Advance Sustainable Science, Engineering and Technology (ASSET)
Vol. 6, No.4, October 2024, pp. 02404016-01 ~ 02404016-010
ISSN: 2715-4211 DOI: https://doi.org/10.26877/asset.v6i4.1003

Utilizing Sequential Pattern Mining and Complex Network Analysis for Enhanced Earthquake Prediction

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Abstract. Earthquakes are natural events caused by the movement of the earth's plates, often triggered by the energy release from hot liquid magma. Predicting earthquakes is crucial for raising public awareness and preparedness in seismically active areas. This study aims to predict earthquake activity by identifying patterns in seismic events using Sequential Pattern Mining (SPM). To enhance the prediction accuracy, Sequential Rule Mining (SRM) is applied to derive rules with confidence values from these patterns. The results show that using betweenness centrality as a weight increases the prediction accuracy to 83.940%, compared to 78.625% without weights. Using eigenvector centrality as a weight yields an accuracy of 83.605%. These findings highlight the potential of using centrality measures to improve earthquake prediction systems, offering valuable insights for disaster preparedness and risk mitigation.

Keywords: Complex Network Analysis; Sequential Pattern Mining; Earthquake Prediction; Seismic Network; Centrality Measurement; Pattern Analysis

(Received 2024-08-26, Accepted 2024-09-14, Available Online by 2024-10-20)

1. Introduction

Indonesia is a country with a high potential for earthquake natural disasters because Indonesia is a country traversed by the Ring of Fire which causes frequent earthquakes and volcanic eruptions [1], [2]. According to BMKG, Indonesia is prone to earthquakes on a small or large scale, based on earthquake data recorded so far, many studies have been carried out on earthquakes, but no one has been able to predict the possibility of earthquakes in the real world well. One of the earthquake research projects uses Complex Network Analysis (CNA) for earthquake network analysis.

Complex Network Analysis (CNA) is a method used to analyze networks consisting of nodes and edges, where nodes represent earthquake locations and edges represent the relationship between events over time [1]–[6]. The goal of CNA is to identify key nodes that have a significant influence on earthquake activities, allowing these nodes to be weighted accordingly in the network. Previous studies, such as Mintzelas et al. [7], used Pearson Correlation and Time Series to examine earthquake patterns, identifying pairs of areas with strong relationships, but without predicting future earthquake locations. Other studies applied machine learning techniques to predict earthquakes [8], [9], focusing on model accuracy rather than predicting future event locations. In contrast, I Made Murwantara et al. [10] used machine learning to predict future earthquake locations based on longitude, latitude, magnitude, and depth.

Earthquake prediction focuses on identifying repeating patterns, making Sequential Pattern Mining (SPM) a suitable method for this purpose. SPM is used to find patterns of event occurrences while considering the order of items based on earthquake timing [11], [12]. Previous studies have supported this approach. Nugroho et al. [13] used SPM with the CM-SPADE algorithm to find patterns in Denial of Service attacks. Phyu et al. [14] demonstrated that the Prefixspan algorithm outperforms Apriori-based GSP and Freespan algorithms for long sequences. Swamy et al. [15] also found Prefixspan superior in execution time, memory usage, and frequent sequence detection across various tests. A summary of these methods is presented in Table 1.

Table 1. *Summary of Previous Method*

Category	Researcher	Year	Methods	Description	Result
Machine Learning	I.M. Murwantara et al.[16]	2020	Multinomial LR, SVM and Naive Bayes	Medium and long-term earthquake prediction in Indonesia using 30 years of historical data	Root Mean Square Error evaluation is 0.751 using support vector machine
	Bilal Adlam et al [17]	2021	SVR-HNN	Earthquake prediction along Chaman fault of Baluchistan based on seismic indicators	The accuracy is 81.2% using supervised learning with category “Yes” and “No” means that earthquake happened or not,.
Deep Learning	Q.Wang et al. [18]	2020	LSTM	Earthquake prediction by learning the spatial-temporal correlation between earthquakes in different areas	LSTM with decomposition with accuracy value is 87.59%
	R. Li et al. [19]	2020	CNN	Earthquake prediction by combining explicit and implicit earthquake features	Accuracy is 92.42% divide of 5 class magnitude
	Bilal Aslam1 et al [20]	2021	ANN	Numerous studies have been conducted to identify the region's seismic characteristics for improved disaster management.	Evaluation using Accuracy with value is 69%

Compared to the previous method, earthquakes are not categorized as dangerous or not, so the earthquake patterns that are formed may not affect the community because they do not have much of an impact. This study observes the pattern of earthquakes that have an impact only for warnings. From table 1. One of potential improvements with Sequential Rule Mining (SRM) method because this method suitable for earthquake dataset. SRM has been used for another domain for example tourist destination, and customer data of a telecommunication service provider. For evaluation of this method using confidence value each rule that created. Vu, H. Q. et al [21] using SRM and get one of confidence value from the rule (Monaco => Paris) is 93.2%. Another research using SRM, Santoso [22] success to implemented on the sales pattern with case study of Indomaret Tanjung Anom. The highest confidence value of a rule is 97.50%.

2. Methods

This chapter discusses the research methodology applied in this research. It describes the research objectives and the methodology for achieving those goals. The purpose of this study is to apply a new approach in predicting the sequence of earthquake events using SPM to get pattern, SRM to evaluate the pattern and CNA as a weight of evaluation. Section 2.1 describes how to be scrapping the earthquake data website at BMKG and Section 2.2 describes the proposed method. The research methodology is depicted in Figure 1 diagram below:

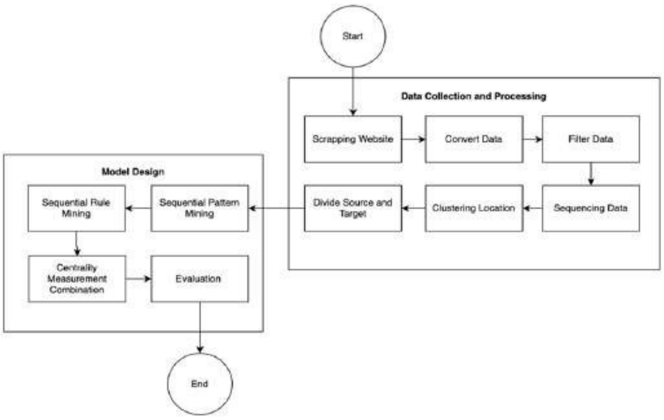

Figure 1. *Research Methodology Diagram*

2.1 Data Collection and Processing

Data is a collection of information that has a hidden meaning for each pattern. Processed data must be from clear and reliable sources so that knowledge can be obtained in the data set. The source of data on earthquake events in Indonesia is accommodated by the Meteorology and Geophysics Agency (BMKG) which is opened to the public at the website url http://repogempa.bmkg.go.id. The data available on the BMKG website was taken with a website scrapping technique using selenium Python.

2.1.1 Scrapping Website

Earthquake data from the BMKG website is freely available, but only for a 20-day range. For data beyond five years, a fee is required. To overcome this limitation and reduce costs, a web scraping technique is used to extract data from HTML tags on the BMKG website. This method automates the browser to gather data efficiently.

To implement web scraping, the selenium library in Python is prepared, and a web driver is installed according to the browser used. The code is then created to retrieve earthquake data such as date, time, latitude, longitude, depth, magnitude, tsunami, and region from the BMKG website.

2.1.2 Convert Data

The data obtained from the scrapping process produces an unstructured txt file, the format must be adjusted to the input in the Sequential Pattern Mining method. The txt data is converted into a data frame in Python so that it is categorized according to the parameters taken. The data parameters taken are date, time, latitude, longitude, depth, magnitude, tsunami, and the area of the earthquake.

2.1.3. Filter Data Based on Magnitude and Depth

This study filters earthquake data to focus on events with magnitudes greater than 4 and depths of less than 100 km, aiming to predict locations that could impact nearby populations. After applying these criteria, the dataset was refined to 64,978 records, covering earthquakes in Indonesia from 2008 to 2022. The purpose of this filtering process is to concentrate on seismic events that are both strong and shallow, which are more likely to cause surface-level damage. By doing so, the study enhances the relevance of its predictions for disaster preparedness and emergency response planning, making the results more applicable to public safety and risk management efforts.

2.1.4 Define Input of SPM

The input for the Sequential Pattern Mining (SPM) method is location data sequences, requiring the conversion of the data frame into a data sequence. The author focuses on two key parameters: location clusters and time difference. Earthquakes in Indonesia are influenced by the activity of three major tectonic plates: Eurasian, Indo-Australian, and Pacific. When the Eurasian and Indo-Australian plates collide, earthquakes can occur in fault zones. Clustering helps identify connections between earthquake locations.

The second parameter, time difference, determines whether locations form sequences or subsequences. Sequences are location events within a time period, while subsequences are simultaneous events in that period. The time difference is calculated between consecutive earthquake events. This study uses three time frames: less than 12, 24, and 48 hours, with subsequences defined as half of the sequence limit (e.g., 6 hours for a 12-hour sequence limit).

2.1.5 Divide Source and Target

This process is aimed to create a new data set. Each record in the new dataset consists of sequence earthquakes within 12 hours in neighbored clusters. In addition to 12 hours period, this research also uses 24 hour period and 48 hours period. An example of defining the source and destination from table 3-3 is the example in the first row, namely the source is in Papua, the destination is in Maluku. The second row is not related to the first line because the second sequence because not in the location cluster and time difference, so for the second row, the first source is in Maluku Utara, the first destination is in Sulawesi Utara. Then the second source is in Sulawesi Utara which was previously the first destination on the second row.

2.2 Model Design

After getting data from official sources at BMKG. The next step is to design a way to process the data that has been obtained by combining the SPM and Centrality Measurement methods. This combination is obtained by calculating the centrality technique which is used as the weight of each node.

2.2.1 Calculate Centrality Measurement

Calculation of centrality makes the nodes in the network more scalable. Each calculation of the centrality technique produces a different value for each node. This study took two centrality measurement techniques, namely betweenness centrality and eigenvector centrality. A high betweenness value means that the node is most often traversed by the shortest path. While a high eigenvector value means that the node is connected to a node that also has high connectivity.

2.2.2 Sequential Pattern Mining using Prefix Span

Sequential pattern mining method is used to get the pattern of a series of earthquake activities with sequenced input data. The collection of patterns found by Prefix Span can be used as a prediction of the next earthquake. The following is an overview of the prefix span system flow that can be seen in the pseudocode table 2.

Table 2. *PrefixSpan Algorithm*

Prefixspan Algorithm

Input : Sequence of database
Output :Pattern of sequence database

Step :

1. Call PrefixSpan(<>,0,S)
2. Procedure PrefixSpan(a, l, $S|_a$)
3. The Parameter are (1) a is a sequential pattern (2) l is the length of a (3) $S|_a$ is a projected-database if $a \neq \langle\rangle$, otherwise it is the sequence database D
4. Scan $S|_a$ once, find each frequent item b, such that:
5. (a) b can be assembled to the last element of a to form a sequential pattern
6. (b) <b> can be appended to a to form a sequential pattern
7. For each freaquent item b, append it to a to form a sequential pattern a'
8. For each a' , construct a' -projected database $S|_{a'}$ and Call PrefixSpan(a' , $l+1$, $S|_{a'}$)

2.2.3 Sequential Rule Mining using RuleGrowth

The Sequential Rule Mining method is used to obtain earthquake rules from the patterns obtained in sequential pattern mining. The results from the sequential rule mining process are used as a decision making for the next earthquake prediction. RuleGrowth uses a pattern-growth approach that it can be much more efficient and scalable for discovering sequential rules.

2.2.4. Combination of Centrality Measurement with SRM

After getting the earthquake patterns and their support. The pattern is calculated by the value of centrality. The pattern has nodes, each node has a centrality value, the centrality value in the pattern is added up and then multiplied by the support value for the pattern. The formula can be seen below.

$$Conf(X,Y) = \frac{Frequency\ (X,Y)}{Frequency(X)} \tag{1}$$

Frequency(X,Y) is the number of occurrences of items X followed by Y in the database sequence, while Frequency(X) is the number of occurrences of item X in the database sequence. The division between the value of Frequency(X,Y) with Frequency(X) gets the confidence value.

$$conf_{cv} = conf(X,\ Y) * cv \tag{2}$$

Where conf_cv is a combination of centrality measurement weighting values with confidence values. conf is the value of the confidence rule, and cv is the centrality value of consequent of the rule generated from SRM.

2.2.5. Accuracy of Rule

The algorithm for calculating accuracy is designed to evaluate how well a model predicts earthquake locations using a set of test data. It begins by initializing counters for correct and incorrect predictions, starting at zero, and an index variable i set to zero to iterate through the test dataset. In each iteration, the algorithm retrieves the location data from two consecutive rows in the dataset. It then checks if the model has a rule applicable to these data points. If such a rule exists, all relevant location values are stored in an array called location_array. The algorithm then checks if the next earthquake location, as predicted by the model and within the specified time range, matches any location in the location_array. If a match is found, the correct prediction counter is incremented; otherwise, the incorrect prediction counter is updated. This process repeats until all data points are evaluated. Finally, the accuracy of the model is calculated by dividing the number of correct predictions by the sum of correct and incorrect predictions, yielding an accuracy value between 0 and 100%.

The researchers calculate the accuracy of the SRM model by accommodating the number of rules that are confirmed to be true and false. For example, there is an earthquake in Maluku in the first row, followed by an earthquake in Papua in the second row.

3. Results and Discussion

This section contains the results and discussion of the research topic, which can be made especially the application of the method used, either simply by presenting the existing data in the study. This section also represents explanations in the form of explanations, pictures, tables and others.

3.1 Experiment

This experiment aims to prove the hypothesis in section 1.4 that the addition of the centrality measurement value factor will increase the accuracy in predicting earthquakes. The amount of the dataset is 64,978 which is divided into training data as much as 51,982 data (80%) and testing data as much as 12,996 data (20%). The parameters observed in the experiment are time selection, number of clusters, and the availability of a centrality measurement. The experimental table can be seen in table 4.

Table 3. *Total Experiments for this research*

Experiment	Time Frame	Cluster Location	Centrality Measurement
1	12 hours	5	No
2	12 hours	7	No
3	12 hours	9	No
4	24 hours	5	No
5	24 hours	7	No
6	24 hours	9	No
7	48 hours	5	No
8	48 hours	7	No
9	48 hours	9	No
10	12 hours	5	Yes
11	12 hours	7	Yes
12	12 hours	9	Yes
13	24 hours	5	Yes
14	24 hours	7	Yes
15	24 hours	9	Yes
16	48 hours	5	Yes
17	48 hours	7	Yes
18	48 hours	9	Yes

3.1.1 Experiment Without Centrality Measurement

Experiments were carried out to find the right combination of parameters so as to produce the best predictions. The output of several experiments are the rules generated by evaluating the confidence value. Table 4-2 is an example of the output from the results of the first experiment by considering the time frame of 12 hours, the number of cluster locations as many as 5 clusters, and the availability of a centrality measurement is not available. In this experiment the rules that have been formed with the confidence value as a reference are used in making decisions to predict the next earthquake. The researcher makes four scenarios to determine whether the prediction is right or wrong. The first scenario takes the rule from the top-1 confidence value, the second scenario takes the rule from the top-3 confidence value, the third scenario takes the rule from the top-5 confidence value, and the fourth takes the top-7 confidence value rule. Accuracy results without using centrality can be seen in Figure 2.

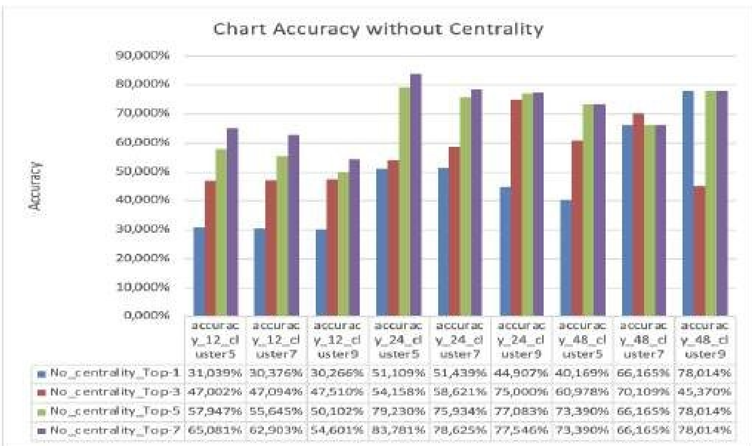

Figure 2. *Experiment without centrality measurement*

3.1.2 Experiment Using Centrality Measurement

The experiment examines the impact of centrality measurement on model accuracy, using two methods: Eigenvector Centrality and Betweenness Centrality. Each node or location has a centrality value, which, combined with the confidence rule value, creates a new centrality weight. This results in two new rule patterns, Confidence Betweenness and Confidence Eigen. Unlike experiments that only consider confidence, incorporating centrality adds another layer of evaluation. Betweenness Centrality focuses on nodes along the shortest path, while Eigenvector Centrality connects with highly connected or popular nodes. The experiment aims to observe the importance of key nodes in a network.

a. Betweenness Centrality

Betweenness centrality is a measure of this indicates its role as a node bottleneck. Nodes are important if it becomes communication bottleneck. Node as a bridge between the two community. Betweenness centrality of nodes calculated by adding all the shortest A path containing nodes. Same with scenarios without centrality, the researcher makes four scenarios to determine whether the prediction is right or wrong. The first scenario takes the rule from the top-1 confidence betweenness, the second scenario takes the rule from the top-3 confidence betweenness, the third scenario takes the rule from the top-5 confidence betweenness, and the fourth takes the top-7 confidence betweenness. This centrality technique is observed with an accuracy value that can be seen in Figure 3.

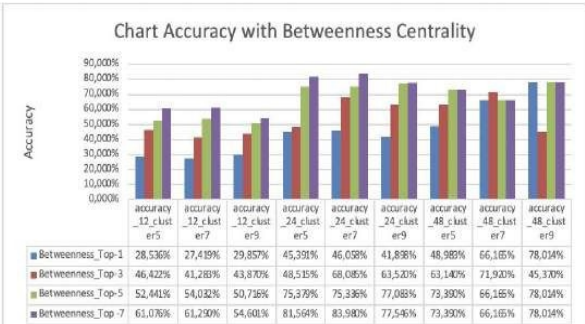

Figure 3. *Experiment using betweenness centrality*

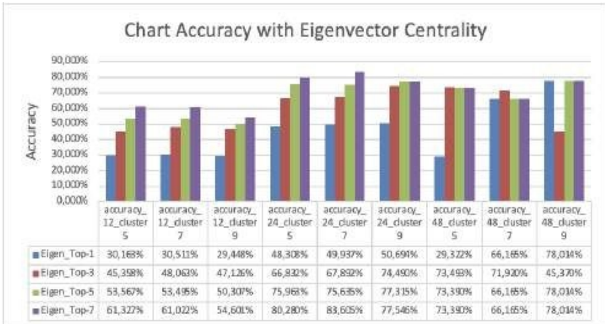

Figure 4. *Experiment using betweenness centrality*

From the chart above, it shows that the time frame is 24 hours with cluster 7 and using the Betweenness Centrality value to get the highest accuracy value, which is 83.980%. The lowest accuracy is when using the parameter time frame of 12 hours with cluster 9 and using the Betweenness value with an accuracy obtained of 27.419%.

b. Eigenvector centrality

Experiments using the centrality eigenvector technique were carried out to give weight of nodes/locations by paying attention to the connection to popular nodes/locations. If the more relationships with popular nodes, then eigenvector value is high. This centrality technique is observed with an accuracy value that can be seen in Figure 4.

From the chart above, it shows that the time frame is 24 hours with cluster 7 and using the Eigenvector value to get the highest accuracy value, which is 83.605%. The lowest accuracy is when using the parameter time frame of 48 hours with cluster 5 and using the Eigenvector value with an accuracy obtained of 29.332%.

3.1.3 Comparison between Previous Method and Proposed Method

The researchers succeeded in building a predictive model, from all experiments the highest accuracy value was obtained in the combination of SRM with betweenness centrality resulting in 83.940%. To see the performance comparison of the previous method can be seen in the table 4.

Table 4. *Comparison between previous methods and proposed method*

Method	Performance
CNN	Accuracy = 92.42%
SVR-HNN	Accuracy = 90,6%
LSTM	Accuracy = 87.59%
Linear Programming Boost Ensemble Classifier	Accuracy = 65%
PrefixSpan	Accuracy = 65%
Sequential Rule Mining	Confidence Value = 93.2%
SPM+SRM+CNA(Proposed-Method)	**Accuracy = 83.980%**

Based on the table above, the highest accuracy is found in the CNN method with accuracy about 92.42%. The scheme that is run uses the division of 5 classes based on the magnitude, the earthquake prediction in this study is to determine the existence of a magnitude class from the next earthquake location. This scheme does not match the scheme in my research. My research wants to predict earthquake if it is known where the location of the previous earthquake was with a predetermined time span. The accuracy value is used by most research on earthquakes to find out how true the model is built by first defining the category class.

The use of betweenness and eigenvector centrality as weights significantly enhances the model's ability to predict earthquakes by focusing on the structural importance of events within the seismic network. This approach not only improves accuracy but also provides a more comprehensive understanding of the underlying dynamics of earthquake occurrences, leading to better preparedness and response strategies.

4. Conclusion

This study introduces an earthquake prediction system using Sequential Pattern Mining to identify patterns from historical data and Sequential Rule Mining to derive rules from those patterns. The experiments revealed that using a 12-24 hour time frame, 7 clustered locations, and centrality measures resulted in an accuracy of 83.980%. When using a 24-hour frame and eigen centrality, accuracy was 83.605%. Without centrality, accuracy dropped to 78.625%. Betweenness centrality improved accuracy by 5.355%, and eigenvector centrality by 4.98%. This research demonstrates that centrality weights can significantly enhance prediction accuracy, making it a valuable tool for disaster preparedness and response, potentially saving lives by providing timely warnings. Future research could improve results by adjusting cluster locations based on latitude and longitude, using more precise city data, and predicting earthquake magnitude and depth.

Acknowledgement

This research was supported by the School of Computing of Telkom University, who gave the opportunity for us to do this research.

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