

PREDICTING EARTHQUAKE PARAMETERS USING RANDOM FOREST: A MULTI-OUTPUT APPROACH WITH P-ARRIVAL DATA

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ABSTRACT

It's interesting to research the topic of earthquake predicting. Earthquakes are still a terrible natural disaster that affects people's lives as well as the economy. In order to reduce fatalities, this led to the idea of developing an early warning system for seismic disasters. For a few years now, scientists have been predicting earthquakes and rating a place's seismic hazard. In this work, we use p-arrival data, which comprises the arrival station's amplitude height and disaster arrival time, to try to predict earthquakes before they happen. The Random Forest method and one of the machine learning techniques have been developed and applied in a number of earthquake prediction research to date. Given the diversity and complexity of the earthquake event itself, there is still uncertainty in the long-studied process of earthquake prediction. It is probabilistic to use a random forest prediction model to determine the structural safety condition of earthquake-damaged buildings. The random forest technique can be used to predict the latitude, longitude, magnitude, and depth of an earthquake. The recorded value and geographic location of each station are used as variables in a random forest with multioutput approach. The predictions made by this study were within 63 percent of reality.

Keywords: *Earthquake Prediction, Random Forest, P-Arrival Data*

1. INTRODUCTION

Earthquakes are one of the most destructive natural disasters, causing significant loss of life, property damage, and economic disruption. Nearly all earthquakes occur along faults, where tectonic forces push or pull the Earth's crust, often leading to seismic activity near the Earth's surface. These seismic events are not only triggered by tectonic movements but also by volcanic eruptions, explosions, and even the collapse of man-made structures. Understanding these events and predicting their occurrence remains a challenging task for scientists due to the inherent unpredictability of geological processes. Historically, earthquake prediction has been a subject of intense research, with limited success in providing timely warnings. Earthquakes often occur along fault lines that have previously shown signs of seismic activity, though predicting the exact time, location, and magnitude remains elusive. The catastrophic earthquake in Nepal on April 25, 2015, which caused over 8,000 fatalities and extensive destruction, serves as a stark reminder of the potential devastation caused by seismic events. The earthquake's impact on both human lives and historical landmarks highlights the urgent need for more effective prediction and early warning systems.

In response to these challenges, **Earthquake Early Warning (EEW)** systems have been developed to alert populations before significant shaking occurs. EEW involves detecting seismic waves as they travel through the Earth and issuing warnings to give people time to take protective actions. The system provides alerts once an earthquake has begun, and the time between detection and the arrival of damaging waves can range from seconds to minutes, depending on the earthquake's proximity. The ability to issue accurate warnings relies on real-time geophysical data and the rapid processing of this information. While the concept of earthquake early warning has been proposed for over a century, the technological and logistical challenges of implementing such systems are complex. These include accurately detecting earthquakes in real-time, estimating their magnitude, predicting the extent of shaking, and delivering timely alerts to at-risk populations. Furthermore, the balance between minimizing false alarms and ensuring timely alerts remains a critical consideration. The 2015 Nepal earthquake exemplifies the devastating consequences of insufficient early warnings, emphasizing the need for ongoing research to refine EEW technologies. This research explores the use of advanced machine learning techniques, particularly the **Random Forest model**, in predicting earthquake parameters such as magnitude, location, and depth. By leveraging P-arrival data—comprised of amplitude height and arrival time from seismic stations—this study aims to improve earthquake prediction and early warning systems. Through the application of a **multi-output Random Forest approach**, the research investigates how effectively this method can predict earthquake characteristics and contribute to minimizing the damage caused by seismic events.

2. LITERATURE SURVEY

An earthquake is one of the most catastrophic natural disasters, primarily due to the fact that there is very little opportunity to prepare for it and there is very little to no advance warning. In spite of the growing interest in the scientific community, the potential of accurately predicting earthquakes continues to be a matter of debate. Due to the fact that earthquakes are caused by the movement of tectonic plates beneath the surface of the earth, they are a characteristic that

is inherent to the geology of the planet. The following are some of the most common causes and factors of earthquakes: Geological conditions, including plate boundaries, faults, depth, and magnitude, are discussed. Earthquakes are a common occurrence that have a significant impact on a vast number of people all over the world. Recently, Mexico was struck by an earthquake with a magnitude of 7.6; nonetheless, the number of fatalities is insignificant. In the past four decades, Bangladesh has seen a total of 284 earthquakes, and Chittagong was struck by a 6.2-magnitude earthquake in the year 2021.

The United States Geological Survey (USGS) estimated that economic losses might range anywhere from nine percent to fifty percent of GDP, with the highest estimate being thirty-five percent. Nepal received economic support from India and China, which amounted to more than one trillion dollars when taken together. A search and rescue team consisting of more than one hundred individuals, also known as Lifesaving Troops, as well as medical professionals and three Chinook helicopters were dispatched by the government of Nepal for use. Nepal received assistance from the Asian Development Bank (ADB) in the form of a grant of three million dollars for support measures and one hundred million dollars for initial recovery. £73 million was contributed by the United Kingdom, of which the government contributed £23 million and the general population contributed £50 million. Also contributing to the relief effort was the United Kingdom, which provided thirty tons of humanitarian aid and eight tons of supplies. Throughout the course of this investigation, we have utilized a dataset that was provided by driven data, carried out exploratory data analysis with the assistance of Tableau, and ultimately constructed a machine learning model that is able to forecast the damage grade severity that the earthquake has caused to the structures. To a certain extent, the models can also be utilized for the purpose of forecasting the level of damage that will be incurred by the buildings. In order to evaluate the effectiveness of the models, the F1-Score was utilized.

2019 "Earthquake Transformer—An Attentive Deep-Learning Model for Simultaneous Earthquake Detection and Phase Picking" S.M. Mousavi, W.L. Ellsworth, W. Zhu, L.Y. Chuang, and G.C. Beroza were the scholars who contributed to the work. An earthquake transformer model, which is a deep learning model, is presented in this study. This model's objective is to expedite seismic monitoring while simultaneously improving its accuracy. Recognizing earthquakes and seismic phases at the same time is the objective of this technology so that it can be used.

The year 2018 The authors of the article titled "Convolutional Neural Network for Earthquake Detection and Location" are T. Perol, M. Gharbi, and M. Denolle. In the context of earthquake detection and location, the authors describe a convolutional neural network (CNN) model and demonstrate its performance in comparison to other methods that are already in use. The year 2020 saw the publication of the work titled "A Machine-Learning Approach for Earthquake Magnitude Estimation" by G.C. Beroza and S.M. Mousavi. In terms of accuracy, the machine-learning strategy that is presented in this article for calculating earthquake magnitudes offers superior performance over more traditional methods. the year 2019 The research paper titled "PhaseNet: A Deep-Neural-Network-Based Seismic Arrival-Time Picking Method" was written by W. Zhu and W.C. Beroza. PhaseNet is a deep neural network that is described by the experts. It is designed to improve earthquake detection and analysis by accurately forecasting when seismic waves would arrive.

The increased sensitivity of structures as a result of main shock damage, as well as the time-variant vulnerability of buildings as a result of the probability of aftershock damage accumulation, are both factors that decision-makers in seismic crises need to take into consideration. The accumulation of aftershock damage has been measured through the utilization of probabilistic models in order to ascertain the extent to which aftershock damage accumulation contributes to the overall damage caused by the mainshock. The evaluation of seismic performance and the construction of damage accumulation models, in addition to a probabilistic assessment of aftershock occurrence, have been carried out with the help of Markov Chain-based approaches, just as the aftershock occurrence evaluation has been carried out. Aftershocks, according to the findings of the vast majority of studies, make a considerable contribution to the prediction of repercussions and losses. When it comes to making judgments that are short-term in nature, one of the most important aspects to take into consideration is the short-term variability of a building's vulnerabilities. This variability is quantified in proportion to the damage that has been accumulated across the whole seismic series.

While it comes to earthquake forecasting, the next field of research pertains to the utilization of machine learning techniques while making predictions. Data-driven, non-parametric, and requiring fewer a priori assumptions are the qualities that characterize these approaches. In their research, Murwantara and colleagues utilized three distinct neural networks, namely multinomial logistic regression (LR), support vector machine (SVM), and Naive Bayes (NB), to forecast the size, location, and depth of earthquakes that occurred in Indonesia. The results of their investigation demonstrated that the SVM algorithm is superior than the other two approaches when it comes to earthquake prediction. A hybrid neural network (HNN) and support vector machine (SVM) methodology was utilized by Khalil et al. in order to facilitate the development of an earthquake prediction method along the Chaman fault in Baluchistan. A probability

back propagation neural network (BPNN) was proposed by Lin [24] for the purpose of earthquake prediction in Taiwan for probabilistic calculations. There is a limitation to the capacity of machine learning algorithms to learn the nonlinear and complicated relationships observed in earthquake data. Furthermore, they are only capable of extracting superficial characteristics from the dataset, and they almost require quite complicated feature engineering methods.

Deep learning algorithms have resulted in considerable advancements in the resolution of a wide variety of earthquake prediction problems. These models have a high generalization power, which has considerably boosted their learning ability in comparison to shallow networks. This is due to the fact that they have numerous hidden layers and a densely connected large number of neurons throughout their structure. A great number of techniques that are founded on deep learning have been developed for the purpose of earthquake prediction. These techniques include convolutional neural networks (CNN) and long short-term memory (LSTM) networks. In the course of their investigation, Huang and colleagues proposed the CNN model as a means of estimating the magnitude of the significant earthquake that occurred in Taiwan by utilizing picture data. In their study, Jozinovic and colleagues provide a CNN-based technique that is able to accurately predict earthquake ground shaking intensity readings in Italy. DLEP is a Deep Learning model for earthquake prediction that was developed by Li et al. These researchers combined explicit and implicit earthquake features in order to develop this model. Within the framework of DLEP, the explicit features consist of eight precursory pattern-based indications, while the implicit features are extracted through the utilization of a CNN. Through the utilization of the LSTM network, Bhandarkar et al. investigated the pattern of forthcoming earthquakes. An LSTM network was utilized by Wang et al. in order to understand the spatial-temporal connection between earthquakes that occurred in various regions and consequently to create predictions based on this information. An attention-based bi-directional LSTM architecture has been proposed by Al Banna and colleagues for the purpose of earthquake prediction in Bangladesh in the time period of the next month.

In situations where the stiffness of buildings gradually decreases before to their collapse, monitoring the lengthening of their fundamental period can be of assistance in determining the extent of seismic damage that has been achieved by such structures. The fundamental period, also known as frequency, is believed to be a substitute when the apparent structural rigidity and structural health are taken into consideration. By utilizing the residual stiffness of masonry structures that is derived from period measurements, for instance, it has been feasible to explore the impact that seismic damage buildup has on an estimate of the magnitude of a macro-seismic event. A series of laboratory experiments were carried out on unreinforced masonry specimens with the purpose of determining the fundamental frequency shift as a function of structural drift and the extent of damage. Using both experimental and computational methods, researchers have shown empirical correlations between the frequency shift and the damage index for RC structures. These relationships were established and discussed. In spite of this, the processes of building tagging frequently assign a red tag to structures that have sustained severe damage without collapsing, as well as to structures that are seen as being dangerous, unrepairable, or unworthy of repair. The following approaches are concerned with the probability of damage states ranging from minor to severe, based on the amount of time that has gone since the collapse was observed. In this regard, the methods are explained below.

For the purpose of training the random forest model, the training set was utilized, whereas the testing set was utilized for the purpose of evaluating the modeling performance. The random forest method was utilized in order to make predictions regarding earthquakes in the testing set. An example of an ensemble learning method is the random forest algorithm, which assembles numerous decision trees and aggregates their predictions to arrive at a final prediction. In addition to being reliable and efficient in a variety of applications, the algorithm can also accurately anticipate earthquakes. Our evaluation of the model's performance included the utilization of a number of variables, including accuracy, precision, recall, and F1 score, among others.

With an accuracy of 99.95% and an F1 score of 0.15, the results demonstrated that the random forest model could forecast earthquake events with high accuracy. With a recall of 0.15, the model could also detect earthquakes that caused substantial damage. In conclusion, seismic activity data from multiple earthquake-prone zones is included in our study area for random forest-based earthquake prediction. We utilized the random forest model to predict earthquakes after dividing the dataset into training and testing sets, selecting features, and oversampling.

Application In Earthquake Catalog Development

The application of machine learning (ML) in seismology is being driven by the method of identifying seismic waveforms, identifying hypocenters, and cataloguing them from seismogram records. This section examines the latest advancements in machine learning applications for earthquake cataloging, with an emphasis on enhancing specific pipeline jobs, paleoseismic record analysis, focal mechanism analysis, and comparable waveform searching.

Importance of improving earthquake cataloging methods and contribution of machine learning techniques

When taking into account the fact that the size distribution of earthquakes is governed by a power law, increasing the detectability of events results in a significant increase in the number of events that can be analyzed, which in turn improves the spatiotemporal resolution of seismicity analysis. The need of compiling comprehensive earthquake catalogs has been brought to light by a number of studies that have highlighted the significance of the role that minor occurrences play in the process of earthquake generation. For instance, Mignan (2014) carried out a meta-analysis of 37 foreshock investigations and discovered that the interpretation of foreshock activity is dependent on the completeness magnitude of the earthquake catalogs that were utilized. A highly comprehensive inventory was utilized by Trugman and Ross (2019) in order to demonstrate that precursory seismicity is more widespread than was previously thought to be the case in southern California.

The template matching technique (Gibbons and Ringdal 2006; Shelly et al. 2007; Peng and Zhao 2009) has been utilized quite frequently for the purpose of detecting minor seismic events that have waveforms that are being obscured by noise. This technique involves the exploration of further events that have waveforms that are comparable to the template waveforms. This method frequently results in a diminished sense of wholeness.

3. METHODOLOGY

In the methodology we have step by step process as mentioned in the below figure.

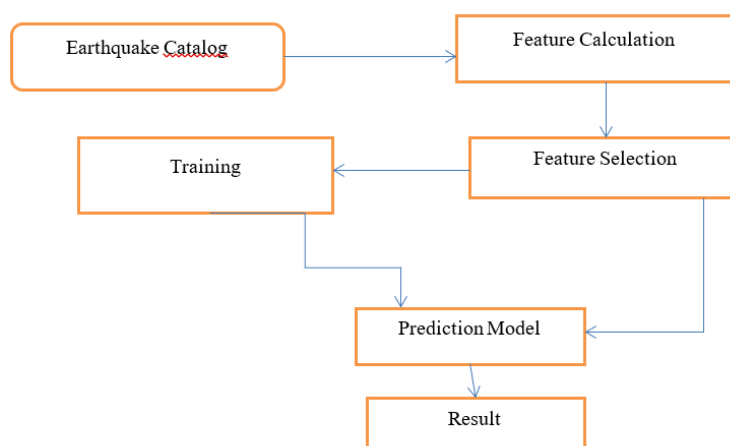


Fig 1: Methodology

Earthquake Catalog: Earthquake cataloguing is the process of gathering prior-year earthquake data source characteristics such as magnitudes, longitude, latitude, date, and time.

Feature Calculation: The act of converting raw data into numerical features that may be handled while retaining the information in the original data set is known as feature calculation. This produces better outcomes than merely applying machine learning to raw data.

Feature Selections: Feature selection is a way to limit the input variables to your model by utilising only relevant data and removing noise from the data. It maximises relevancy while reducing redundancy. This stage also involves the testing of data.

Train With Machine Learning Model : A training model is a dataset that is used to train a machine learning algorithm. It consists of the sample output data and the corresponding sets of input data that have an influence on the output. The training model is used to run the input data through the algorithm to correlate the processed output against the sample output. The result of this correlation is used to modify the model.

Prediction Model: A prediction model is a tool for forecasting future events or outcomes by analysing patterns in a set of input data.

Result: It is the end result of our model

ALGORITHM

Random Forest

The Random Forest algorithm is a widely used machine learning technique that runs in a synchronous fashion and finds broad application in a variety of machine learning applications. The method in question is a decision tree-based approach that integrates multiple decision trees in order to provide a model that is both reliable and accurate. For earthquake prediction, random forests are a popular choice because of their capacity to handle big data sets with complex features, to manage noisy and missing data, and to provide predictions that are accurate and reliable. random forests are used to forecast earthquakes by constructing several decision trees based on various seismic features and data. These

characteristics and data include the location, duration, depth, and severity of the earthquake. Random forests are used in the context of earthquake prediction. An individual prediction is generated by each decision tree on the basis of a subset of the data, and the predictions generated by all of the trees are then pooled to provide the ultimate prediction. Building numerous trees and aggregating their predictions is what makes the model more robust and accurate. This approach is what makes the model more accurate. It is possible for Random Forests to handle datasets that have an imbalanced class distribution, which is something that is frequently seen in seismic occurrences, when the majority of the cases do not result in severe damage or loss. Through the utilization of oversampling strategies such as SMOTE (Synthetic Minority Oversampling Technique), it is possible to achieve a more balanced dataset in order to overcome this issue.

By generating synthetic samples from the minority class, the training data can provide a sample that is more representative of the population being studied by the model. When used for earthquake prediction, random forests have the ability to discover features that are most significant to the incidence and behavior of earthquakes. This is one of the benefits of employing random forests. The most important characteristics, such as the magnitude of the earthquake, the distance between the earthquake and the nearest fault, and the time of day, can be identified with the help of feature selection techniques like Boruta. Another benefit of random forests is that they offer a measurement of the importance of features, which can assist researchers in gaining a better understanding of the factors that drive earthquake behavior and occurrence.

The implementation of earthquake early warning systems and disaster management strategies can both benefit from the utilization of this information. In a nutshell, Random Forest is a highly effective and extensively utilized machine learning method that has demonstrated significant potential in the field of earthquake forecasting. It has the ability to handle big and complicated data sets, as well as data that is imbalanced, and it can produce predictions that are accurate and strong. The ability of random forests to choose features and provide a measure of the relevance of those features can be of great assistance to researchers in their efforts to gain a better understanding of the factors that govern earthquake behavior and occurrence.

ARCHITECTURE DIAGRAM

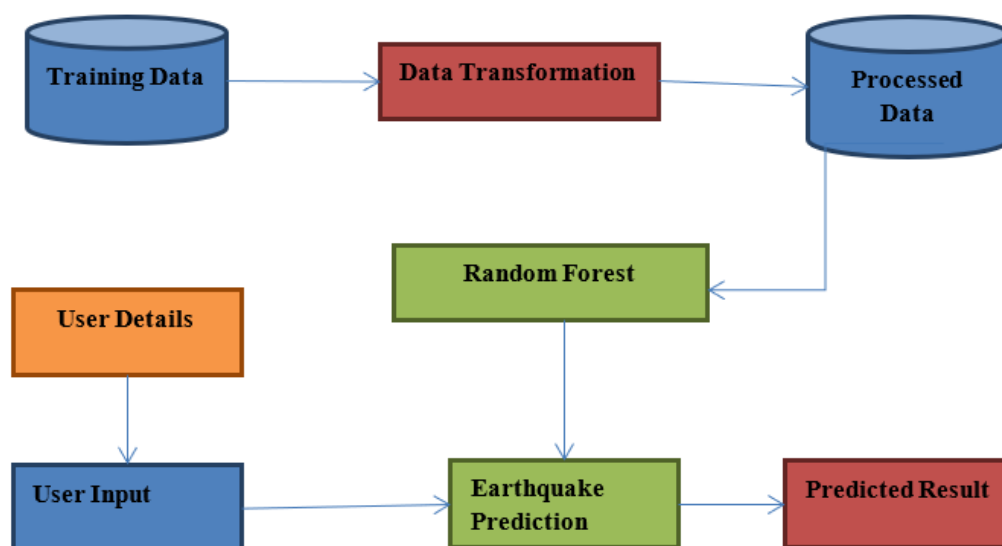


Fig2: System design

DATASET

Earthquake prediction using random forests includes seismic activity data from various regions prone to earthquakes. The dataset used for this study is the earthquake catalog provided by the National Earthquake Information Center (NEIC). This catalog includes earthquake events recorded worldwide from 2000 to 2016. We selected earthquake events with magnitudes of 5.0 or greater, as these events are more likely to cause significant damage and have a greater impact on society.

It is bounded by latitudes -77.08° to $+86.005^{\circ}$ and longitudes -179.66° to $+179.88^{\circ}$ which comprises the lowest Magnitude record of 5.5 and highest magnitude record of 9.1. The seismic data included in our dataset includes features such as location, time, depth, magnitude, and various measures of seismic activity, such as P-wave and S-wave arrival times, seismic intensity, and energy release. We used the earthquake data to train and test our random forest model for earthquake prediction. We randomly split the dataset into training and testing sets, with a 70:30 ratio.

4. RESULTS

Evolution Metrics

Precision: Precision is a metric that measures the accuracy of positive predictions by determining the ratio of true positives (correctly identified positive instances) to the total number of instances predicted as positive, including both true positives and false positives.

$$\text{Precision} = (\text{True Positive}) / (\text{True Positive} + \text{False Positive}) \quad (1)$$

Recall /: Recall is a metric that measures the effectiveness of a model's ability to identify positive instances by calculating the ratio of true positives (correctly identified positive instances) to the total number of actual positive instances, which includes both true positives and false negatives.

$$\text{Recall} = (\text{True Positive}) / (\text{True Positive} + \text{False Negative}) \quad (2)$$

F1-score: F1-score is a single metric that combines both precision and recall values to determine the overall performance of a model. It is the harmonic mean of precision and recall, which gives equal weight to both metrics and emphasizes the balance between them.

$$\text{f1-score} = 2((\text{precision} \times \text{recall}) / (\text{precision} + \text{recall})) \quad (3)$$

To use Random Forest for earthquake prediction, a dataset of historical earthquake data must be prepared. The dataset should include features such as earthquake magnitude, location, time, and other relevant geological data. The dataset should also include a label indicating whether an earthquake occurred or not. Once the dataset is prepared, it can be divided into training and testing sets. The Random Forest algorithm can then be trained on the training set, and the performance of the algorithm can be analyzed on the testing set. Random Forest algorithm can be used to classify the event as either an earthquake or not an earthquake. In summary, the methodology for earthquake prediction using Random Forest involves preparing a dataset of historical earthquake data, training the Random Forest algorithm on the dataset, and using the trained algorithm to make predictions for new earthquake events.

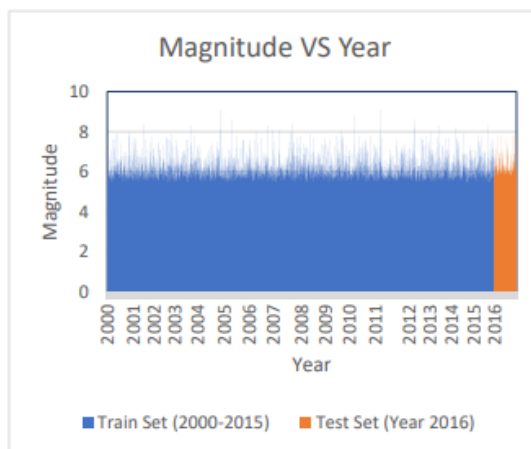


Fig 3: Histogram plot for earthquake prediction

having Year on the X-axis whereas Magnitude on the Y-axis with the dataset of 2000 to 2015 for training purposes and of 2016 for testing purposes.

	precision	recall	f1-score	support
2000	0.24	0.24	0.24	119
2001	0.13	0.15	0.14	75
2002	0.15	0.11	0.13	109
2003	0.17	0.16	0.16	103
2004	0.11	0.11	0.11	105
2005	0.14	0.13	0.14	100
2006	0.11	0.10	0.10	111
2007	0.15	0.19	0.17	111
2008	0.13	0.14	0.14	99
2009	0.15	0.12	0.13	109
2010	0.15	0.17	0.16	103
2011	0.29	0.31	0.30	134
2012	0.12	0.10	0.11	98
2013	0.17	0.20	0.18	84
2014	0.08	0.09	0.09	99
2015	0.15	0.16	0.15	90
2016	0.11	0.10	0.11	100
accuracy			0.15	1749
macro avg	0.15	0.15	0.15	1749
weighted avg	0.15	0.15	0.15	1749

Fig 4: Precision, Recall and f1-score

To determine the precision, recall, F1-score, and support values using the Random Forest algorithm on a dataset, you need to train the model, make predictions, and evaluate its performance. These metrics can be computed by comparing the predicted labels with the actual labels of the dataset.

5. CONCLUSION

The problem with the current studies is that they use future data (CVSS ratings) to anticipate if a CVE will be exploited. Using only Twitter discussion data and the CVE IDs provided by MITRE, we attempt to forecast when a vulnerability will be exploited before NIST issues CVSS scores to the CVEs in order to remedy this problem. Additionally, we are the first to forecast when exploits will occur in addition to whether they will occur. We suggest the FEEU and FRET frameworks with two sets of new features to enhance prediction. We start by creating a series of multi-layer graphs from which we generate a set of meta CVE popularity features. The characteristics of popularity are described in a way that reinforces one another. The suggested TFI algorithm is used to solve the calculation, and its convergence and uniqueness qualities are demonstrated. Second, as an extra feature, we estimate the future retweet volume of a CVE using the Hawkes process model. The experimental results indicate that FEEU beats natural adaptations of prior research by an average of 25.1% in terms of F1 score, despite the fact that no previous studies have tackled the issue of when a CVE will be exploited. Furthermore, it has been demonstrated that FRET is accurate in predicting the day that a vulnerability will be exploited (from the date of CVE issuance) to within 35.71 days for PoC exploits and 11.90 days for real-world exploits.

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