An Innovative LSSVM-FPA Hybrid Model for Earthquake Prediction System

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***Abstract* – Damage to infrastructure, human casualties, and the economy can all take a nosedive when an earthquake strikes, making it one of the deadliest and most unpredictable natural disasters. Factors such as height, ground motion, rainfall, rock bed material, and area tectonics all have a role in their occurrence. Geologists and seismologists still have a significant obstacle when trying to predict when, where, and how big of an earthquake will be. Using data preprocessing techniques like transformation and cleaning in conjunction with advanced feature extraction methods based on precursory patterns, this study presents an Earthquake Prediction System. The system expands upon previous research that found precursory indicators like changes in animal behaviour, increasing temperatures, radon gas emissions, and variations in seismicity. Particular attention was given to the LSSVM-FPA hybrid model, which integrates the LS-SVM and the FPA, in the development of two predictive models that make use of seismic indicators and hybrid ML techniques. When compared to other models, the LSSVM-FPA model outperforms them all with a prediction accuracy of 97.43%. In light of these findings, it is reasonable to conclude that the proposed Earthquake Prediction System provides a solid basis for enhancing early detection and reducing the devastating effects of future seismic events.**

***Keywords*— Earthquake Early-Warning (EEW), Radial Basis Function (RBF), Flower Pollination Algorithm (FPA), Least Square Support Vector Machine (LS-SVM), Support Vector Machine (SVM).**

I. INTRODUCTION

Earthquakes are among the most destructive natural disasters that can occur, impacting not only people but also economy and structures. A great deal of attention from seismologists has focused on the problem of earthquake prediction. The Earth's outer shell is not entirely static, though, therefore it is still regarded as an extremely complex subject today. The earlier approaches to earthquake prediction relied on established information, statistical regularities, signal analysis, and historical earthquake occurrences however, these methods are relatively less accurate. Building cohesive models that can be used to create precise forecasting systems is particularly difficult due to the variances in geology and the uncertainty of the forces at play[1]. Data loss during earthquake monitoring can occur for a number of reasons, including malfunctioning instruments and communication systems. This problem is reflected in seismic monitoring data when there are continuous missing values in numerous fields or when solitary values arise. This will significantly affect data analysis and business applications in the future. Maintenance work cannot be finished quickly because of the intricacy of the geographic dispersion of earthquake monitoring stations and the unpredictability of hardware equipment replacement[2]. Thus, it is a practical and significant issue to determine the ways to employ technical methods to fill in the missing data and guarantee data integrity during the time when the monitoring station cannot function normally. Earthquake monitoring stations differ substantially in terms of the hardware they use and the data they monitor.

The earthquake has devastating effects. Therefore, it quickly ends a region's socioeconomic activities. There is a great deal of thought that must go into the design, construction, and structural building system in light of the effects of earthquakes. Building structures are subject to earthquake loads of varying magnitudes depending on a number of factors, including the following: ground conditions, earthquake zones, seismic behavior, weight and stiffness of structural materials, configuration and structural system, vibration time, and horizontal and vertical forces[3]. Predicting dynamic analysis processes is challenging since they include categorizing earthquake loads and the building's seismic reaction. Factors such as the structure's resistance model, the frequency and energy content of earthquakes, the compressive strength of concrete and steel, and the building's construction features all contribute to the uncertainty around the building's collapse capacity during earthquakes. Therefore, it sets off a plethora of procedures and dangers associated with earthquake responses that are fraught with unpredictability[4]. Performing seismic hazard analyses can help reduce the societal effect of earthquakes by reducing the amount of damage to buildings and infrastructure. The ability to forecast seismic occurrences using continuous data and either feed it into early warning

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systems in real-time or analyze it offline to search for earthquakes that weren't predicted before is a crucial challenge. Normal algorithms have little trouble predicting earthquakes with moderate to high magnitudes since these events are rare and hard to find in seismic databases[5]. Expert analysts or automated detection systems could miss a small-magnitude earthquake if certain conditions are met, such as a poor signal-to-noise ratio in the traces or the recording of overlapping events. This means that earthquake inventory can be lacking in terms of smaller earthquakes[6]. An important area of research for emergency response recently has been the early automatic prediction of earthquakes using raw waveform data gathered by seismic station sensors. In order to fulfil this purpose, EEW systems immediately send out warnings about possible dangers in high-risk areas as soon as the waves of an earthquake are identified.

The following is the outline for the remainder of the paper. The most relevant research on earthquake prediction methods is presented in Section II. After an introduction to the proposed LSSVM-FPA system model for earthquake prediction in Section III, the results and discussions of the simulations follow in Section IV. Section V serves as the paper's conclusion.

II. Literature Survey

In order to forecast earthquakes of magnitude and above, they used genetic programming and Adaboost as an ensemble approach, after computing seismic indicators to take into account the maximum amount of information on seismic activity in different regions. In addition, the experts predict earthquakes in three separate regions by combining a SVM regressor with a hybrid neural network that combines three distinct ANNs. They calculate seismic features using geophysical and seismological concepts[7]. In addition, there are ANN methods that can be used to forecast earthquakes by analyzing signals that occur before they do. For example, as seismic electric signals are thought to occur before an earthquake and are thus regarded as earthquake precursors, scientists use them as features for input data in ANN that forecast the magnitude of forthcoming seismic occurrences[8]. They provide an exhaustive survey of all the IoT solutions that have gone live around the world. Their usefulness in alerting and real-time monitoring systems is demonstrated by the study. Several studies have utilized machine learning approaches from CNNs, LSTM networks, and hybrid models to forecast when earthquakes may occur. In the case of seismic data, for instance, LSTM networks have effectively captured temporal dependencies[9]. They point out, however, that extended seismic sequences are often ineffective due to these models' diminishing gradients. Despite showing improvements over conventional GRU and LSTM models, limited research has investigated the combined usage of GRU, a bidirectional GRU-based model, with other state-of-the-art machine learning algorithms for earthquake magnitude prediction[10]. There is a need for study into improving operational effectiveness and forecast accuracy by optimizing and integrating LSTM with state-of-the-art machine learning models.

A GCNN is a prominent hybrid deep learning model that has recently come into vogue due to its remarkable capacity to use seismic data to provide accurate earthquake forecasts. They demonstrated the potential application of graph-based networks with sensor position data and time-series data using the GNN model[11]. They proved it by using graph-based networks. Studies performed on two seismic datasets containing earthquake waveforms have shown encouraging results[12]. In order to categories earthquake events utilizing a network of many stations, a DCNN and a GNN model called GCNN was created. In order for the GNN to make reliable earthquake predictions, it uses the spatial data supplied by the stations in conjunction with the features extracted from the waveform data by the CNN layers. A CNN and GNN model were released to forecast earthquakes using data from geophysical arrays. An approach known as graph partitioning forms the basis of this model. Despite using data from a large number of seismic stations, they paid no attention to the locations of these stations. The primary goal of the study is to identify earthquake-prone places, particularly on islands with a high human density, in order to lessen the severity of calamities[13]. To pinpoint the exact location of an earthquake's epicenter, K-Means Clustering is applied to the distribution data collected from the island. Furthermore, the dataset is further organized according to the decade of the occurrence in order to facilitate more efficient disaster mitigation strategies.

In summary, the contributions of this paper can be summarized as follows:

- SVM is a popular deep learning technique for regression that uses kernel methods to produce accurate predictions. To get around the ANN shortage, a machine learning technique called SVM was developed. Using SVM, you may avoid issues with local minima and get optimal global solutions.
- The SVM technique has been refined into LS-SVM, which stands for LSSVM. LSSVM streamlines the SVM approach; yet, it requires kernel parameters, which play a crucial role in regression issues. Because of this, optimising LS-SVM with FPA is necessary for making the best possible parameter choices.
- With the help of pollination, an algorithm called FPA was created. FPA yielded excellent results when used to numerous non-linear problems.

III. Proposed System

Earthquakes are among the most devastating natural catastrophes that humans have ever faced, particularly in densely populated areas. A number of recent earthquakes, both in and out of China, have highlighted the need for pre-disaster urban earthquake disaster prevention planning in order to mitigate damage and casualties. Urban earthquake catastrophe prevention plans must be put in place in order to address seismic threats. Predicting seismic hazards is a fundamental tool for preventing earthquake disasters.

Out of the 59,276 total readings of the gyroscope and accelerometer in the produced IoT dataset, 28,678 were not related to earthquakes and 30,598 were. If there was an earthquake, the result would show up in column 1, and if there was none, it would show up as 0. In contrast to the gyroscope, the accelerometer displays the large and frequent changes in coordinates[14]. The reason behind this is that the gyroscope measures changes in angular velocity and the accelerometer measures changes in acceleration.

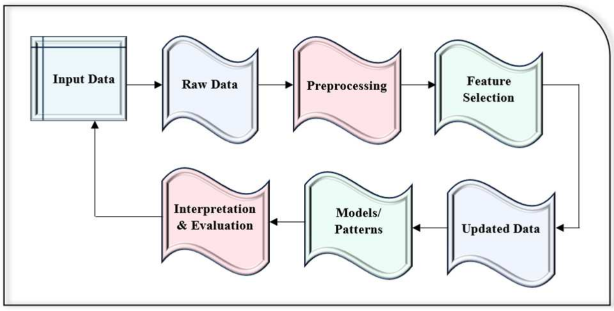

Fig. 1. Block Diagram Of Proposed Method

Educators, particularly those without experience in data mining, nevertheless face challenges when trying to adapt the numerous published case studies on educational data mining to their own unique academic issues. Several judgements and parameter setups are required for each step in Figure1, and these have an impact on the final product quality.

A. *Data Preprocessing:*

1) *Data Cleaning:*

The process of data cleansing began with the removal of unnecessary columns. The next step is to fill in any blanks with the most likely numbers after verifying for missing data. Among the several approaches to deal with missing values in data preparation are:

- Eliminating the whole row or column containing the empty string: If the missing data cannot be restored and the null value is in a critical feature, then this technique is suitable.
- Using a predefined value instead of the null value: This method works well when data is missing at random; it just uses the feature's mean, median, or mode to fill in the blank.
- The missing value is interpolated: When a time series has missing data and the values in neighbouring rows may be used to fill the gap, this approach is suitable.
- Imputing missing data using a ML algorithm: Certain ML algorithms, such as KNN imputation, may fill in missing data.

2) *Data Transformation:*

The specific job at hand and the available tools dictates the strategy to data transformation that is used. The following are some examples of common data transformation processes that they have used with our dataset:

- In order to begin transforming data, you must first determine which columns or aspects of the data require transformation and what kind of transformation is required.
- Data preparation is making sure the data is clean and in a usable format for transformation by performing any necessary pretreatment or cleaning. Data type conversion, outlier removal, and filling in missing numbers are all examples of what may fall under this category.
- The next step is to apply the transformation, which entails transforming the data using a predetermined technique. Some possible steps in this direction include normalising the data, encoding categorical variables, or scaling the data.
- Verify the quality and format of the transformed data as well as the accuracy of the transformation itself to validate the transformed data.
- It is possible to construct machine learning models, visualise the data, or conduct additional investigation using the modified data.

Depending on the task at hand and the equipment at your disposal, these stages may need to be done several times in a certain order[15]. Checking the model's performance after each transformation step is also crucial for determining if the model is improving.

B. *Feature Selection:*

The suggested technique can be utilised to identify possible patterns that may indicate an impending earthquake, and the extraction of feature method can provide an approximation of the time horizon for the outcomes of the predictions. By integrating the strengths of these two approaches, it offers a pattern-based precursory features extraction method that can forecast the magnitude range of future earthquakes and derive the time effective range of prediction findings[16]. Particularly, the Φ sequence of historical seismic records Φ is initially separated into M $-$day time periods.

The range of magnitudes for the greatest earthquake in the corresponding period of time, also known as the mainshock, and designated as V_r^n. In contrast to previous research, which has defined the precursory pattern as a series of events with a fixed duration preceding the main shock, this paper defines it as a two-part pattern sequence: the sequence of internal pattern KR_r and the sequence of external pattern KV_r^d. A length of KV_r is denoted by d here. A series of intrinsic patterns Since KR_r represents the chain of events leading up to the major shock in the current time period r, its duration could vary between periods due to differences in the relative positions of V_r^n. The preceding external pattern listing KV_r^d is the past time series of occurrences of size w leading up to the present time period. When KR_r & KV_r^d are combined in a precursory pattern, it can produce reliable seismic indicators. In order to determine seismic indicators, KV & KR are combined to form HO. In a formal sense, the following equations (1)&(2) define HO.

$$HO = \{HO_r \backslash r = 1, \dots, m\} \quad (1)$$

$$HO_r = \langle KV_r \cup KR_r \rangle \quad (2)$$

C. Model Training:

1) LSSVM:

A combination of DL and supervised learning, it can both categorise data and make value predictions. SVM's new version, LSSVM, fixes SVM's flaws. Instead of solving a quadratic programming issue, which is involved in SVM, LSSVM allows the answer to be based on solving a set of linear equations. The input data matrix is denoted by x. In order to demonstrate how the output is dependent on the input, LSSVM is useful for building the function using training data. Here is the equation (3) of the function:

$$u(c) = D^g \mu(c) + y \quad (3)$$

when $y\epsilon I$ is a member of I and D and $\phi\ (c){:}\ I_k \rightarrow\ I_m$ are column vectors with size $m * 1$. This function is now computed by LSSVM by use of the identical minimisation issue in SVM. This demonstrates the key distinction between LSSVM and SVM, namely that the former uses equality constraints while the latter uses inequality ones. There is a reliance on the least square function in LSSVM. Equation $(4) - (5)$ of optimisation allows us to minimise the error:

$$\min q\ (d, v, y) = \frac{1}{2} d^g d + X \frac{1}{2} v^g \quad (4)$$

$$b_r = D^g \mu(c_r) + y + v_r \quad (5)$$

The parameter between solution size and training errors is denoted as $X\epsilon I^+, and\ v\ is\ a\ m * 1$ column vector. The Lagrangian is produced in 2 dimensions and varies with respect to d, y, v & z where an is the Largrangian multiplier as shown in equation (6).

$$\begin{bmatrix} 1 & 0 & 0 & -A^g \\ 0 & 0 & 0 & -1^g \\ 0 & 0 & X & -R \\ A & 1 & R & 0 \end{bmatrix} \begin{bmatrix} d \\ y \\ v \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ b \end{bmatrix} \quad (6)$$

Identity matrix and $A = [\mu(c_1), \dots, \mu(c_m)]^G$

$D = AG$ and $Dv = z$ are obtained by utilising the four from row 1, as shown in row 3. The conditions for optimality provide the following solution, which should be noted: the kernel matrix $K = AA^g$ and the parameter $\lambda = X^{-1}$ is shown in equation(7).

$$\begin{bmatrix} 0 & 1^g \\ 1 & p + \lambda O \end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ b \end{bmatrix} \quad (7)$$

K, the kernel function, type:

Initial step: linear kernel is shown in equation (8).

$$K(c, c_r) = c_r^G C \quad (8)$$

Secondly, the d-degree polynomial kernel is shown in equation (9).

$$K(c, c_r) = (1 + c_r^G c / x)^w \quad (9)$$

Thirdly, the radial basis function (RBF) kernel is shown in equation(10).

$$K(c, c_r) = \exp(-\left||c - c_r|\right|^2 / \sigma^2) \quad (10)$$

Number four: the MLP kernel is shown in equation(11).

$$K(c, c_r) = tans(pc_r^G c + \theta) \quad (11)$$

2) FPA (Flower Pollination Algorithm):

The optimisation method known as FPA is based on the concept of pollination. Two types of pollination occur: biotic pollination, in which insects distribute pollen, and abiotic pollination, in which water or wind carry the pollen, which occurs in 10% of flowers. There are two ways to harvest pollen. The process of self-pollination happens when pollen from one bloom travels to another or to other flowers on the same plant.

The proposed hybrid model integrates LSSVM for regression/classification with the Flower Pollination Algorithm (FPA) for hyperparameter optimization. LS-SVM provides efficient learning using kernel functions, while FPA optimizes parameters such as kernel width and regularization coefficient. The hybridization enhances prediction accuracy and convergence speed.

The process of cross-pollination occurs when pollen from one plant's flower goes to another plant's blossom of a different species. Methods used by the FPA algorithm 1.

- The Levy battle occurs during globa pollination, which is a form of cross-pollination that involves living organisms.
- By definition, self-pollination occurs at the local level.
- Since the likelihood of reproduction is directly proportional to the degree of similarity between any two flowers, they can think of flower constancy in this way.
- The process pollination, whether global or local, is determined by a probability switch $k \in \{0,1\}$.

Global pollination relies on the ability of pollinators to transport pollens over great distances. That way, they can be guaranteed that the Best (fittest) solution follows the levy distribution as shown in equation (12).

$$c_r^{g+1} = c_r^g + O\left(Best - c_r^g\right) \quad (12)$$

Equation (13) is a formula that represents the possibility that other factors can transport pollen during local pollination.

$$c_r^{g+1} = c_r^g + F\left(c_q^g - c_p^g\right) \quad (13)$$

IV. Result and Discussion

Earthquakes are a tremendous disaster, and the fact that they can happen at any time makes them even more devastating in terms of human lives lost and money lost. Two competing schools of thought have emerged in the heated discussion over whether or not earthquakes can be reliably predicted. Some academics have devoted time and energy to trying to forecast this event, while others think it's completely impossible. After more than a century of trying, the seismologist community still hasn't figured out how to anticipate earthquakes. The dataset was divided into training (70%), validation (15%), and testing (15%) sets. A stratified sampling approach was used to maintain class distribution. Model performance was evaluated using accuracy, precision, recall, and F1-score. Additionally, 5-fold cross-validation was conducted to ensure robustness.

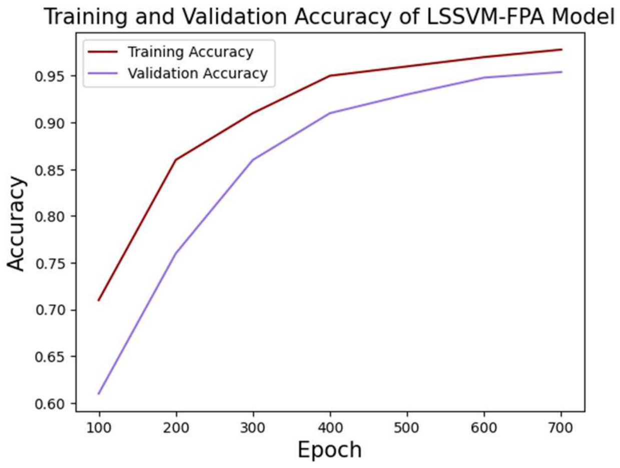

Fig. 2. Training and Validation Accuracy of LSSVM-FPA Model

Fig. 2. shows that the verification set exhibits far more pronounced variations due to the increased effects of the minor fluctuations. In addition, after 600 iterations, the model stabilises and the loss on the verification set stops decreasing.

TABLE I. PERFORMANCE COMPARISON

Models	Precision	Recall	F1-Score
SVM-FPA	93.78	91.69	95.68
RBF	85.69	83.78	87.79
SVM-RNN	90.48	88.92	92.91
SVM	88.59	86.86	90.62
LSSVM	87.79	85.43	89.79
LSSVM-FPA	**95.82**	**93.86**	**97.86**

Table 1 compares the capabilities of six distinct models, including SVM-FPA, RBF, SVM-RNN, SVM, LSSVM, and LSSVM-FPA. With a precision of 95.82%, recall of 93.86%, and an F1-Score of 97.86%, our suggested LSSVM-FPA model outperforms existing models.

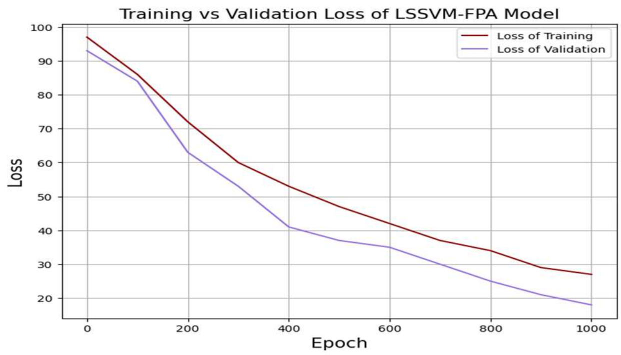

Fig. 3. Training and Validation Loss of LSSVM-FPA Model

Fig. 3. shows the training set and validation set loss and accuracy curves, which show that the model performs best after 800 iterations. In the first iteration, the training set's loss and accuracy curves exhibit less variation when contrasted with the validation set.

TABLE II. PERFORMANCE ANALYSIS

Models	Accuracy	Time Consuming (s)
SVM-FPA	95.12	2172
RBF	87.49	1816
SVM-RNN	92.36	2048
SVM	90.02	2378
LSSVM	89.29	1929
LSSVM-FPA	**97.43**	**1246**

Table 2 displays the results of the performance analysis for six distinct models, including SVM-FPA, RBF, SVM-RNN, SVM, LSSVM, and LSSVM-FPA. With an accuracy of 97.43% and a low time consuming value of 1246, our suggested LSSVM-FPA model outperforms previous models.

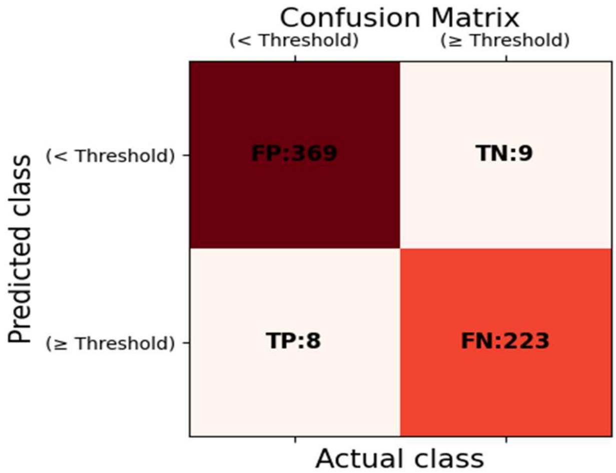

Fig. 4. Confusion Matrix

Fig. 4. shows how a confusion matrix shows classification model effectiveness. The difference between actual and anticipated classes is divided into four categories: FN, FP, TN, and TP. Darker shades indicate 369 false positives and 223 false negatives. This makes positive instance detection difficult for the model.

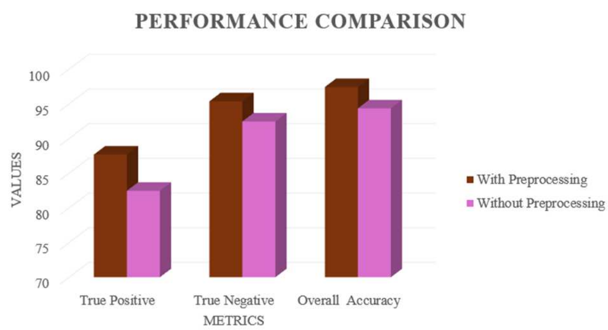

Fig. 5. Performance Comparison

Fig. 5. compares Performance Comparison model metrics with and without preprocessing. It measures Overall Accuracy, True Negative, and True Positive. With Preprocessing is perform better then without Preprocessing.

Despite achieving high accuracy, the proposed model has certain limitations. The dataset is limited to specific geographic regions, which may affect generalization. Additionally, real-time deployment requires high computational resources. Future work will focus on integrating deep learning architectures and expanding datasets across multiple seismic zones.

V. CONCLUSION

Among the natural occurrences discussed in this article are differences in gravity, radon emission, abnormal electric fields, and changes in meteorological factors such as relative humidity and temperature, which can occur before an earthquake. The first warning of an impending earthquake is explained, the Earthquake Preparation Zone. All of the ground-based pre-earthquake signals are created within this zone, according to this notion. Participating nations in space-based earthquake prediction studies complement those conducting ground-based studies. Data transformation and data cleaning are utilised in their pretreatment. For the purpose of earthquake prediction, the suggested method of extracting features based on precursory patterns using the chosen CART model is an encouraging approach. Two models for earthquake prediction based on seismic indicators and hybrid ML approaches are presented in this study. The LSSVM-FPA combines features of FPA with those of the LS-SVM, a neural network architecture. They compare and evaluate the performance of these two models. With an impressive accuracy rate of 97.43%, our suggested model, LSSVM-FPA, outperforms the competition in this study. When it comes to lowering the ratio of false alarms in earthquake prediction, LSSVM-FPA is also tops.

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