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Forecast earthquake precursor in the Flores Sea

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ABSTRACT

Artificial intelligence (AI) can use seismic training data to discover relationships between inputs and outcomes in real-world applications. Despite this, particularly when using geographical data, it has not been used to predict earthquakes in the Flores Sea. The algorithm will read the seismic data as a pattern of iterations throughout the operation. The output data is created by grouping based on clusters using the most effective WCSS analysis, while the input features are derived from the original international resource information system (IRIS) web service data. Given that earthquake prediction is an effort to reduce seismic disasters, this research is essential. By generating predictions, it can reduce the devastation caused by earthquakes. Using the support vector machine (SVM), hyperparameter support vector machine (HP-SVM), and particle swarm optimization support vector machine (PSO-SVM) algorithms, this study seeks to forecast the Flores Sea earthquake. According to the estimation results, the SVM algorithm's evaluation value is less precise than that of the HP-SVM, especially the linear HP-SVM and HP-SVM Polynomial models. However, the HP-SVM RBF model's accuracy rating is identical to that of the traditional SVM model. The improvement of the PSO-SVM model, which has the finest gamma position and a value of 9.

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1. INTRODUCTION

The Flores back arc thrust is the cause of the Flores Sea's seismic activity [1], [2]. The Kalaotoa fault, which was discovered by the December 14, 2021, earthquake, is a new fault [3]–[5]. According to the Meteorological, Climatological, and Geophysical Agency (BMKG) study, East Nusa Tenggara will experience an increase in the number of earthquakes in 2022, with a total of 3,621 occurrences. This data pertains to the Flores Sea's geographic location, with water depths ranging from 300 metres (in the centre) to 5,500 metres (in the south) and a precipitous and undulating morphological structure in the southeast see Figure 1. Therefore, geological structure may govern the Flores Sea [6], [7]. The study of earthquake forecasting is one of the numerous endeavours scientists make to mitigate the effects of earthquake disasters [8]. Marhain *et al.* [9], claims that an artificial intelligence (AI) method can be used to predict earthquakes. Using earthquake data compiled and recorded in a database, it is possible to calculate algorithm parameters [10]. As a first step in mitigation, it is necessary to take steps to reduce earthquake damage [11], [12]. One of them is using algorithms to forecast the future.

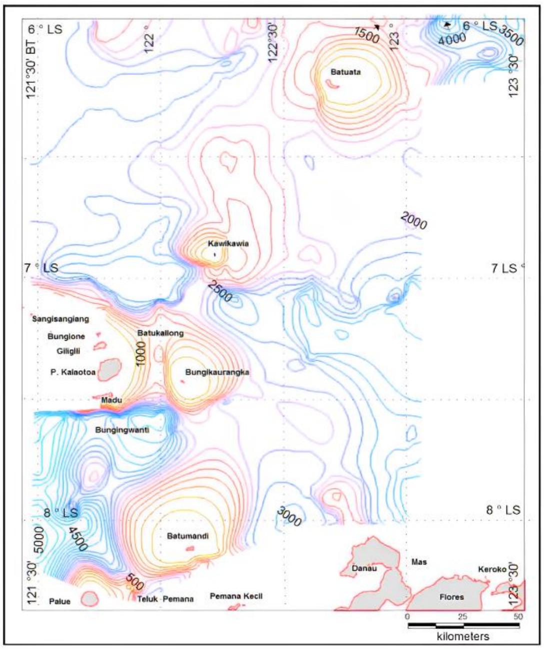


Figure 1. Flores Sea bathymetry

This study presents and investigates the effect of spatial parameters on the performance of three earthquake prediction algorithms in the Flores Sea, one of the most earthquake-prone regions in Indonesia. This study contrasts the effectiveness of the support vector machine (SVM), hyperparameter support vector machine (HP-SVM), and particle swarm optimization support vector machine (PSO-SVM). This study aims to determine the optimal optimisation of the SVM, HP-SVM, and PSO-SVM algorithms for earthquake prediction given this context.

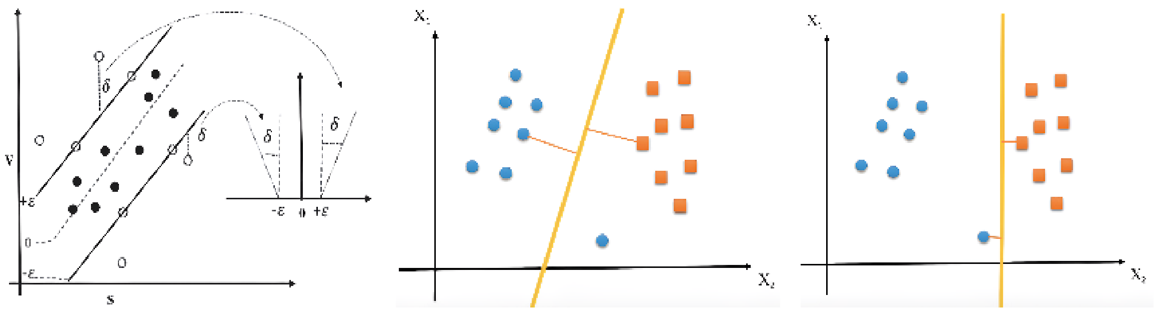
2. RELATED WORK

Since the 19th century, research on earthquake prediction has been conducted. Uyeda [13] has devised the van method as a seismo-electromagnetic signal-based short-term earthquake prediction technique. In contrast, Geller [14] has examined earthquake precursors within a specific time frame in the same year. Based on the findings of these two investigations, it is evident that the seismo-electromagnetic signal is insufficient for use as precursor data. Because it still contains noise or noise data. This is due to factors such as local characteristics, permittivity, and background disturbance [15]. Seismic, geoelectromagnetic, geodesic, gravity, and soil fluids are additional parameters that can be introduced to the precursor [16]. The mathematical model developed by Gutenberg and Richter is used to predict the distribution of earthquakes over time by establishing a relationship between their attributes [17]. On the other hand, Petersen *et al*. [18] put up a model that is independent of time and conforms to the poisson distribution. A few methods also make use of artificial neural networks. Negarestani *et al.* [19], for instance, employs back propagation neural network to distinguish between several aberrant antecedents and typical environmental fluctuations. Using information on the magnitude of earthquakes that have occurred in China, Liu *et al.* [20] employed the radial basis function. Hossain *et al.* [21] created an expert system technique in the meantime by using historical data that uses a 24-hour period to partition the world into several segments.

AI algorithms are machines that are capable of learning just like humans. This is determined without the need for prior knowledge [22] based on data trends that occur within a specific time frame. One of the many scientific disciplines in which AI has been applied thus far is the geohazard field. Wieland *et al.* [23] reported that machine learning (ML) utilising SVM can be used to forecast earthquakes. Syifa *et al.* [24] asserts that SVM and artificial neural network (ANN) have comparable correlation results and accuracy values for tracing earthquake damage when compared. Other evaluations explain that the compared algorithms SVM, decision tree, random forest, and logistic regression have limitations for each data signalling station [9]. Due to the high number of false alarms and missed detections generated by these algorithms, human supervision is always required. Therefore, ongoing research is needed to produce practical results for the application of highly reliable real-time seismic event detectors on continuous seismic data.

Figure 2 shows the SVM algorithm parameters. The particle filter estimates the values of parameters C, Epsilon, and Kernel Scale in order to enhance support vector regression performance. Testing and experimenting are typically necessary to establish these values. They are essential to the loss function that measures the approach's accuracy. As seen in Figure 2(a), these values approach zero, indicating that the forecasts fall inside the intended range. The number of support vectors with these parameters and the accuracy of the prediction results are generally closely correlated. Results inside the intended range will be smoothed out by a properly fitted support vector regression [25]. Figure 2(a) illustrates this point: if the chosen values significantly exceed the data range, it will be difficult to get good results. Conversely, if the values are near to zero, we will have an issue with overfitting, which occurs when the model has more freedom than is necessary and yields undesirable results when testing the data; in other words, the model is generated more accurately on training data than on test data.

The next step is to determine the kernel function parameters used to map non-linear data into linear form, and this must be done manually. This parameter represents a compromise between the error rate during training and the complexity of the model [25]. The greater the final error reduction results, however, if the C value is increased too much, it will increase the risk of losing the generally applicable classification ability. Therefore, it is recommended to use the support vector regression approach judiciously to achieve optimal results applicable to all data points. Additionally, this can also affect the time required during the training phase. If the C value is too small, then the classification model will become very complex. Therefore, C values must be chosen carefully to minimize errors during training and allow generally applicable results. The large number of C values can be seen in Figure 2(b), while the small number of C values can be seen in Figure 2(c).



(a) (b) (c)

Figure 2. SVM algorithm; (a) control function parameters, (b) large parameters, and (c) small parameters [26]

3. METHOD

In the process, the algorithm will read the earthquake data as an iteration pattern. Time of occurrence, latitude data, longitude data, profundity data, and magnitude data are used as input features. While the output data is derived by grouping based on clusters using the best WCSS analysis, the data is grouped based on clusters. Meanwhile, the output data obtained is accuracy by grouping based on clusters using the best WCSS analysis. Figure 3 depicts the complete research flow and the researcher as control.

The research data were obtained from earthquake and seismological repository data mining sources, which were retrieved from the international resource information system (IRIS) database. In this step, data processing is carried out by presenting data in GeoCSV formats obtained previously through web scraping from the IRIS data center using the IRIS data management center (DMC) federation of digital seismograph networks web services (FDSNWS) event Web Service Documentation. Next, the feature engineering process was carried out as the initial stage of data preprocessing consisting of 1,531 data. This section identifies data sets as useful information. This stage is important because it compresses the quantity of data into data that can be processed by the algorithm without disturbing the relationships between the data [1]. The next stage is to clean the data. Data cleansing is necessary to eliminate errors. This necessitates the elimination of superfluous signals or noise, such as interference from individuals or machinery. Using techniques to filter, blend, and eradicate outliers, clean seismic data can be processed. After identifying and segregating the significant phases, feature extraction is carried out to elucidate the relevant seismic properties. The normalisation process is then implemented. In certain situations, data normalisation can be used to guarantee consistency and an accurate comparison of extracted features. Normalisation can be achieved by adjusting the scale or range of feature values so that they are uniform and simple to compare. Next is the model training scenario stage with a comparison of 70% training data and 30% test data. Training the model affects the availability of activation functions, the number of neurons used, and optimization as a performance criterion obtained from the values obtained by contrasting accuracy parameters [9]. The final stage is to carry out validation data and evaluate algorithm performance.

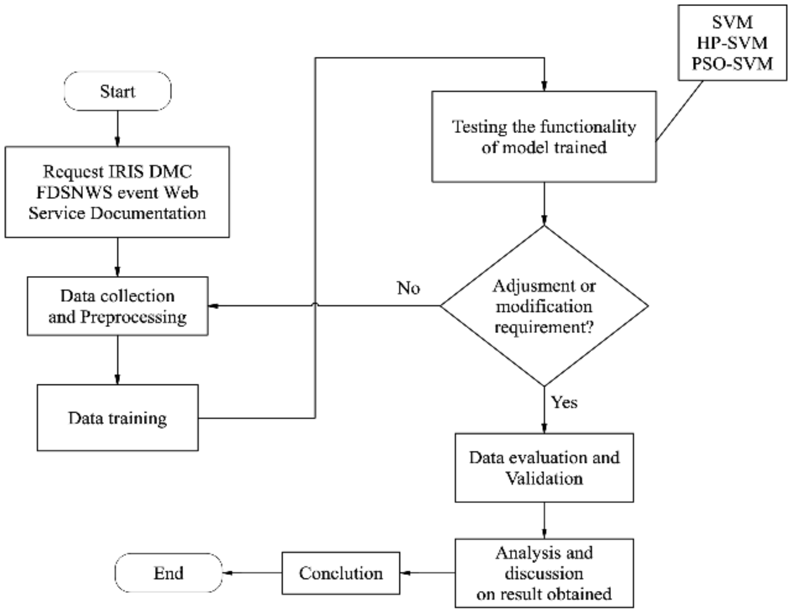


Figure 3. Research flow

4. RESULTS AND DISCUSSION

The algorithm proposed in this study will be evaluated using seismic data from the IRIS DMC web service between 1992 and 2022. This investigation compares SVM, HP-SVM, and PSO-SVM using seismic data. Seismograph networks can now record even minor earthquakes due to technological advancements in earthquake recording and the global expansion of seismograph stations over the past four decades. As traditional seismographs only detect significant earthquakes, seismological researchers have tremendously benefited from small earthquake data recorded over a number of earlier time periods that have become available due to advancements in the field of earthquake data recording. Nevertheless, because large earthquakes have a wider geographic reach, cause more damage to the Earth’s surface, and have a higher probability and greater accuracy of being recorded over a lengthy period of time, they are becoming increasingly significant for the study of earthquake trends. Three sections make up the visual representation of seismic data in Figure 4. Two-dimensional seismic data plots are shown in part Figure 4(a), while three-dimensional seismic data plots are shown in part Figure 4(b). A graph in part Figure 4(c) displays the average seismic data trend for the Flores Sea region over a 30-year period. The seismic data used to examine the region’s geological structure and seismic activity is represented visually in this Figure 4.

This information is retrieved using a URL builder and service implementations employing FDSNWS, specifically service interface event v.1. The limiting parameter employed is the minimal magnitude value 4 [27], which was measured for 1,531 events. This data is collected only for the magnitude of the earthquake that can be felt, so as to reduce the effects of noise caused by precursors that the recording station did not observe. This will also be beneficial during the data preprocessing and data cleansing phases. Cleaning the data of missing, incorrect, or inconsistent values is a crucial phase in the process of data analysis. The imputation technique is one method for handling missing data values. Imputation techniques are used to estimate absent values based on currently available data or data patterns. To prevent data loss, the categorization procedure is based on seismic data collected prior to the data cleaning stage. In this section, we use MCMC imputation [28]. This method is used to fill in missing values in a dataset by simulating the probability distribution of the missing values based on the information presently available [29]. Using the concept of a “Markov Chain”, each iteration modifies the calculated values to bring the algorithm closer to a sample that is more representative of the in-question probability distribution [30]. In addition, the effectiveness of MCMC imputation relies on the selection of suitable parameters and models [31]. Figure 5 illustrates the effectiveness of imputation because it was able to provide the dominant colour block with no missing data.

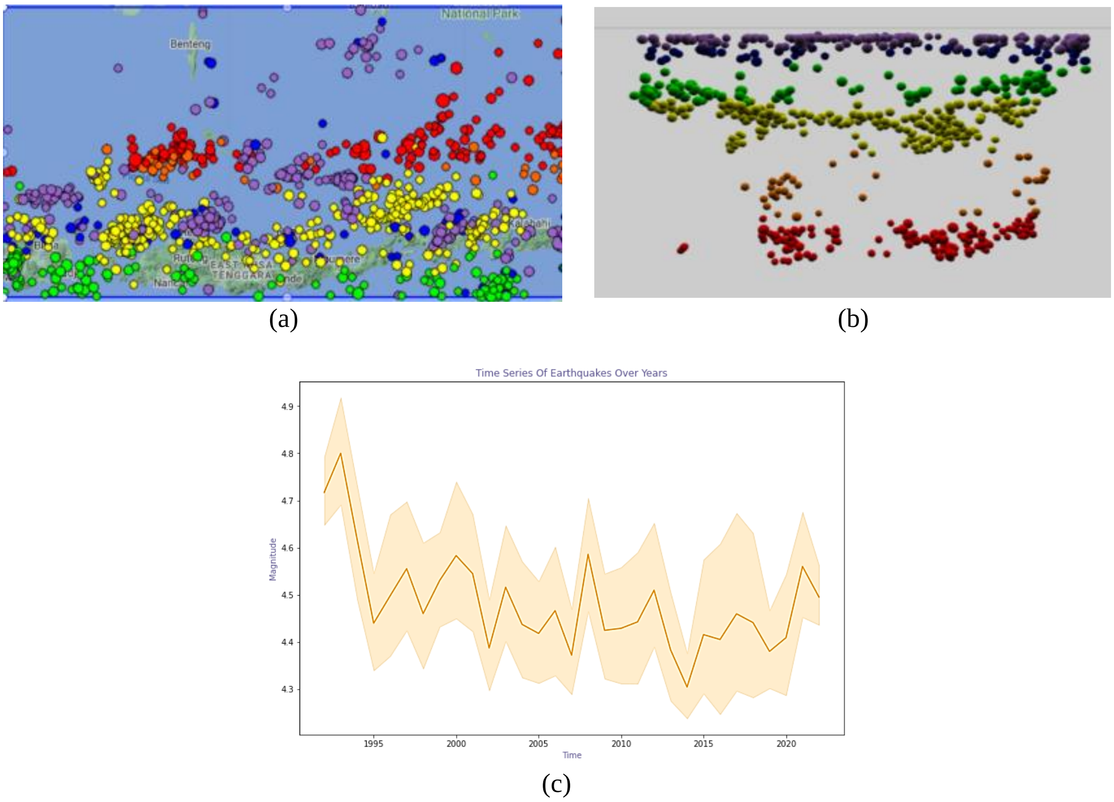


Figure 4. The visual representation of seismic data; (a) seismic data plot, (b) 3D seismic, and (c) trends in Flores Sea 30-year seismic average data

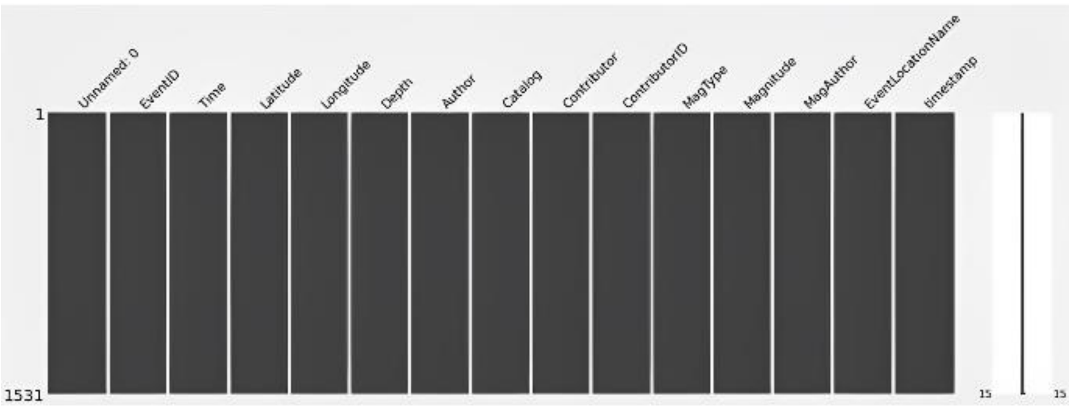
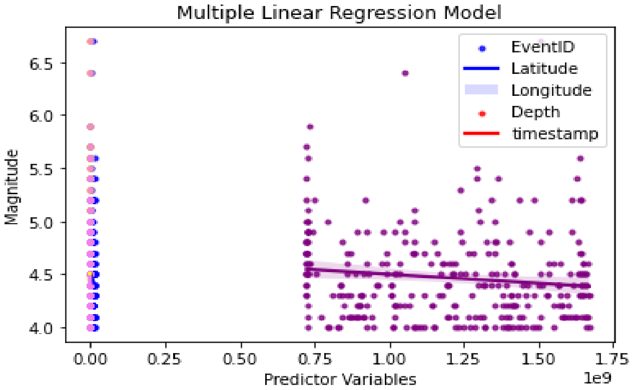
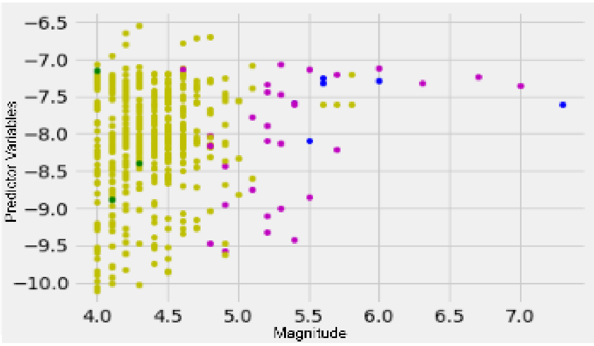


Figure 5. The process of imputation and feature cleaning

Determine the dependent variable and the independent variable as the next step. The independent variables in this section are the EventID data, the latitude data, the longitude data, the depth data, and the addition of timestamps. A timestamp is a piece of information that specifies the exact time and date an earthquake occurred. Typically, the timestamp includes the date and time an event occurred. Utilising timestamps permits the recording and chronological tracking of events or actions, thereby facilitating data analysis and administration [32]–[34]. While the dependent variable is magnitude data. With a coefficient of determination of -0.02 SVM and an MSE value of 0.17, it comes out that the obtained results are still quite small. There are two sections to Figure 6. The linear regression test result is shown in part Figure 6(a), and the SVM technique prediction result is shown in part Figure 6(b), employing magnitudes of mb (yellow), mww (blue), and MLv (magenta). This picture shows how various magnitude types are used to produce predictions by linear regression models and SVM, as well as how the predictions vary depending on the three magnitude types (mb, mww, and MLv).



(a)



(b)

Figure 6. Regression test and SVM prediction (a) linear regression test and (b) prediction of SVM with magnitude type sizes, namely mb (yellow), mww (blue), and MLv (magenta)

Body-wave (mb) is a method for quantifying the size of an earthquake by its magnitude. This magnitude is calculated based on the amplitude of the earthquake's P (primary) and S (secondary) waves [35], [36]. The magnitude mb is typically used to measure weak to moderate earthquakes whose epicentres are near the monitoring station. The moment magnitude scale (mww) is a more modern and inclusive method of measuring magnitude [37], [38]. This method utilises more comprehensive seismic data that encompasses the surface area involved in the earthquake fault. MLv (local magnitude) is a magnitude derived from the amplitude of the earthquake wave recorded by the local seismic station [39], [40]. This technique is best suited for measuring small to moderately powerful earthquakes with epicentres close to the monitoring station. Therefore, the primary distinction between the three magnitude types resides in the calculation method, the seismic data employed, and the range of earthquake intensities that can be accurately measured by each magnitude type. mww is a more modern technique that tends to produce more accurate results, particularly for large earthquakes, whereas mb and MLv are better suited for minor to moderate earthquakes. Due to the complexity of the data and the fact that the correlation value is still quite low, the labelling procedure is carried out using an int64-converted label encoder for the data object type. This procedure involves a number of the characteristics shown in Table 1 and Figure 7 represents the correlation using the heatmap following the label encoder operation.

This procedure generates a new data structure, which is then used to add cluster attributes, which are the dependent variables. The cross-validation method, which divides data into training data and test data, is used as the initial phase in calculating validation values [1]. Using the WCSS tool and the Elbow methodology, we ultimately divided the cluster into four clusters see Figure 8. According to Santosa [41], an approach to categorization will classify objects. Consequently, each categorization attribute in the new data will be pertinent [42], [43]. After the train-validation split, there are 1,071 training data and 460 test data, which is a significant difference. The two variables constitute the set of independent variables and magnitudes for training. Table 2 provides a comprehensive comparison of the SVM and HP-SVM algorithms' precision.

Table 1. Unique data

	Author	Catalog	Contributor	Contributor ID	Mag type	Mag author	Event location name
Count	1,531	1,531	1,531	1,531	1,531	1,531	1,531
Unique	13	2	2	1,531	11	11	6
Top	ISC	ISC	ISC	us6000j6aa	mb	NEIC	FLORES REGION INDONESIA
Freq	1,088	1,162	1,162	1	1,336	774	773

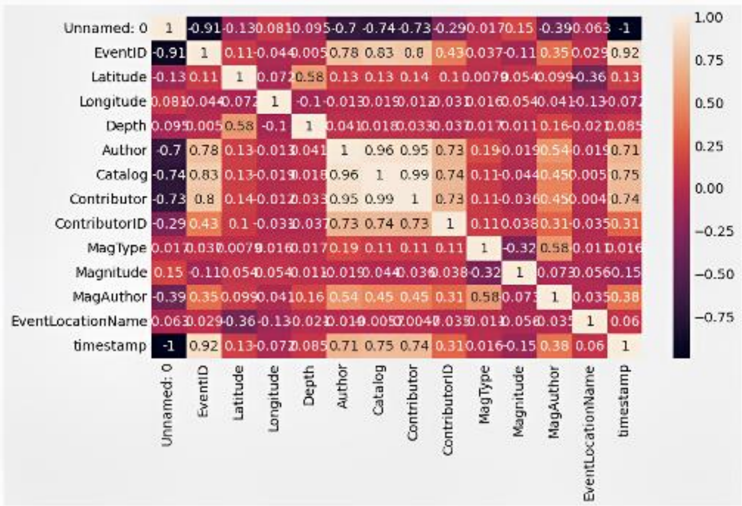


Figure 7. Correlation results using a heatmap after the conversion process with encoder labels

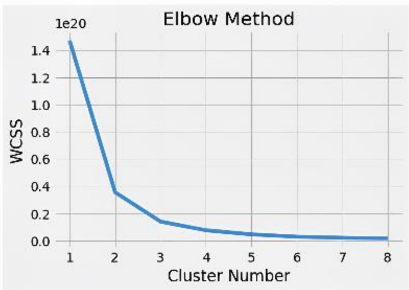


Figure 8. Elbow method

Table 2. Algorithmic accuracy

Algorithm	Accuracy
SVM	0.58
SVM hyperparameters	
1. Linear SVMs	0.99
2. SVM polynomials	1.00
3. SVM RBF	0.58

We employ 15 data features for this analysis. The SVM-PSO algorithm is nearly the quickest in all phases. In other words, the accuracy of the method is unaffected by the use of distinct data at each cross-authentication stage. To assess the effect of various topographies on performance, we've categorised the characteristics into categories. Figure 9 demonstrates that the SVM-PSO algorithm has the highest level of accuracy, with a gamma value of 9.

A particle with identification number 100 in this experiment has successfully attained an error level of 0.0 in both the test and training datasets. The two model parameters that are being checked are gamma and c. When an error of 0.0 is reached, 100 particles yield a gamma value of around 8.90189894 and a c value of approximately 2.08802304. The 10th iteration yielded the best results, though, with the optimal position [9. 2.13218182], which likewise yields an error rate of 0.0 on both datasets. All things considered, this experiment was successful in identifying a model-parameter configuration that produces outstanding model performance with zero error on both training and test data, with gamma of around 9 and c of about 2.13218182.

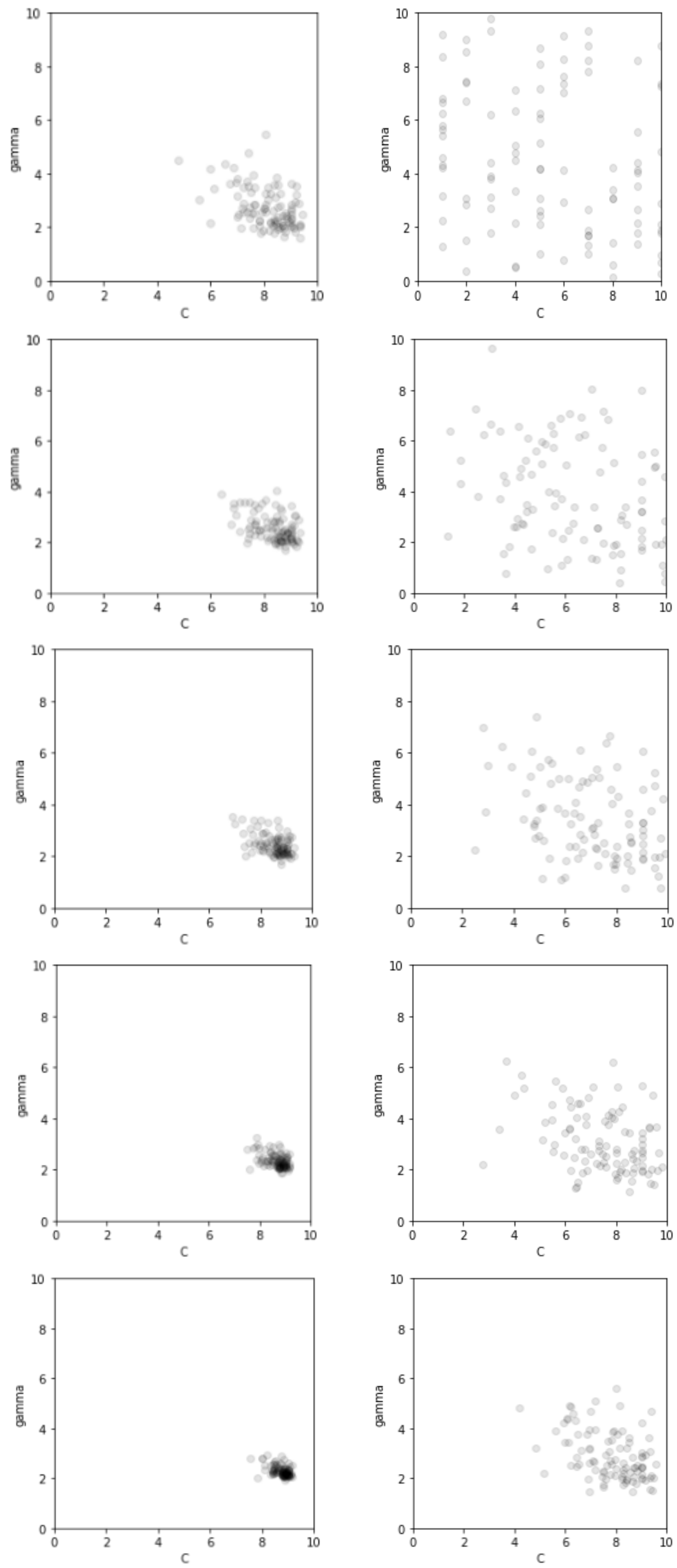


Figure 9. SVM-PSO

Typically, the gamma parameter in PSO is used to regulate two crucial factors in exploratory search algorithms. Gamma regulates the amount by which particle velocity can vary between iterations. High gamma values permit particles to undergo significant positional changes and provide the capacity to explore a larger region of the search space. A low gamma value, on the other hand, limits the change in particle velocity, causing the particles to concentrate more on locations identified as potentially containing optimal solutions. This improves the convergence of algorithms to improved solutions and aids in the exploitation of promising regions. Choosing the optimal gamma value can have a significant impact on the efficiency of the PSO algorithm [44]. The optimal value depends on the characteristics of the problem being solved and may necessitate repeated experimentation with a variety of values in order to determine the most appropriate configuration [45]. Gamma values may go by other names in PSO implementations, such as inertia weight or weight factor [46]. Nonetheless, the fundamental principle remains the same, namely regulating how much the particle's velocity varies between iterations.

Scientists have long been interested in earthquake prediction in order to provide opportune warnings that save lives and reduce property damage. In recent decades, scientists have been able to record and categorise the effective parameters of earthquakes through meticulous research, including the application of the SVM algorithm [42], [43], [47]. SVM has made numerous contributions to earthquake prediction research as a predictor. Consequently, SVM is the best prediction method used in recent investigations [26], [48]. The objective of the SVM algorithm is to search in N-dimensional space (N is the number of features) for hyperplanes that unambiguously classify the input points [49]. There will be numerous hyperplanes separating the two classes of data points. After training, SVM returns the field with the greatest margin, that is, the field with the greatest distance between the data points of the two classifications. Increasing margin spacing increases the likelihood that future data points will be correctly classified.

Particle swarm optimization is a swarm intelligence-based global random search algorithm. Similar to other evolutionary algorithms, PSO has robust search comprehension properties. The PSO algorithm is also based on the concepts of population and evolution, which enable the search for optimal solutions in complex spaces through the cooperation and competition of individual agents [50]. The absence of evolutionary operator operations such as crossover, mutation, and selection for individuals is an advantage of the PSO algorithm. Therefore, PSO has a strong socio-biological foundation with few parameters, is simple to comprehend, and can solve nonlinear problems [51], [52].

5. CONCLUSION

A comprehensive evaluation of novel earthquake prediction scenarios is necessary. Extremely crucial for risk assessment for future preventative measures and early warning. This will be difficult to accomplish due to the impact of factors such as data noise on seismic detectors on the availability of data. To accomplish this, it is necessary to conduct a preliminary analysis that can be used to filter noise data, enabling the sensor to record only seismic data sources and not other data. The technique employs a cross-correlation alignment procedure that can generate coherent, in-phase P and S waves. It is very beneficial when the detector is converted to a normalised value structure in order to calculate the estimated value. The estimation results indicate that the SVM algorithm's evaluation value is less accurate than the HP-SVM, particularly the linear HP-SVM and HP-SVM Polynomial models. However, the accuracy value for the HP-SVM RBF form is identical to that of the conventional SVM model. This result is also bolstered by an improvement in the PSO-SVM model, which is distinguished by the greatest gamma position, which ha ,lps a value of 9.

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