#### PROJECT SPARTA

## DATA SCIENTIST CAPSTONE PROJECT

# PHILIPPINE EARTHQUAKE PREDICTION MACHINE LEARNING MODEL

EDMAR C. BEATINGO

#### CAPSTONE OVERVIEW



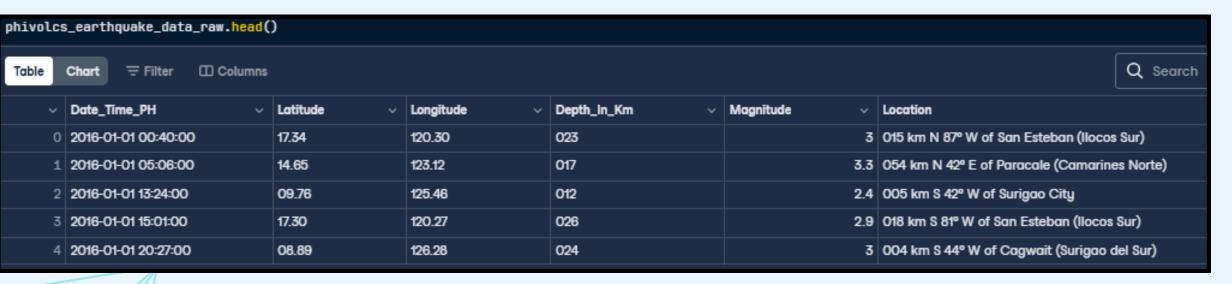
This project aims to analyze earthquake data provided by the Philippine Institute of Volcanology and Seismology (PHIVOLCS) using machine learning algorithms to predict the recurrence of earthquakes in specific locations.

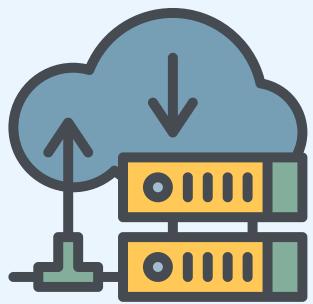


#### THE RAW DATASET

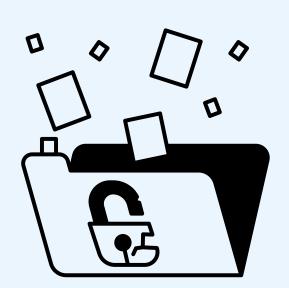


The raw dataset phivolcs\_earthquake\_data\_raw.csv was obtained from Kaggle.com, credited to Bwandowando, who extracted Philippine earthquake data from PHIVOLCS starting in 2016.

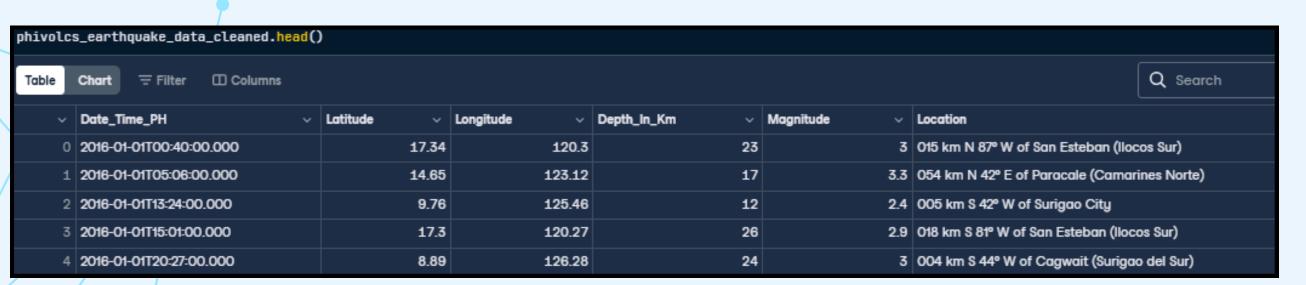


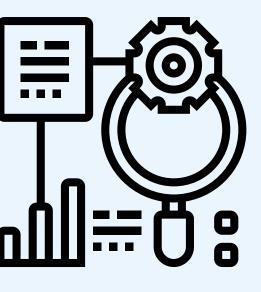


#### DATA CLEANING



- Oropped rows with any missing values.
- Convert date column to date format.
- Onvert Latitude, Longitude, Depth\_In\_Km, and Magnitude columns to numeric.
- Onvert Latitude, Longitude and Magnitude columns to float.
- Onvert Depth\_In\_Km column to integer.
- Round Latitude, Longitude, and Magnitude columns to 2 decimal places.
- Orop rows with any NaN values that resulted from the conversion and removed duplicates.

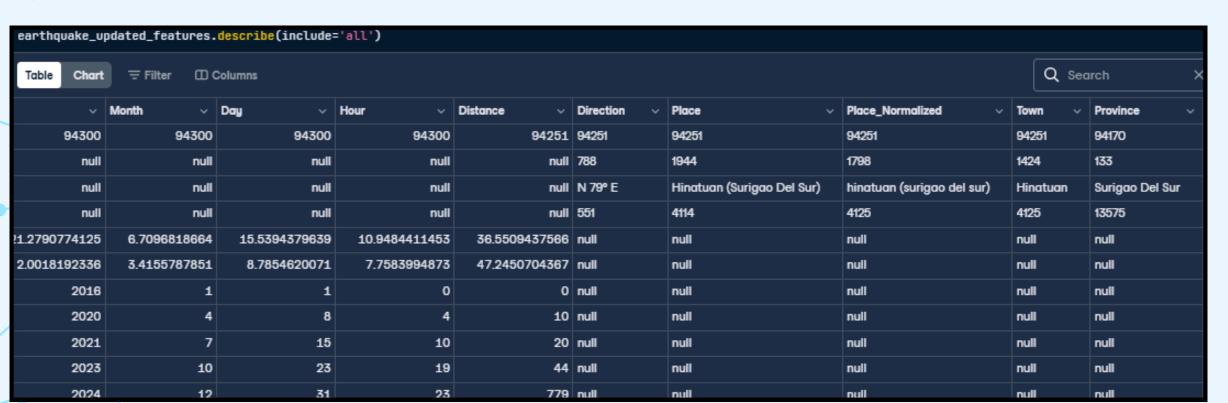




### FEATURE ENGINEERING



- Extract new feature columns (Year, Month, Day and Hour) from Date\_Time\_PH columns.
- Split the 'Location' column into 'Distance', 'Direction', and 'Place'
- Onvert month and day columns to string equivalent and create new columns 'Month\_Str' and 'Day\_Str'.
- Normalized place names by removing spaces and converting to lowercase.
- Extract town and province from normalized place column.
- 🕢 Identify anomalies by checking and dropping duplicates.



#### EXPLORATORY DATA ANALYSIS



Orop any rows with missing values.

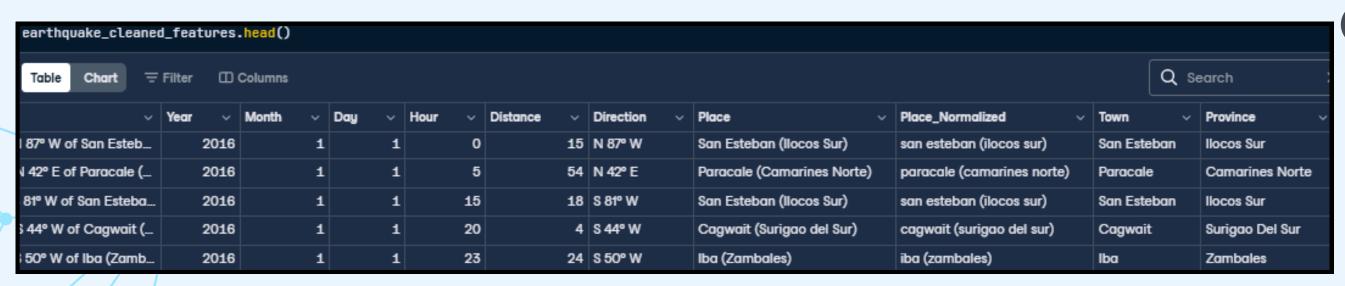
Convert 'Year', 'Month', 'Day', and 'Hour' columns to integer type.

Convert 'Distance' to float type.

Convert 'Direction' and 'Place' to string type.

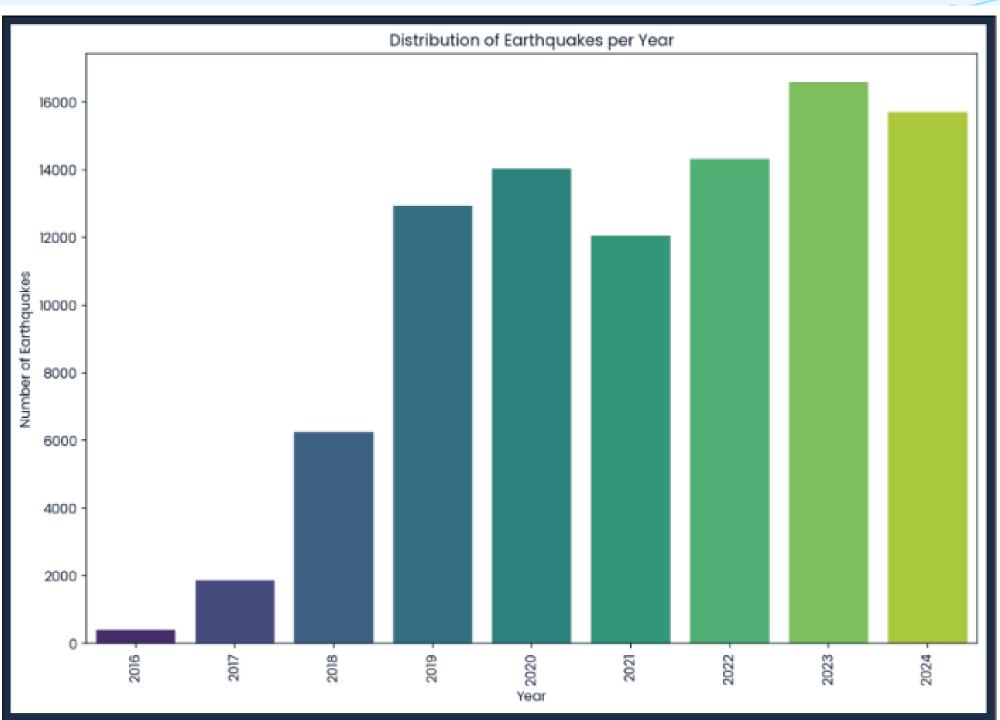
Clean the 'Province' column by removing leading/trailing spaces, extra parenthesis characters, and converting to proper case.

Clean the 'Town' column by removing leading/trailing spaces, extra parenthesis characters, and converting to proper case.



#### EXPLORATORY DATA ANALYSIS



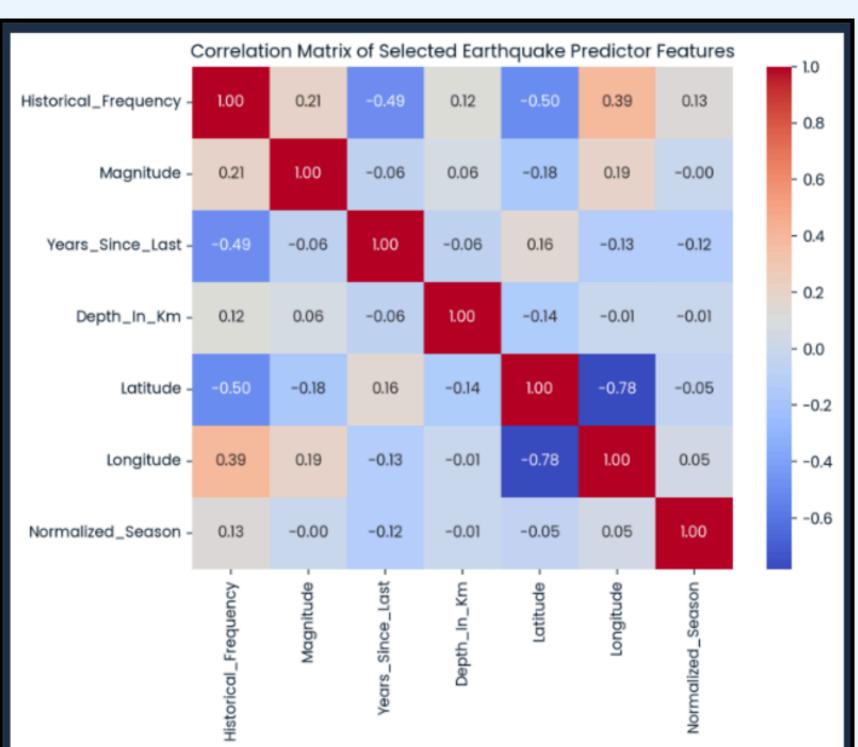


There has been a notable increase in recorded earthquakes from 2016 to 2024, with a significant rise starting in 2019. Earthquakes have stabilized at over 12,000 occurrences annually since then, peaking in 2023 before a slight decline in 2024.



#### EXPLORATORY DATA ANALYSIS





The graph implies that high historical frequency of earthquakes is strongly associated with larger

magnitudes.

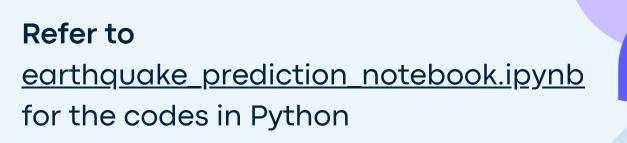
#### MACHINE LEARNING MODEL



- Openitude column.
- One-hot encode categorical features.
- Split the data into training and testing sets.
- Initialize and train the Random Forest Classifier.
- Predict probabilities for the test set and evaluate the model.
- Operating Characteristic) score and classification report.

ROC AUC SCO	re: 0.7066			
	precision	recall	f1-score	support
0	1.00	1.00	1.00	18800
1	0.00	0.00	0.00	34
accuracy			1.00	18834
macro avg	0.50	0.50	0.50	18834
veighted avg	1.00	1.00	1.00	18834

A score of 0.7066 suggests that the model has a good ability to distinguish between earthquakes with magnitude  $\geq$  5.5 and those with lower magnitudes.



#### MACHINE LEARNING MODEL



Filtered the town and province earthquake records with magnitude 5.5 or higher.

Group by Province and Town, then calculate the mean of relevant features.

Prepare the features and target variable for the logistic regression model.

Handle missing values by imputing the mean.

Standardize the features.

Split the data into training and testing sets.

Initialize and train the logistic regression model.

Predict the probabilities for the test set.

Add the forecast probabilities to the dataframe.

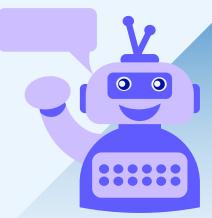
Round the forecast probabilities to 3 decimal places.

Group by Province and calculate the mean forecast probability for each province.

Merge the forecast probabilities with the original grouped dataframe to include towns.



The graph illustrates the top 5 provinces in the Philippines with the highest probability of experiencing a 5.5-magnitude earthquake occurrence.



#### MACHINE LEARNING MODEL



Mean Squared Error (MSE): 7.301277521815001e-31
R-squared (R2): 1.0
Mean Absolute Error (MAE): 6.433799607076993e-16
Explained Variance Score (EVS): 1.0
The model explains a high proportion of the variance.
The model has a low mean squared error, indicating good performance.

**Refer to** <u>earthquake prediction notebook.ipynb</u> for the codes in Python

Train the model.

Predict on the test set.

Opefine metrics.

Generate predictions for the next occurrence of earthquakes.

Add projected year, month, day, and time.

Filter out past dates.

Relevant columns for the output file selection.

Forecast live the next occurrence.

Add magnitude level to the predictions output.

Add a probability column predicting the certainty of the

predicted magnitude to occur in the future.

Convert probability to percentage with 2 decimal places.

	Tab	le Chart = Filter	□ Columns						Q Sear	ch :
		Province v	Town v	Projected_Year v	Projected_Month v	Projected_Day v	Projected_Hour v		Magnitude_Level v	Probability v
		Surigao Del Sur	Hinatuan	2025	2	2	2	3.3	Moderate	33
40	67	La Union	Pugo	2025	2	2	2	2.7	Low	27
40	68	Negros Oriental	Basay	2025	2	2	2	2.7	Low	27
40	69	Surigao Del Sur	Hinatuan	2025	2	2	2	2.3	Low	23
4	70	Quezon	San Andres	2025	2	2	3	2.6	Low	26
4	71	Davao Oriental	Tarragona	2025	2	2	3	3.8	Moderate	38
4	72	Surigao Del Sur	Marihatag	2025	2	2	4	2	Low	20
4	73	Surigao Del Sur	Hinatuan	2025	2	2	5	2.2	Low	22
4	74	Samar	Basey	2025	2	2	5	2.3	Low	23
4	75	Surigao Del Sur	Hinatuan	2025	2	2	5	2.2	Low	22
4	76	Surigao Del Sur	Marihatag	2025	2	2	5	2.5	Low	25
4	77	Surigao Del Sur	Cagwait	2025	2	2	6	3.5	Moderate	35
4	78	Surigao Del Sur	Hinatuan	2025	2	2	7	2.1	Low	21
4	79	Ahra	San Isidro	2025	2	2	7	23	Low	93

Define features and target variables.

Drop rows with NaN values in the target variable.

Align X with y after dropping NaN values.

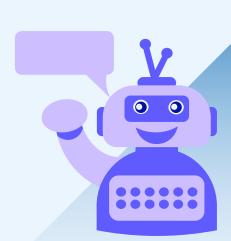
Split the data into training and testing sets.

Define preprocessing for numerical features: impute missing values and scale.

Bundle preprocessing for numerical features.

ODefine the model.

Create and evaluate the pipeline.



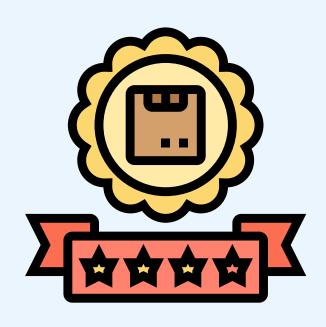
#### CONCLUSIONS



- There is a strong link between high historical earthquake frequency and larger magnitudes.
- The ROC curve analysis reveals a moderate AUC score of approximately 0.7066, suggesting some predictive capability.
- The key feature influencing earthquake predictions is Historical\_Frequency.
- There is a widespread seismic risks across the Philippines, especially in Surigao del Sur, Agusan del Norte, and Eastern Samar



#### RECOMMENDATIONS



- Prioritize Earthquake Preparedness in High-Risk Areas especially in terms of budget allocation.
- Enhance Predictive Models Using Historical Data.
- Refine Predictive Capabilities with Machine Learning.
- Strengthen Infrastructure in Vulnerable Regions.
- Develop Comprehensive Regional Risk Maps.
- Public Awareness Campaigns, Information Drive and Trainings.

