523	-94.9727	10.000	4.40	mb	34.0	180.0	2.735	0.6

9714 rows × 22 columns

In [6]:
```
data.head()
```

Out[6]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms	.
0	2024-03-18T00:18:03.554Z	-6.2159	146.9556	86.441	5.1	mb	96.0	67.0	3.175	0.57	.
1	2024-03-18T00:45:47.063Z	64.6558	-17.7271	10.000	4.7	mb	157.0	59.0	1.549	1.08	.
2	2024-03-18T01:25:01.175Z	33.6817	93.1840	10.000	4.0	mb	25.0	90.0	4.336	0.78	.
3	2024-03-18T01:39:31.936Z	-22.2034	-176.6137	150.411	4.5	mb	39.0	90.0	1.667	0.60	.
4	2024-03-18T02:10:38.894Z	38.5875	70.4189	12.980	4.1	mb	46.0	114.0	1.395	0.76	.

5 rows × 22 columns

In [7]:
```
data.describe()
```

Out[7]:

	latitude	longitude	depth	mag	nst	gap	
count	9714.000000	9714.000000	9714.000000	9714.000000	9008.000000	9008.000000	8999.0
mean	17.824587	-29.209848	66.582442	3.860644	43.302731	119.889833	2.5
std	30.117838	128.706527	117.616662	0.860700	38.384349	66.834599	4.3
min	-65.277000	-179.989500	-1.660000	2.500000	0.000000	11.000000	0.0
25%	-5.999875	-155.209417	10.000000	2.952500	19.000000	69.000000	0.3
50%	19.387750	-69.079500	18.102000	4.200000	31.000000	104.000000	1.1
75%	41.561200	121.731725	65.738000	4.500000	53.000000	159.000000	3.0
max	86.525000	179.998400	658.420000	7.400000	401.000000	355.000000	53.2

In [8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9714 entries, 0 to 9713
Data columns (total 22 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   time             9714 non-null   object 
 1   latitude         9714 non-null   float64
 2   longitude        9714 non-null   float64
 3   depth            9714 non-null   float64
 4   mag              9714 non-null   float64
 5   magType          9714 non-null   object 
 6   nst              9008 non-null   float64
 7   gap              9008 non-null   float64
 8   dmin             8999 non-null   float64
 9   rms              9714 non-null   float64
 10  net              9714 non-null   object 
 11  id               9714 non-null   object 
 12  updated          9714 non-null   object 
 13  place            9714 non-null   object 
 14  type             9714 non-null   object 
 15  horizontalError  8937 non-null   float64
 16  depthError       9714 non-null   float64
 17  magError         8953 non-null   float64
 18  magNst           9000 non-null   float64
 19  status           9714 non-null   object 
 20  locationSource   9714 non-null   object 
 21  magSource        9714 non-null   object 
dtypes: float64(12), object(10)
memory usage: 1.6+ MB
```

In [9]:
```
#some of the columns in this dataset are not beneficial for predicting our c
data=data.drop(["id","updated","status","locationSource","magSource","depthE
data
```

Out[9]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms
0	2024-03-18T00:18:03.554Z	-6.2159	146.9556	86.441	5.10	mb	96.0	67.0	3.175	0.5
1	2024-03-18T00:45:47.063Z	64.6558	-17.7271	10.000	4.70	mb	157.0	59.0	1.549	1.0
2	2024-03-18T01:25:01.175Z	33.6817	93.1840	10.000	4.00	mb	25.0	90.0	4.336	0.7
3	2024-03-18T01:39:31.936Z	-22.2034	-176.6137	150.411	4.50	mb	39.0	90.0	1.667	0.6
4	2024-03-18T02:10:38.894Z	38.5875	70.4189	12.980	4.10	mb	46.0	114.0	1.395	0.7
...	...	...	...	...	...	...	...	...	...	..
9709	2024-08-18T15:58:57.520Z	18.7645	-64.9665	53.710	3.41	md	11.0	242.0	0.410	0.2
9710	2024-08-18T18:05:38.347Z	-31.2599	117.6740	7.210	4.60	mb	35.0	79.0	1.703	0.8
9711	2024-08-18T18:33:40.498Z	-31.1853	117.6124	10.069	4.40	mb	25.0	92.0	1.766	0.7
9712	2024-08-18T18:44:00.241Z	2.1882	126.6833	44.615	4.50	mb	44.0	112.0	1.564	0.8
9713	2024-08-18T19:28:20.845Z	16.0523	-94.9727	10.000	4.40	mb	34.0	180.0	2.735	0.6

9714 rows × 12 columns

In [10]:
```
#adding a column earthquake which has value as 0 when magnitude of earthquał
data['earthquake']=np.where(data['mag']>=3,1,0)
data
```

Out[10]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms
0	2024-03-18T00:18:03.554Z	-6.2159	146.9556	86.441	5.10	mb	96.0	67.0	3.175	0.57
1	2024-03-18T00:45:47.063Z	64.6558	-17.7271	10.000	4.70	mb	157.0	59.0	1.549	1.08
2	2024-03-18T01:25:01.175Z	33.6817	93.1840	10.000	4.00	mb	25.0	90.0	4.336	0.78
3	2024-03-18T01:39:31.936Z	-22.2034	-176.6137	150.411	4.50	mb	39.0	90.0	1.667	0.60
4	2024-03-18T02:10:38.894Z	38.5875	70.4189	12.980	4.10	mb	46.0	114.0	1.395	0.70
...	...	...	...	...	...	...	...	...	...	..
9709	2024-08-18T15:58:57.520Z	18.7645	-64.9665	53.710	3.41	md	11.0	242.0	0.410	0.20
9710	2024-08-18T18:05:38.347Z	-31.2599	117.6740	7.210	4.60	mb	35.0	79.0	1.703	0.87
9711	2024-08-18T18:33:40.498Z	-31.1853	117.6124	10.069	4.40	mb	25.0	92.0	1.766	0.73
9712	2024-08-18T18:44:00.241Z	2.1882	126.6833	44.615	4.50	mb	44.0	112.0	1.564	0.80
9713	2024-08-18T19:28:20.845Z	16.0523	-94.9727	10.000	4.40	mb	34.0	180.0	2.735	0.68

9714 rows × 13 columns

In [11]:
```
data['earthquake'].value_counts()
```

Out[11]:
```
earthquake
1    7250
0    2464
Name: count, dtype: int64
```

In [12]:
```
data.isnull()
```

Out[12]:

	time	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms	net	pla
0	False	False	False	False	False	False	False	False	False	False	False	Fal
1	False	False	False	False	False	False	False	False	False	False	False	Fal
2	False	False	False	False	False	False	False	False	False	False	False	Fal
3	False	False	False	False	False	False	False	False	False	False	False	Fal
4	False	False	False	False	False	False	False	False	False	False	False	Fal
...	...	...	...	...	...	...	...	...	...	...	...	
9709	False	False	False	False	False	False	False	False	False	False	False	Fal
9710	False	False	False	False	False	False	False	False	False	False	False	Fal
9711	False	False	False	False	False	False	False	False	False	False	False	Fal
9712	False	False	False	False	False	False	False	False	False	False	False	Fal
9713	False	False	False	False	False	False	False	False	False	False	False	Fal

9714 rows × 13 columns

In [13]:
```
#finding the no of null values in each column
data.isnull().sum()
```

Out[13]:
```
time           0
latitude       0
longitude      0
depth          0
mag            0
magType        0
nst          706
gap          706
dmin         715
rms            0
net            0
place          0
earthquake     0
dtype: int64
```

In [14]:
```
#nst,gap,dmin are the columns with the null values.
#finding the datatype of each of them
print("nst has dtype ",data["nst"].dtype)
print("gap has dtype ",data["gap"].dtype)
print("dmin has dtype ",data["dmin"].dtype)
```

```
nst has dtype  float64
gap has dtype  float64
dmin has dtype  float64
```

In [15]:
```
#since all of the columns having null values are numeric
#therefore replacing the null values with the mean of each of the columns
data["nst"].fillna(data["nst"].mean(),inplace=True)
data["gap"].fillna(data["gap"].mean(),inplace=True)
data["dmin"].fillna(data["dmin"].mean(),inplace=True)
```

In [16]:
```
print(data["nst"].isnull().sum()," ",data["gap"].isnull().sum()," ",data["d
```

```
0   0   0
```

In [17]:

```
#working with the dates
#converting the data type of date_time column from object to datetime
data['time']=pd.to_datetime(data['time'])
data["month"]=data["time"].dt.month
#dropping the time column from the dataset
data=data.drop("time",axis=1)
data
```

Out[17]:

	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms	net	place
0	-6.2159	146.9556	86.441	5.10	mb	96.0	67.0	3.175	0.57	us	56 km N of Lae, Papua New Guinea
1	64.6558	-17.7271	10.000	4.70	mb	157.0	59.0	1.549	1.08	us	115 km S of Akureyri, Iceland
2	33.6817	93.1840	10.000	4.00	mb	25.0	90.0	4.336	0.78	us	266 km NNE of Nagqu, China
3	-22.2034	-176.6137	150.411	4.50	mb	39.0	90.0	1.667	0.60	us	177 km SW of Houma, Tonga
4	38.5875	70.4189	12.980	4.10	mb	46.0	114.0	1.395	0.76	us	49 km S of Rasht, Tajikistan
...	...	...	...	...	...	...	...	...	...	...	...
9709	18.7645	-64.9665	53.710	3.41	md	11.0	242.0	0.410	0.20	pr	46 km N of Charlotte Amalie, U.S. Virgin Islands
9710	-31.2599	117.6740	7.210	4.60	mb	35.0	79.0	1.703	0.87	us	62 km WNW of Merredin, Australia
9711	-31.1853	117.6124	10.069	4.40	mb	25.0	92.0	1.766	0.73	us	71 km WNW of Merredin, Australia
9712	2.1882	126.6833	44.615	4.50	mb	44.0	112.0	1.564	0.86	us	156 km WNW of Tobelo, Indonesia
9713	16.0523	-94.9727	10.000	4.40	mb	34.0	180.0	2.735	0.68	us	17 km S of San Mateo del Mar, Mexico

9714 rows × 13 columns

In [18]:
```
#extracting the exact places which are affected
data['place'] = data['place'].apply(lambda x: x.split(', ')[1] if ', ' in x
data['place']
```

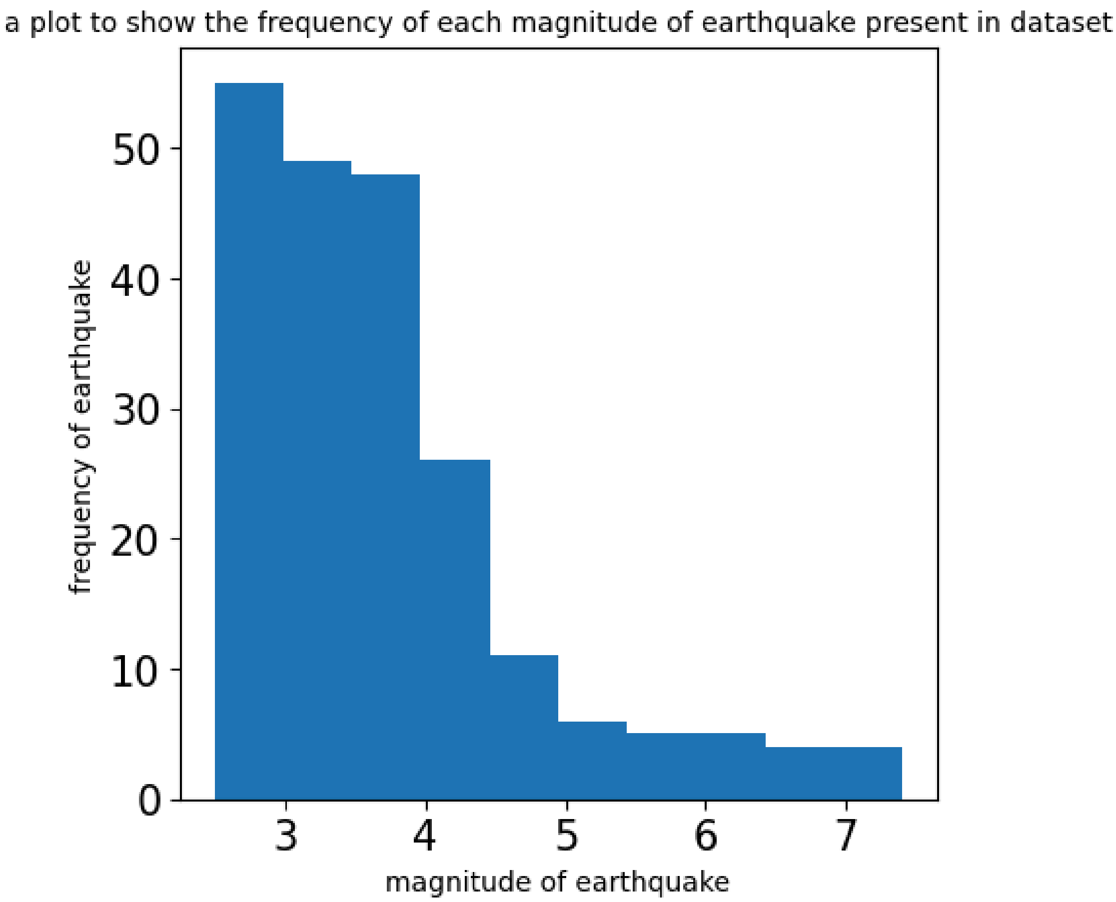
Out[18]:
```
0           Papua New Guinea
1                    Iceland
2                      China
3                      Tonga
4                 Tajikistan
                   ...      
9709     U.S. Virgin Islands
9710               Australia
9711               Australia
9712               Indonesia
9713                  Mexico
Name: place, Length: 9714, dtype: object
```

In [19]:
```
#visualising our dataset
data["place"].value_counts()
```

Out[19]:
```
place
Alaska           1759
Indonesia         575
Hawaii            469
Puerto Rico       442
CA                419
                 ... 
Grenada             1
Mozambique          1
Nunavut             1
Norwegian Sea       1
Saint Lucia         1
Name: count, Length: 240, dtype: int64
```

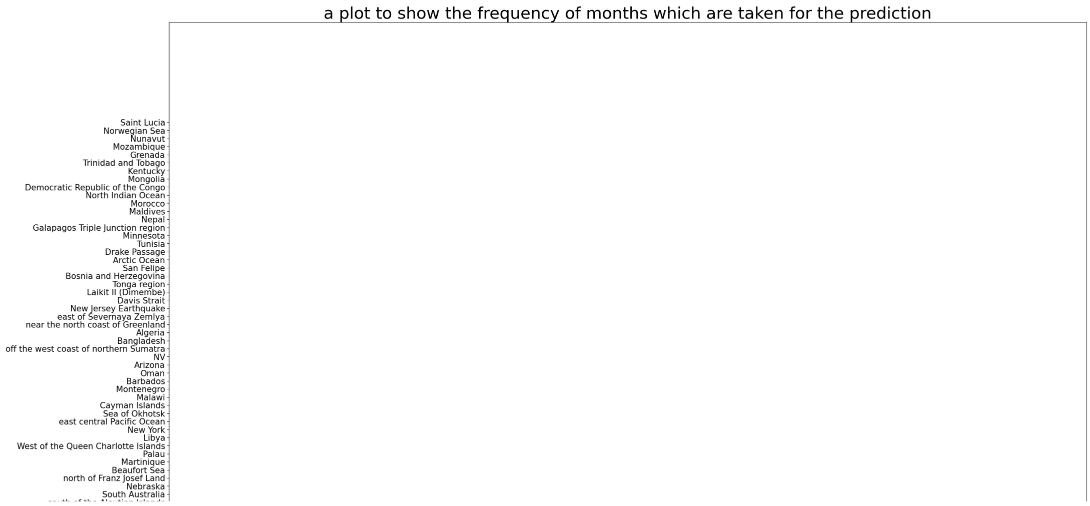
In [20]:
```
series3=data["mag"].value_counts()
x2=np.array(series3.index)
y2=series3.values
print("datatype of x2 ",type(x2))
print("datatype of y2 ",type(y2))
print("\n")
fig=plt.figure(figsize=(5,5))
plt.hist(x2)
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.ylabel("frequency of earthquake",fontsize=10)
plt.title("a plot to show the frequency of each magnitude of earthquake pres
plt.xlabel("magnitude of earthquake",fontsize=10)
plt.show()
```

```
datatype of x2  <class 'numpy.ndarray'>
datatype of y2  <class 'numpy.ndarray'>
```

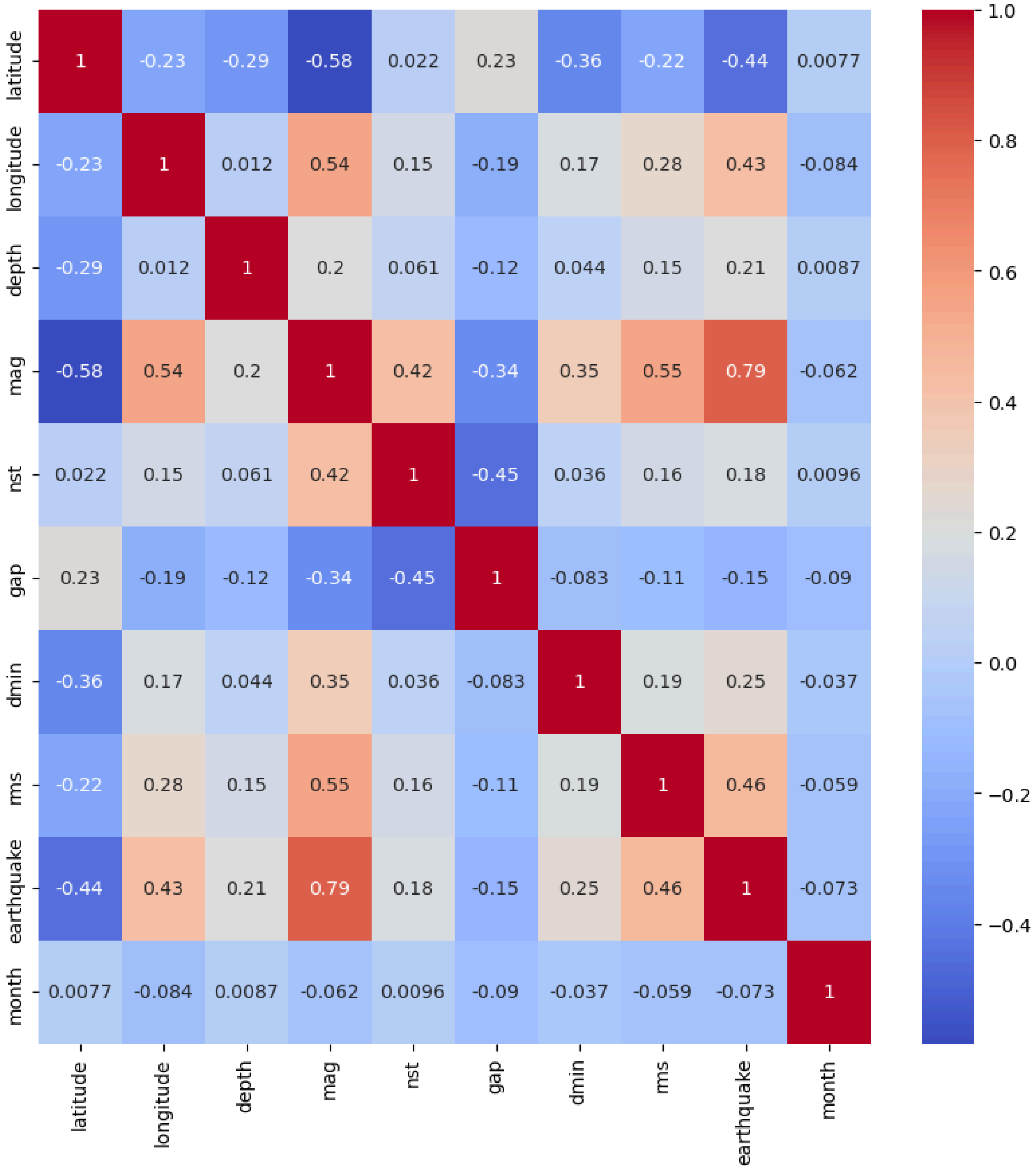


In [21]:
```
series2=data["place"].value_counts()
x1=np.array(series2.index)
y1=series2.values
print("datatype of x1 ",type(x1))
print("datatype of y1 ",type(y1))
print("\n")
fig=plt.figure(figsize=(30,70))
plt.barh(x1,y1)
plt.xticks(fontsize=30)
plt.yticks(fontsize=15)
plt.ylabel("name of place",fontsize=30)
plt.title("a plot to show the frequency of months which are taken for the pr
plt.xlabel("frequency",fontsize=30)
plt.show()
```

```
datatype of x1  <class 'numpy.ndarray'>
datatype of y1  <class 'numpy.ndarray'>
```



In [22]:
```
#visualising correlations
fig=plt.figure(figsize=(10,10))
correlation_matrix=data.corr(numeric_only=True)
sns.heatmap(correlation_matrix,annot=True,cmap='coolwarm')
plt.show()
```



In [23]:
```
data
```

Out[23]:

	latitude	longitude	depth	mag	magType	nst	gap	dmin	rms	net	place
0	-6.2159	146.9556	86.441	5.10	mb	96.0	67.0	3.175	0.57	us	Papua New Guinea
1	64.6558	-17.7271	10.000	4.70	mb	157.0	59.0	1.549	1.08	us	Iceland
2	33.6817	93.1840	10.000	4.00	mb	25.0	90.0	4.336	0.78	us	China
3	-22.2034	-176.6137	150.411	4.50	mb	39.0	90.0	1.667	0.60	us	Tonga
4	38.5875	70.4189	12.980	4.10	mb	46.0	114.0	1.395	0.76	us	Tajikistan
...	...	...	...	...	...	...	...	...	...	...	...
9709	18.7645	-64.9665	53.710	3.41	md	11.0	242.0	0.410	0.20	pr	U.S. Virgin Islands
9710	-31.2599	117.6740	7.210	4.60	mb	35.0	79.0	1.703	0.87	us	Australia
9711	-31.1853	117.6124	10.069	4.40	mb	25.0	92.0	1.766	0.73	us	Australia
9712	2.1882	126.6833	44.615	4.50	mb	44.0	112.0	1.564	0.86	us	Indonesia
9713	16.0523	-94.9727	10.000	4.40	mb	34.0	180.0	2.735	0.68	us	Mexico

9714 rows × 13 columns

In [24]:
```
data.columns
```

Out[24]:
```
Index(['latitude', 'longitude', 'depth', 'mag', 'magType', 'nst', 'gap',
       'dmin', 'rms', 'net', 'place', 'earthquake', 'month'],
      dtype='object')
```

In [25]:
```
data=data[['month','latitude', 'longitude', 'depth', 'magType', 'nst', 'gap
```

In [26]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9714 entries, 0 to 9713
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   month       9714 non-null   int32  
 1   latitude    9714 non-null   float64
 2   longitude   9714 non-null   float64
 3   depth       9714 non-null   float64
 4   magType     9714 non-null   object 
 5   nst         9714 non-null   float64
 6   gap         9714 non-null   float64
 7   dmin        9714 non-null   float64
 8   rms         9714 non-null   float64
 9   net         9714 non-null   object 
 10  place       9714 non-null   object 
 11  earthquake  9714 non-null   int32  
 12  mag         9714 non-null   float64
dtypes: float64(8), int32(2), object(3)
memory usage: 910.8+ KB
```

In [27]:
```
#Encoding the categorical data ie converting datatypes of those columns whi
#using label encoding
label_encoders={}
categorical_columns=['net','magType','place',]
for column in categorical_columns:
    label_encoders[column]=LabelEncoder()
    data[column]=label_encoders[column].fit_transform(data[column])
data
```

Out[27]:

	month	latitude	longitude	depth	magType	nst	gap	dmin	rms	net	place	e
0	3	-6.2159	146.9556	86.441	0	96.0	67.0	3.175	0.57	11	137	
1	3	64.6558	-17.7271	10.000	0	157.0	59.0	1.549	1.08	11	68	
2	3	33.6817	93.1840	10.000	0	25.0	90.0	4.336	0.78	11	36	
3	3	-22.2034	-176.6137	150.411	0	39.0	90.0	1.667	0.60	11	179	
4	3	38.5875	70.4189	12.980	0	46.0	114.0	1.395	0.76	11	174	
...	...	...	...	...	...	...	...	...	...	...	...	
9709	8	18.7645	-64.9665	53.710	2	11.0	242.0	0.410	0.20	8	186	
9710	8	-31.2599	117.6740	7.210	0	35.0	79.0	1.703	0.87	11	15	
9711	8	-31.1853	117.6124	10.069	0	25.0	92.0	1.766	0.73	11	15	
9712	8	2.1882	126.6833	44.615	0	44.0	112.0	1.564	0.86	11	74	
9713	8	16.0523	-94.9727	10.000	0	34.0	180.0	2.735	0.68	11	100	

9714 rows × 13 columns

In [28]:
```
#training our model and predicting the outcome
X=data.iloc[:,:-2].values
Y=data.iloc[:,-2].values
```

In [29]:
```
Y
```

Out[29]:
```
array([1, 1, 1, ..., 1, 1, 1])
```

In [30]:
```
#feature engineering
#feature selection
from sklearn.feature_selection import SelectKBest,f_classif
selector=SelectKBest(f_classif,k=11)
X_new=selector.fit_transform(X,Y)
print(X_new)
```

```
[[  3.      -6.2159 146.9556 ...   0.57    11.     137.    ]
 [  3.      64.6558 -17.7271 ...   1.08    11.      68.    ]
 [  3.      33.6817  93.184  ...   0.78    11.      36.    ]
 ...
 [  8.     -31.1853 117.6124 ...   0.73    11.      15.    ]
 [  8.       2.1882 126.6833 ...   0.86    11.      74.    ]
 [  8.      16.0523 -94.9727 ...   0.68    11.     100.    ]]
```

In [31]:
```
#Feature scaling
scaler=StandardScaler()
scaled_features=scaler.fit_transform(X_new)
scaled_features
```

Out[31]:
```
array([[-1.65444944, -0.79825532,  1.36880794, ..., -0.02499242,
         0.51854647,  0.65863436],
       [-1.65444944,  1.55501283,  0.08922111, ...,  1.75592468,
         0.51854647, -0.32900333],
       [-1.65444944,  0.52652949,  0.95100187, ...,  0.70832639,
         0.51854647, -0.7870382 ],
       ...,
       [ 1.84022784, -1.62735485,  1.14081087, ...,  0.53372667,
         0.51854647, -1.08762358],
       [ 1.84022784, -0.51920034,  1.21129189, ...,  0.98768593,
         0.51854647, -0.24312179],
       [ 1.84022784, -0.05884811, -0.51097826, ...,  0.35912695,
         0.51854647,  0.12903154]])
```

In [32]:
```
#Splitting the dataset
X_train,X_test,Y_train,Y_test=train_test_split(scaled_features,Y,test_size=
#CLASSIFICATION ALGORITHMS
classifiers={
    'Logistic Regression':LogisticRegression(),
    'Support Vector Machine ':SVC(),
    'Decision Tree':DecisionTreeClassifier(),
    'Random Forest':RandomForestClassifier(),
    'Naive Bayes':GaussianNB(),
    'K Nearest Neighbour':KNeighborsClassifier()
}
```

In [33]:
```
#Training and evaluating classifiers
from sklearn.metrics import confusion_matrix,ConfusionMatrixDisplay
results={}
for name,clf in classifiers.items():
    clf.fit(X_train,Y_train)
    Y_pred=clf.predict(X_test)
    cm=confusion_matrix(Y_test,Y_pred)
    print(f"Confusion matrix for {name} is \n",cm)
    accuracy=accuracy_score(Y_test,Y_pred)
    results[name]=accuracy
    print(f"{name} has accuracy of {accuracy*100:.2f} ")
    print(classification_report(Y_test,Y_pred,zero_division=1))
    print("\n\n")
```

```
Confusion matrix for Logistic Regression is
 [[ 667  151]
 [ 291 2129]]
Logistic Regression has accuracy of 86.35
              precision    recall  f1-score   support

           0       0.70      0.82      0.75       818
           1       0.93      0.88      0.91      2420

    accuracy                           0.86      3238
   macro avg       0.82      0.85      0.83      3238
weighted avg       0.87      0.86      0.87      3238




Confusion matrix for Support Vector Machine  is
 [[ 780   38]
 [ 337 2083]]
Support Vector Machine  has accuracy of 88.42
              precision    recall  f1-score   support

           0       0.70      0.95      0.81       818
           1       0.98      0.86      0.92      2420

    accuracy                           0.88      3238
   macro avg       0.84      0.91      0.86      3238
weighted avg       0.91      0.88      0.89      3238




Confusion matrix for Decision Tree is
 [[ 608  210]
 [ 216 2204]]
Decision Tree has accuracy of 86.84
              precision    recall  f1-score   support

           0       0.74      0.74      0.74       818
           1       0.91      0.91      0.91      2420

    accuracy                           0.87      3238
   macro avg       0.83      0.83      0.83      3238
weighted avg       0.87      0.87      0.87      3238




Confusion matrix for Random Forest is
 [[ 720   98]
 [ 249 2171]]
Random Forest has accuracy of 89.28
              precision    recall  f1-score   support

           0       0.74      0.88      0.81       818
           1       0.96      0.90      0.93      2420

    accuracy                           0.89      3238
   macro avg       0.85      0.89      0.87      3238
weighted avg       0.90      0.89      0.90      3238
```

```
Confusion matrix for Naive Bayes is
 [[ 771   47]
 [ 434 1986]]
Naive Bayes has accuracy of 85.15
              precision    recall  f1-score   support

           0       0.64      0.94      0.76       818
           1       0.98      0.82      0.89      2420

    accuracy                           0.85      3238
   macro avg       0.81      0.88      0.83      3238
weighted avg       0.89      0.85      0.86      3238



Confusion matrix for K Nearest Neighbour is
 [[ 673  145]
 [ 260 2160]]
K Nearest Neighbour has accuracy of 87.49
              precision    recall  f1-score   support

           0       0.72      0.82      0.77       818
           1       0.94      0.89      0.91      2420

    accuracy                           0.87      3238
   macro avg       0.83      0.86      0.84      3238
weighted avg       0.88      0.87      0.88      3238
```

In [34]:

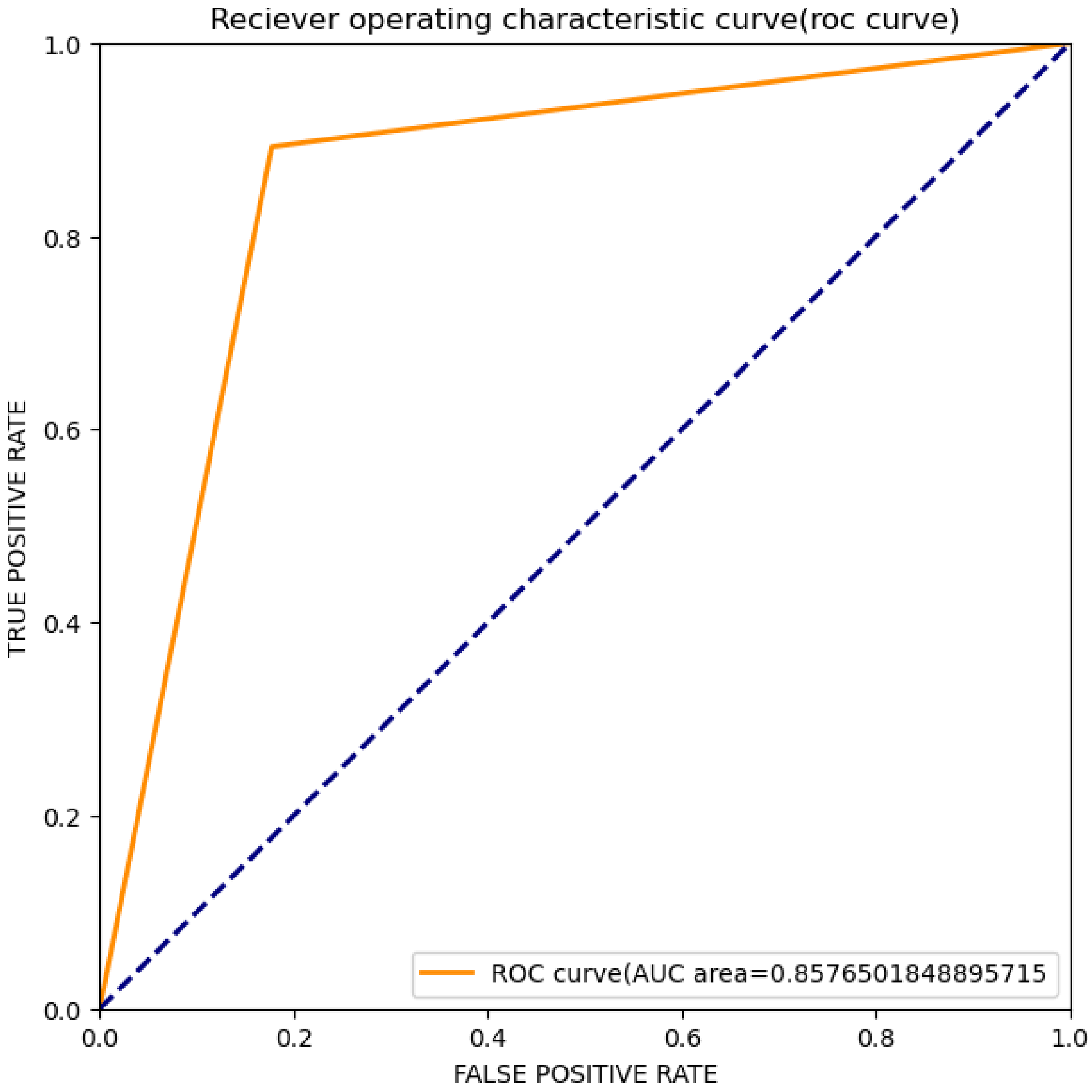
```
#finding the best classifier
best_classifier=max(results,key=results.get)
print("best classifier is ",best_classifier," with an accuracy of ",results
```

```
best classifier is  Random Forest  with an accuracy of  0.8928350833848054
```

In [35]:
```
fpr,tpr,thresholds=roc_curve(Y_test,Y_pred)

#calculating the auc
roc_auc=auc(fpr,tpr)

#plot the roc curve
plt.figure(figsize=(7,7))
plt.plot(fpr,tpr,color='darkorange',lw=2,label=f'ROC curve(AUC area={roc_au
plt.plot([0,1],[0,1],color='navy',lw=2,linestyle='--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.0])
plt.xlabel('FALSE POSITIVE RATE')
plt.ylabel('TRUE POSITIVE RATE')
plt.title('Reciever operating characteristic curve(roc curve)')
plt.legend(loc='best')
plt.show()
```

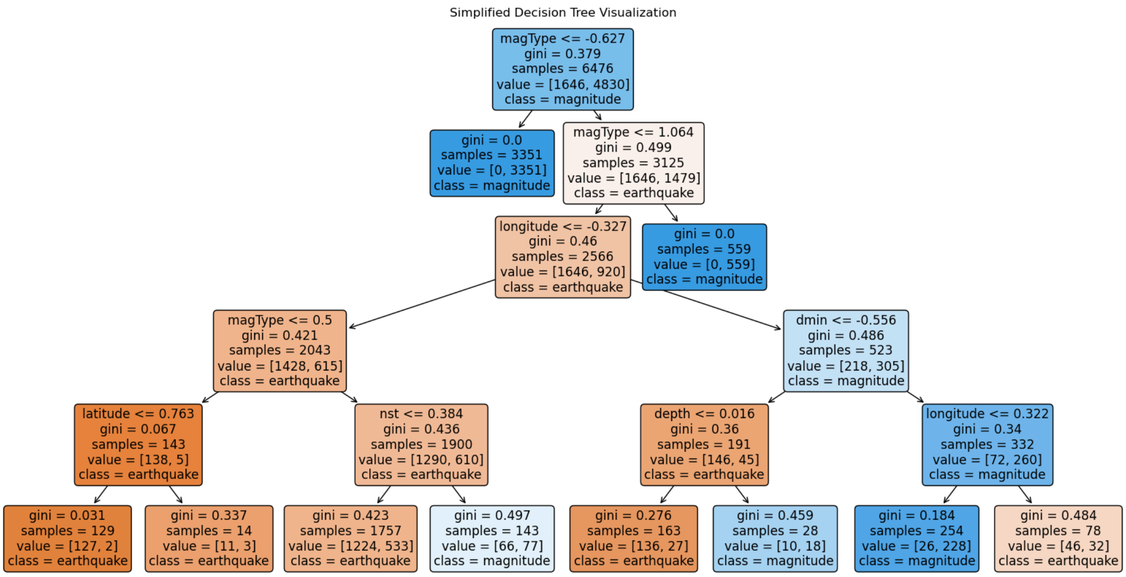


In [36]:
```
#as our dataset is huge but we have made a simplified version of decision tr
from sklearn.tree import plot_tree
model = DecisionTreeClassifier(
    max_depth=5,              # Limit the depth of the tree
    min_samples_split=10,     # Minimum number of samples required to split
    min_samples_leaf=5,       # Minimum number of samples required to be at
    random_state=42
)
model.fit(X_train, Y_train)

# Print the number of features and classes to verify
print("Number of features in model:", model.n_features_in_)
print("Number of classes in model:", len(model.classes_))

# Plot the decision tree
plt.figure(figsize=(20,10))
plot_tree(model, feature_names=['month','latitude','longitude','depth','mag
plt.title("Simplified Decision Tree Visualization")
plt.show()
```

```
Number of features in model: 11
Number of classes in model: 2
```



In [37]:
```
import pickle
with open("earthquakePrediction.pkl","wb") as file1:
    pickle.dump(best_classifier,file1)
```

In [ ]:

In [38]:
```
#predicting the magnitude of earthquake
x=data.iloc[:,:-1].values
y=data.iloc[:,-1].values
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=1/3,random_sta
```

In [39]:
```
#feature engineering
#feature selection
from sklearn.feature_selection import SelectKBest,f_classif
selector1=SelectKBest(f_classif,k=12)
x_new=selector1.fit_transform(x,y)
print(x_new)
```

```
[[  3.      -6.2159 146.9556 ...  11.     137.       1.    ]
 [  3.      64.6558 -17.7271 ...  11.      68.       1.    ]
 [  3.      33.6817  93.184  ...  11.      36.       1.    ]
 ...
 [  8.     -31.1853 117.6124 ...  11.      15.       1.    ]
 [  8.       2.1882 126.6833 ...  11.      74.       1.    ]
 [  8.      16.0523 -94.9727 ...  11.     100.       1.    ]]

C:\ProgramData\anaconda3\Lib\site-packages\sklearn\feature_selection\_univ
ariate_selection.py:113: RuntimeWarning: divide by zero encountered in div
ide
  f = msb / msw
```

In [40]:
```
#Feature scaling
scaler1=StandardScaler()
scaled_features1=scaler.fit_transform(x_new)
scaled_features1
```

Out[40]:
```
array([[-1.65444944, -0.79825532,  1.36880794, ...,  0.51854647,
         0.65863436,  0.5829769 ],
       [-1.65444944,  1.55501283,  0.08922111, ...,  0.51854647,
        -0.32900333,  0.5829769 ],
       [-1.65444944,  0.52652949,  0.95100187, ...,  0.51854647,
        -0.7870382 ,  0.5829769 ],
       ...,
       [ 1.84022784, -1.62735485,  1.14081087, ...,  0.51854647,
        -1.08762358,  0.5829769 ],
       [ 1.84022784, -0.51920034,  1.21129189, ...,  0.51854647,
        -0.24312179,  0.5829769 ],
       [ 1.84022784, -0.05884811, -0.51097826, ...,  0.51854647,
         0.12903154,  0.5829769 ]])
```

In [41]:
```
#Splitting the dataset
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=1/3,random_sta
```

In [42]:
```
#here multilinear regression is used.
regressor=LinearRegression()
```

In [43]:
```
regressor.fit(x_train,y_train)
```

Out[43]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [44]:
```
y_predictAll=regressor.predict(x)
y_predictAll
```

Out[44]:
```
array([4.83855039, 4.81685316, 4.1326252 , ..., 4.59060059, 4.52350276,
       4.04888751])
```

In [45]:
```
#finding the regression coefficients
regressor.coef_
```

Out[45]:
```
array([ 3.18811908e-03, -7.50369430e-03,  8.50414311e-04, -2.68181482e-04,
        1.54327518e-03,  6.52682306e-03, -8.06352869e-04,  1.30715081e-02,
        5.12739137e-01,  3.32658213e-02,  2.19984185e-04,  7.93414443e-0
1])
```

In [46]:
```
#finding the intercepts
regressor.intercept_
```

Out[46]:
```
2.5847635202107133
```

In [47]:
```
#model evaluation
#printing the r squared
print("r squared ",r2_score(y,y_predictAll)*100)
```

```
r squared  87.06575124792693
```

In [48]:
```
#printing the mean squared error
print("mean squared error is ",mean_squared_error(y,y_predictAll))
```

```
mean squared error is  0.09580773489963246
```

In [49]:
```
regressor.score(x,y)*100
```

Out[49]:
```
87.06575124792693
```

In [50]:
```
regressor.score(x_train,y_train)*100
```

Out[50]:
```
87.18469261285573
```

In [51]:
```
regressor.score(x_test,y_test)*100
```

Out[51]: 86.82240448046048

In [52]:
```
#as our model gives a score of 86.82 % score on the testing data which is ve
```

In [53]:
```
with open("magnitudePrediction.pkl","wb") as file2:
    pickle.dump(regressor,file2)
```

In [ ]:

In [ ]:

In [ ]: