Italian Journal of Engineering Geology and Environment
www.ijege.uniroma1.it

A HYBRID MACHINE LEARNING MODEL FOR DISASTER PREDICTION USING HISTORICAL GEOLOGICAL DISASTER DATA

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EXTENDED ABSTRACT

Con l'aumento della frequenza dei disastri e l'intensificarsi degli eventi meteorologici estremi, le comunità e i governi di tutto il mondo si trovano ad affrontare difficoltà sempre maggiori. Per affrontare questi problemi, è fondamentale una preparazione precisa ai disastri. Questa ricerca esamina in dettaglio l'impatto trasformativo che gli algoritmi di apprendimento automatico hanno sul rafforzamento dei sistemi di preparazione e risposta ai disastri. Oltre a una semplice panoramica, il nostro studio, basato sull'algoritmo Enhanced Pelican Optimization con memoria a lungo termine per la previsione dei disastri (EPO-DPLSTM), si distingue per le sue capacità avanzate di apprendimento automatico (ML) nella previsione di un'ampia gamma di fenomeni meteorologici e disastri naturali, come ondate di calore, uragani, inondazioni, siccità e altro ancora. Per migliorare l'efficacia dei modelli predittivi nella preparazione ai disastri, abbiamo condotto osservazioni approfondite sulle complessità dell'applicazione dell'apprendimento automatico. Oltre a delineare i fondamenti teorici, lo studio offre prove empiriche dei notevoli vantaggi offerti dagli algoritmi di apprendimento automatico. Utilizzando queste previsioni precise di disastri geologici passati e nuove tendenze meteorologiche, è possibile implementare misure preventive, salvando vite umane e riducendo l'entità dei danni. Il sistema di allerta precoce per le frane a livello regionale è uno strumento cruciale per la prevenzione e la mitigazione dei disastri in Cina, dove i disastri sono particolarmente gravi. I dati sui disastri passati sono stati acquisiti tramite la Commissione Nazionale Cinese per la Riduzione dei Disastri (NCDR-China), e comprendono diverse tipologie di disastri, come terremoti, inondazioni, tifoni, siccità, tempeste di vento, danni da gelo e frane. In questa ricerca è stato presentato un approccio proposto per l'allerta regionale sui disastri. Il processo di creazione del modello include l'output di allerta, l'ottimizzazione dei parametri del modello, l'apprendimento e l'addestramento del campione, la costruzione del set di campioni e così via. L'80% del set di campioni è stato utilizzato come set di addestramento, e il restante 20% come set di test per la convalida incrociata nel processo di apprendimento e addestramento del campione. I parametri del modello sono stati ottimizzati utilizzando l'algoritmo Enhanced Pelican Optimization basato sulla memoria a lungo termine per la previsione dei disastri (LSTM), e l'accuratezza, la curva ROC (Receiver Operating Characteristic) e il valore AUC (Area Under the Curve) sono stati utilizzati per confermare la capacità di generalizzazione e l'accuratezza del modello. Gli esperimenti hanno dimostrato che il modello EPO-DPLSTM proposto è molto più efficace dei classificatori classici come l'albero decisionale, la foresta casuale, la macchina a vettori di supporto e il classificatore Naïve Bayes. L'accuratezza, la precisione, la sensibilità e l'AUC dell'approccio proposto sono rispettivamente del 99.5%, 95.6%, 96.1% e 0.989, il che dimostra la buona capacità di generalizzazione e l'elevata capacità discriminatoria tra eventi disastrosi e non disastrosi. Sulla base di un'analisi comparativa, l'approccio ibrido di ottimizzazione e apprendimento profondo si dimostra valido per migliorare l'accuratezza predittiva, la robustezza e la stabilità, soprattutto quando si ha a che fare con la non linearità e gli effetti temporali a lungo termine, come nel caso dei dati storici disponibili sui disastri geologici.

I risultati di questo studio dimostrano che i modelli ibridi intelligenti hanno un grande potenziale nello sviluppo di sistemi di previsione e allerta precoce per i disastri. Il quadro proposto può essere di grande aiuto per i responsabili politici, le agenzie di risposta alle emergenze, i pianificatori urbani e le autorità di gestione dei disastri, consentendo di mitigare proattivamente il rischio, allocare le risorse, pianificare le infrastrutture e prepararsi alle emergenze, fornendo previsioni altamente accurate e tempestive del rischio in questione. Inoltre, la metodologia suggerita fornisce una base scalabile ed estendibile che può essere ulteriormente migliorata in futuro attraverso la combinazione di informazioni in tempo reale provenienti da sensori IoT, immagini ad alta risoluzione da sensori di telerilevamento, approcci di combinazione di dati multimodali e framework di apprendimento profondo di nuova concezione. Nel complesso, questo articolo di ricerca fornirà un contributo significativo allo sviluppo di un quadro di gestione dei disastri resiliente e basato sui dati, in grado di affrontare le conseguenze dei disastri e proteggere lo sviluppo sostenibile.

IJEGE, 2 (2025): 123-136, DOI: 10.4408/IJEGE.2025-02.O-08
E-ISSN 2035-5688 | ISSN 1825-6635 / ©Author(s)

ABSTRACT

As disasters are occurring more frequently and weather extremes get harsher, communities and governments around the world are facing more and more difficulties. In order to address these problems, disaster preparedness must be done precisely. This research examines in detail the transformative impact that machine learning algorithms have on bolstering disaster preparedness and response systems. Beyond a simple synopsis, our study's Enhanced Pelican Optimization based on Disaster Prediction long short-term Memory (EPO-DPLSTM) is remarkable and shows off the advanced capabilities of Machine Learning (ML) in predicting a wide range of patterns of the weather and natural disasters, such as waves in heat, hurricanes, floods, droughts, and more. In order to assist the improved efficacy of prediction models in disaster preparedness, we made useful observations into the intricacies of application using ML. In addition to outlining the theoretical underpinnings, the study offers empirical evidence of the substantial advantages that machine learning algorithms offer. By using these precise forecasts of past geological disasters and new weather trends, preventative measures might be put in place, ultimately saving lives and lessening the extent of the damage. Regional landslide catastrophe early-warning is a crucial tool for disaster prevention and mitigation in China, where disasters are severe. A proposed approach to regional disaster warning was presented in this research. The model creation process includes warning output, model parameter optimization, sample learning and training, sample-set construction, and so forth. Eighty percent of the training sample set was used as the trained set, and twenty percent was utilized as the testing set for cross-validation in the sample learning and training process. The model parameters were optimized using the Enhanced Pelican Optimization based on the Disaster Prediction Long Short-Term Memory (LSTM) algorithm, and the accuracy, Receiver Operating Characteristic (ROC curve), and Area Under the Curve (AUC) value were utilized to confirm the model's generalization capacity and accuracy. To improve model training, five machine learning methods were used; the results indicated that the suggested algorithm was the model with the best generalization capacity (AUC was 0.989) and performed the best, with an accuracy of 99.5%. The findings of this study provide critical scientific support for policymakers, emergency planners, and local stakeholders, enabling the development of more targeted, data-driven disaster mitigation strategies and strengthening regional resilience against future geological hazards.

KEYWORDS: disaster prediction, historical geological disaster data, EPO-DPLSTM, prevention

INTRODUCTION

China has made significant strides in building infrastructure, but environmental degradation and human activity have reduced the amount of forest cover, which in turn has resulted in a number of geological catastrophic issues. Geological disasters caused by both natural and man-made causes, such as mudslides, mountain collapses, landslides, and flash floods, have become increasingly catastrophic in recent years and present a serious risk to property safety and human life (Zhang *et alii*, 2023). For instance, unexpected geological hazards like mud and water surges have happened during the construction of the Cenis Peak Tunnel in France, the Dayaoshan and Jundu Mountain Tunnels in China, and a Major Sichuan earthquake in China, in 2008. Additionally, a significant earthquake and resulting tsunami 2011 in Japan had a significant impact on Japanese production and people's quality of life. Geological disasters killed 300400 people and cost the economy over 10 billion yuan year between 1985 and 1995, according to statistics (Hu *et alii*, 2021). Since 1995, they have resulted in about 1000 annual fatalities and economic losses of almost 20 billion yuan. China has been and will continue to be in the midst of extensive engineering construction and land development. If precise early warning and emergency analysis are not conducted after a geological disaster event, plenty of time and appropriate strategies for control and prevention cannot be proposed, putting people's lives, property, and living conditions in grave danger. Additionally, this will restrict the long-term growth of the economy, culture, environment, and humanities and make it more difficult to build and ensure the safety of large national projects (Yao, 2020). Consequently, conducting early prediction warning and monitoring studies on geological risks is extremely important and valuable.

Predicting and detecting disasters helps to lower the death toll and financial damages. In certain situations, such as storms and floods, early warning systems can help protect properties and natural resources (Gupta *et alii*, 2021). People can still take precautions against injury and death even if they have little warning before a tragedy strikes. Governments must thus make significant investments to improve catastrophe detection and management systems by utilizing the latest technological advancements in computer science, which have made it easier to access massive amounts of data (Bilal *et alii*, 2022).

Algorithms for machine learning (MLs) are a portion of artificial intelligence (AI) that allow algorithms to identify patterns in massive datasets without explicit programming. These algorithms are capable of scanning large data sets and finding patterns that human analysts might miss (IEEE, 2024). Algorithms that use ML may examine a range of information sources, including satellite data, atmospheric data, and historical weather and disaster data, to produce precise weather and natural disaster forecasts (Guha *et alii*, 2022).

Historical disasters data from 1900 to 2025 show, in Fig. 1, extensive research has been done in the past few years on the use of artificial intelligence to aid in handling disasters from several viewpoints, such as prediction, forecasting natural disasters, and identifying hazards in real-time. In this broad spectrum of applications, deep learning techniques - a kind of AI - have emerged as a powerful tool to help the appropriate agencies manage the complexities of natural catastrophes (Rokaya Eltehewy *et alii*, 2023; Ghali & Akhloufi, 2023).

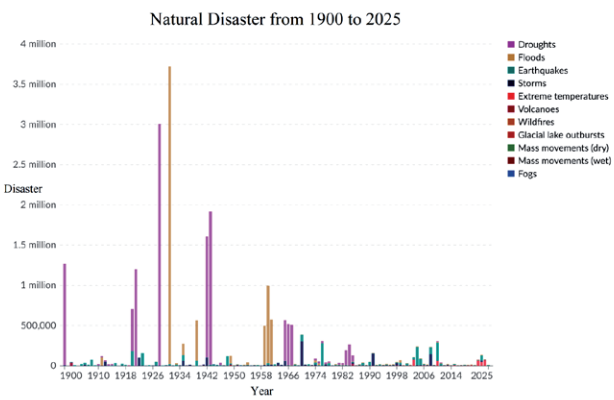

Fig. 1 - Historical data of disaster from 1900 to 2025

From DL methods, especially Long Short-Term Memory, is able to learn complex patterns of particular Disasters from nature derived from extensive datasets, which makes They are helpful in evaluating disasters that occur naturally; they can use information from satellite imagery to determine the impacted regions and gauge the degree of damage; they can help detect disasters in real-time, such as forest fires, by detecting fires and monitoring their development of the fire (Fang *et alii*, 2020); In a number of use-case situations, this technique has demonstrated remarkable success when applied to imaging data, outperforming humanoperated systems, particularly in the most taxing computer-vision tasks: tasks involving segmentation, identifying objects, and categorization.

The structure of this study is as follows: the opening section offers a concise synopsis of the background, importance, and current state of research on intelligent algorithm based historical disaster prediction detection; the research technique sec provides a synopsis of the technical techniques employed in this work; the detailed introduction of the methodology of the proposed method based on Enhanced Pelican optimization based on Disaster Prediction LSTM (EPO-DPLSTM) algorithm for disaster prediction for prior notification detection follows; the result and discussion section elaborates on geological historical data regarding disaster monitoring; and the conclusion section provides a summary of the entire work.

RELATED WORKS

- Houston's industrial facilities sustained damage and experienced severe floods as a result of Hurricane Harvey. The damage was examined using government incident records. Roof sinking is a major failure mode, and atmospheric storage tanks were shown to be the most vulnerable (Qin *et alii*, 2020);
- This author proposes a CNN based technique for quick flood mapping that is totally automated. The technique may be incorporated into end-to-end pipelines for ongoing flood monitoring and cuts down on the time needed to create flood maps by 80% (Nemni *et alii*, 2020);
- Typhoon Hagibis caused major damage in Japan, especially in Marumori Town, where it caused landslides and flooding, leaving ten people dead and one missing. Roads and railroads were among the infrastructures damaged by the disaster, which also made future disaster mitigation imperative (Moriguchi *et alii*, 2021);
- The significance of open data, open governance, and new technologies in catastrophe risk reduction are covered in this study readily available accessible by default, co-created, authorized, documented, and owned locally, and varied user communication are the five guiding principles for open data. The development of new technologies in Japan and their use in catastrophe risk reduction are also examined in this article (Kanbara & Shaw, 2021);
- The study focuses on socioeconomic characteristics like poverty, crime, employment, and race in order to estimate employing ML algorithms to assess the risk of flooding in London, England. The findings indicate a strong relationship between flood risk and these factors (Gau & Singh, 2024);
- The study evaluates the forest-fire vulnerability in Iran's Fars Province using machine-learning techniques based on geographic information systems. The findings demonstrate that BRT and MDA models predict FFS more accurately than GLM. The most helpful factors influencing FFS are land use, rainfall, and slope angle, which improves the planning and management of forest resources (Pourghasemi *et alii*, 2020);
- The study suggests a unique method for locating and evaluating possible geohazards in China's railway network by utilizing integrated remote sensing technologies. The approach, which was tested in southeast Gansu, improved disaster risk management and railway network sustainability by identifying 3976 dangers, including severe landslide threats (He *et alii*, 2023);
- It is possible to prevent, mitigate, and respond to technological disasters using the neo-deterministic seismic hazard assessment (NDSHA) approach. Instead than trying to "cure" a disaster, it focuses on

prevention, mitigation, and readiness with the goal of saving lives and minimizing infrastructure damage (Laor & De Vivo, 2021);

- A paradigm for using unpredictable and adaptive without seismic activity in earthquake forecasting into account is developed in this paper. To increase accuracy, it makes use of LSTM modeling, optimization, and location and date data. Tested on current datasets, the framework improves preparedness and mitigation strategies for disasters while lowering seismic risk (Rubidha *et alii*, 2024);
- Based on international project management standards and existing literature, this study offers a novel paradigm for catastrophe risk management. Using sensitivity analysis and a maximized utility function, it creates an optimization model to determine the best risk response tactics. In disaster management, this method enhances practitioners' resource allocation and decision-making (Safaeian *et alii*, 2024).

METHODOLOGY

Data Collection and Preprocessing for Disaster Predictive Analytics

A web crawler collected this web text dataset of disasters in China (see Fig. 2) from the China National Commission for Disaster Reduction (NCDR-China) website, which focuses on the full cycle of disaster management and is one of the top organizations that assists the government in addressing disaster-related issues: *https://ikcest-drr.data.ac.cn/info/98cfe*. The crawler chooses the website's "latest disaster" column as its seed pages. Title, time, and text are all included in the dataset. Excel is the data format. China is the geographical scope. The time frame is 2018-20. There are 457 text accounts of earthquakes, typhoons, floods, wind, hail, freezing damage, and other calamities.

In the present research, the historical geological-disaster data set was split into three parts: 70 percent of which could be trained, 15 percent could be validated, and 15 percent could be tested. The machine-learning and deep-learning models were fitted to the training set, and to avoid overfitting and to optimize the hyperparameters, the validation set was utilized. Objective evaluation of the model performance was done using the last testing set that was not visible at all in the model development. Hyperparameter tuning was done with grid search and 5-fold cross-validation applied to the training / validation section of the data, to all machine-learning models, namely Naive Bayes, SVM, Random Forest, and Decision Tree. Systematic optimizations of parameters like the type of the kernel and C-value of SVM, depth of the tree, and the number of estimators of Random Forest, and the splitting criterion of Decision Tree were performed. The learning rate, number of LSTM units, batch size, dropout rate, and activation functions were optimized using a validation-directed search strategy based on an initial deep-learning model with the proposed deep-learning model. It was done this way to make sure that all models were created with similar and streamlined conditions, enhancing the consistency of the end results and comparison of the performance.

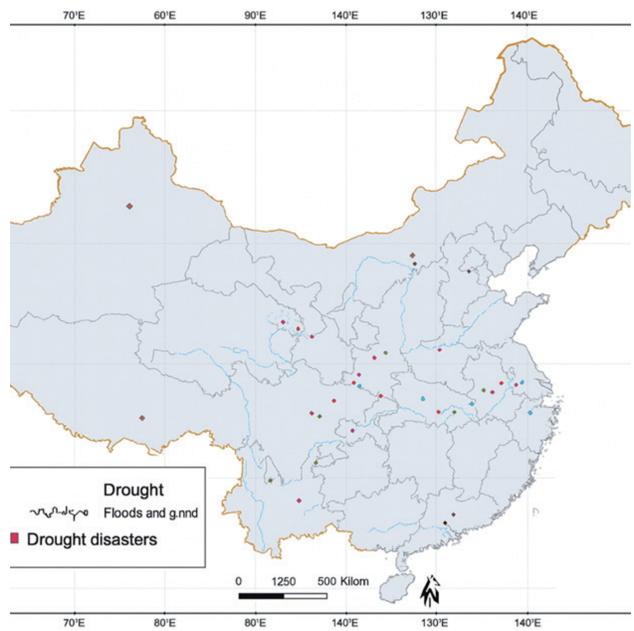

Fig. 2 - Map for disasters affected area in China

Disasters affected area in China is shown in Fig. 2: the brown diamond denotes the region where drought calamities have occurred; the green circle denotes the regions impacted by geological disasters and floods. The figure's blue triangle denotes the region where wind and hail disasters have occurred. The area affected by seismic disasters is represented by the pink diamond in the illustration. The regions impacted by low-temperature freezing and snow disasters are shown in the figure by the purple triangle.

Data preparation ensures the information used by the ML technique is correct, reliable, and appropriate. Data cleaning using Python's pandas, data integration, min-max normalization, feature selection via PCA, and temporal alignment are common preprocessing methods. The effectiveness and dependability of disaster prediction models are significantly influenced by the quality. While low-quality data might lead to erroneous predictions, high-quality data enables models to spot subtle patterns and relationships. The accuracy, sensitivity, generalizability, and temporal and geographical resolution of the model are all impacted by the quality of the data. Researchers and disaster prevention organizations use techniques such as ongoing data quality reviews, data validation, and routine calibration. By identifying discrepancies or gaps in data, predictive analytics models can enhance data quality by guiding future data collection initiatives. Better data yields a better method, which can lead to highly efficient data-gathering techniques, creating a positive feedback cycle.

Enhanced Pelican Optimization based on Disaster Prediction long short-term Memory (EPO-DPLSTM) Algorithm

The Pelican is a big bird with a lengthy beak that catches and swallows prey with the help of a massive bag in its throat. Living in flocks of several hundred pelicans, this bird enjoys socializing and being a part of groups (Xiong *et alii*, 2023). The following physical traits are present in pelicans: they are from 2.74 and between 16 kg in weight, 1.05 to 1.82 m height, and have a wings distance end to end of 0.4 to 4 m. Fish make up majority of a bird's diet, with frogs, turtles, and crustaceans appearing less frequently. If the pelican is extremely starving, it may even eat seafood. During hunting, pelicans often cooperate. Once they have found their food, the enhanced pelican dive to them from a tall of 11 to 19 meters. At lower elevations, specific species, and also drop to their target. In-order to make the fish go to water that is shallow and make it easier for them to catch them, they then spread and flap their wings on the surface of water. When a fish is caught, a lot of water gets into the lengthy beak of pelican, which pushes the forward motion and then swallows the fish to get rid of extra water (Garmroudi *et alii*, 2024). Because pelicans have an intelligent hunting technique and behavior, they are proficient hunters. Modeling of the previously described method functioned as the main inspiration for the design of the POA.

Mathematical Model of the Proposed EPO Algorithm

Using a population-based methodology, the proposed EPOA considers pelicans to be part of this population. In optimization algorithms, every historical geological in the prediction is a exact solution. Depending on where they are in the search the location using satellite, each prediction suggests location for the variables in the optimization technique problem. Using equation (1), locations are first initiate at randomly based on the disaster from bottom and upper bounds:

$$x_{m,n} = l_n + rand.(u_n - l_n), M = 1,2,\ldots i, N = 1,2,\ldots j, \qquad (1)$$

where M is the number of disaster location, N is the prediction parameters, rand is a randomly number in the intervals [0, 1][0, 1], l_n is n^{th} low bound, u_n is n^{th} upper-limit of prediction variables, and $x_{(m,n)}$ is the location of the n^{th} parameters identify by the m^{th} location disaster solution.

Equation (2) uses a matrix known as the historical matrix to predict the measurement from the population in the proposed EPOA. The columns of this disaster historical matrix show the suggested values for the prediction parameters, and each row shows a effective solution.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m} \end{bmatrix}_{N\times m}, \qquad (2)$$

Where X is the matrix of prediction in Enhanced pelicans and X_i is the i^{th} pelican.

Each prediction of the location in the EPOA is a data, which is a exact remedy for the problem at hand. Consequently, the objective function of the given circumstance may be evaluated using each of the possible solutions. Equation (3) computes the values acquired for the desired function using a vector called the goal function vector.

$$P = \begin{bmatrix} P_1 \\ P_i \\ P_N \end{bmatrix} = \begin{bmatrix} P(z_1) \\ : \\ P(z_1) \\ : \\ P(z_N) \end{bmatrix} \qquad (3)$$

Where P is the desired function vector and P_i is the value of the goal function of the ith historical solution.

The proposed EPOA imitates pelican behavior and tactics during prey seeking and attack in order to update prospective solutions. This hunting strategy is represented by the following two stages:

(i) Moving closer to the prey (exploration phase);
(ii) Afloat on the water's surface (exploitation era).

- Moving closer to the prey (exploration phase).

In the first step, the pelicans find their prey and then move toward the predetermined location. Modeling this pelican's strategy leads to search area scanning and the proposed EPOA-DPLSTM exploration capabilities in discovering different search space locations. The fact that the prey's location inside the search region is randomly chosen is a key component of EPOA. This increases the exploratory power of EPOA in the exact search of the solving issues domain. The aforementioned concepts and the pelican's approach to the prey site are mathematically simulated by equation (4):

$$y_{m,n}^{P_1} = \begin{cases} y_{m,n} + rand \cdot (P_n - I \cdot y_{m,n}) & p_p < p_i; \\ y_{m,n} + \text{rand.}(y_{m,n} - P_n), \text{else,} & \end{cases} \qquad (4)$$

where $y^{P1}_{m,n}$ is the updated status of the m^{th} pelican in the n^{th}

dimension based on its first phase, P_n is the prey's position in the nth dimension, p_p is the value of its objective function, and I is a random location that may be one or two. The random integer I in the argument might be either 1 or 2. For each member and iteration, this parameter is selected at random. A member's displacement is increased when this parameter is set to two, which may lead them to more recent areas of the search space. Therefore, parameter I affects the EPOA-DPLSTM exploration capacity to accurately explore the search space.

The suggested EPOA accepts the new pelican location if the objective function's value is raised. This kind of updating, known as effective updating, keeps the algorithm from straying into less-than-ideal regions. Equation (5) is utilized to model this process:

$$y_m = \begin{cases} y_{m,}^{P_1} \; p_i^{P_1} < p_{i^{;}} \\ y_{m,else,} \end{cases} \tag{5}$$

where y_m^{P1} is the i^{th} pelican's new position and p_i^{P1} is the goal variable value based on the first phase.

- Afloat on the water's surface (exploitation era).

When the pelicans arrive to the water's surface in the second phase, they expand their wings to lift the fish upward and then gather the prey in their neck pouch. Pelicans use this tactic to capture greater quantities of fish in the targeted region. The suggested EPOA-DPLSTM converges to better locations in the hunting region when this pelican behavior is modeled. This procedure boosts EPOA's capacity for local searches and exploitation. From a mathematical perspective, in order to converge to a better answer, the algorithm has to look at the locations around the pelican site. Equation (6) provides a mathematical simulation of this pelican hunting behavior:

$$y_{m,n}^{P_2} = y_{m,n} + D \cdot \left(1 - \frac{t}{T}\right) \cdot (2 \cdot rand - 1) \cdot y_{m,n} \tag{6}$$

D(1-t/T) is the surrounding radius of $y^{P2}_{m,n}$ t is the iteration clock, T is the maximum number of iterations, and D is a constant equal to 0.2. According to phase 2, the new state of the m^{th} pelican in the n^{th} dimension is $y^{P2}_{m,n}$. To discover a better solution, the coefficient D represents the radius of the local neighborhoods of the population members.. In order to approach the ideal global solution, this coefficient has an impact on the EPOA exploitation power. Because this coefficient has a high value in the first iterations, a wider region surrounding each member is taken into account. Each member's neighborhood radii get smaller as the *D(1-t/T)* As the process duplicates more, the coefficient decreases. This allows us to scan the area around every part of the community in fewer and more accurate stages, allowing the EPOA to come together to solutions that are nearer to the worldwide (and even exactly global) ideal based on the utilization concept.

The new pelican status, represented by equation (7), was additionally approved or disapproved at this point by effective updating:

$$y_m = \begin{cases} y_{m,}^{P_2} \; P_{\mathrm{i}}^{P_2} < P_{\mathrm{i}}^{;} \\ x_{\mathrm{m}} \end{cases} \tag{7}$$

where P_i^{P2} is the value of the target prediction function based on second phase and y^{P2}_m is the new status of the m^{th} pelican.

Pseudo-Code of the Suggested EPO-DPLSTM Algorithm

After all prediction in different location of historical parameters have been updated based on both phases, the population's new status, and the values of the objective prediction function, the best prediction solution to date will be updated. As the algorithm advances to the next iteration, the different phases of the proposed EPO based on Equations (4)-(7) are repeated until the whole execution is finished. The best catastrophe prediction solution found throughout the algorithm's iterations is eventually presented as a quasi-optimal solution to the current situation.

Algorithm 1 presents the pseudo-code for the several phases of the proposed EPO-DPLSTM (Table 1).

```
Algorithm 1: Pseudo-Code for EPO-DPLSTM

Starts with  EPO-DPLSTM.
Insert past geological forecast data into the optimizer.
Ascertain the EPOA size as (N) and the no. of parameters as (T).
Calculating the goal function and initializing the pelican positions.
For m = 1:M
    Create the prey's location at randomly.
    For n= 1:N
    Moving closer to the prey (exploration phase).
        For n = 1:m
        | Utilizing Equation (4), determine the new prediction status for the nth dimension.
        End.
        Revise the mth disaster predictive location using Equation (5).
    Second Phase: Afloat on the water's surface (exploitation era).
        For n = 1:i.
        | Calculate new suggested status of the nth matrix using Equ (6).
        End.
        Equation (7) is used to update the mth group component.
    End.
    Update as best as can disaster prediction data solution using Equ (14),(15),(16).
End.
Outcome of the  best prediction solution acquired by EPO-DPLSTM.
End EPO-DPLSTM.
```

Tab. 1 - Alghorithm for EPO-DPLSTM

Disaster prediction LSTM

LSTM is a special kind of RNN that captures the long-term dependence of sequential data. The DPLSTM network is similar to RNN in structure and consists of an input layer, a hidden layer, and an output layer. The difference between LSTM and RNN, however, is that the latter substitutes a memory block for the fundamental unit of a typical RNN. The memory block has three gate functions, each of which has a distinct function in the information flow process, as seen in Fig. 3.

Given a sequential input of $X=\{x_1, x_2, \ldots, x_N\}$ and an outcome sequences of $Y=\{y_1, y_2 \ldots, y_N\}$. One important condition that decides whether the present information should be remembered

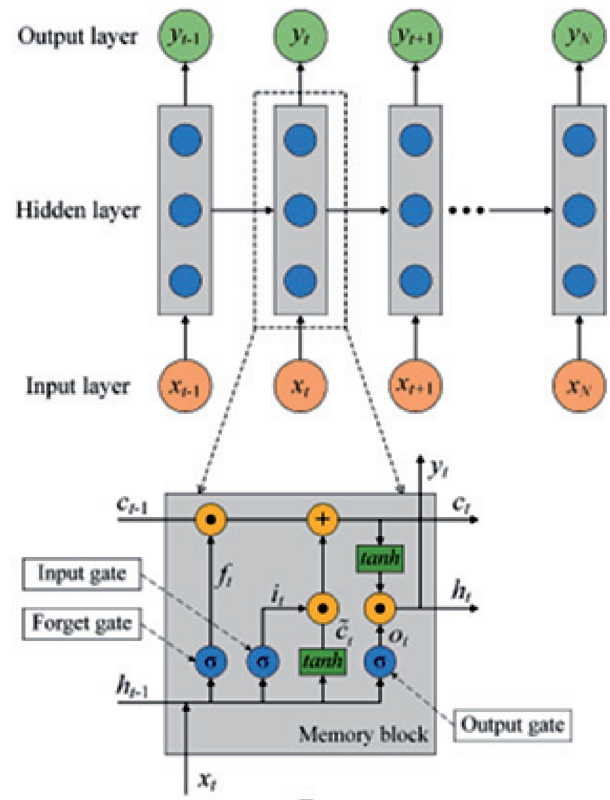

Fig. 3 - Architecture of the LSTM network

or forgotten is the forget gate. It can be computed in the following way for a given time step *t* in equation 8:

$$f_t = \sigma(w_{f_x} x_t + w_{fh} h_{t-1} + b_f) \quad (8)$$

where f_t forget gate activation vector at time, x_t input vector, $h_{(t-1)}$ previous hidden, $w_{(fx)} x_t$ weight matrices, state σ is the function of sigmoid, b_f is the forget gate's bias, and w_{cx} and w_{cn} are the forget matrix by weight and forget-hidden matrix of weight, respectively. Information update and memorization of new information are determined by the input gate, which is defined as follows:

$$i_t = \sigma(w_{ix} x_t + w_{in} h_{t-1} + b_i) \quad (9)$$

$$C_t = tanh(w_{cx} x_t + w_{cn} h_{t-1} + b_c) \quad (10)$$

where i_t input gate vector, b_i bias, $w_{ix} x_t$ weight matrices, b_i and b_c are the gate's with input and the update state's with cell bias vectors, respectively, and w_{cx} and w_{cn} stand for the weight matrix. Next, the following modification is made to the new memory cell state C_t:

$$C_t = f_{t\,\theta\, c_{t-1} + i_t \cdot \theta} C_t \quad (11)$$

The EPO-DPLSTM cell is an effective structure using gate units to regulate the data flow, but it has the same outputs and inputs as a regular RNN cell. A present-time input of C_t as update cell state; C_{t-1} previous cell state, $w^{(s)}$ and an output of $g^{(s-1)}$ from the prior moment determine the weight of the self-loop cell status that the FG uses to refresh the memory cell.

$$E_j^{(s)} = \sigma\left(a_j^E + \sum_i V_{j,i}^E w_i^{(s)} + \sum_i X_{j,i}^E g_i^{(s-1)}\right) \quad (12)$$

Where:
σ - Sigmoid function;
X^E - RWs of the FG;
V^E - IWs of the FG and
a^E - Respective biases of the FG.

The value that the FG sets in the range of 0 to 1.The data delivered into the memory cell is regulated by the IG.

$$J_i^{(s)} = \sigma\left(a_j^J + \sum_i V_{j,i}^J w_i^{(s)} + \sum_i X_{j,i}^J g_i^{(s-1)}\right) \quad (13)$$

Where:
X^J - RWs of the IG;
V^J - IWs of the IG and
a^J - Respective biases of the IG.

Following that, the LSTM cell's internal condition is modified in the manner described below:

$$T_j^{(s)} = E_j^{(s)} T_j^{(s-1)} + J_j^{(s)} \tanh\left(a_j + \sum_i V_{j,i} w_i^{(s)} + \sum_i X_{j,i} g_i^{(s-1)}\right) \quad (14)$$

X - RWs into the LSTM cell;
V - IWs into the LSTM cell and
a - Respective biases into the LSTM cell.

The weight of cell output is controlled by the OG:

$$P_j^{(s)} = \sigma\left(a_j^P + \sum_i V_{j,i}^P w_i^{(s)} + \sum_i X_{j,i}^P g_i^{(s-1)}\right) \quad (15)$$

where:
X^P - RWs of the OG;
V^P - IWs of the OG and
a^P - Respective biases of the OG.

Subsequently, the DEPO- LSTM cell's output is:

$$g_j^{(s)} = \tanh\left(T_j^{(s)}\right) . P_j^{(s)} \quad (16)$$

Long-term dependencies can be acquired by EPO-DPLSTMs using these gated units.

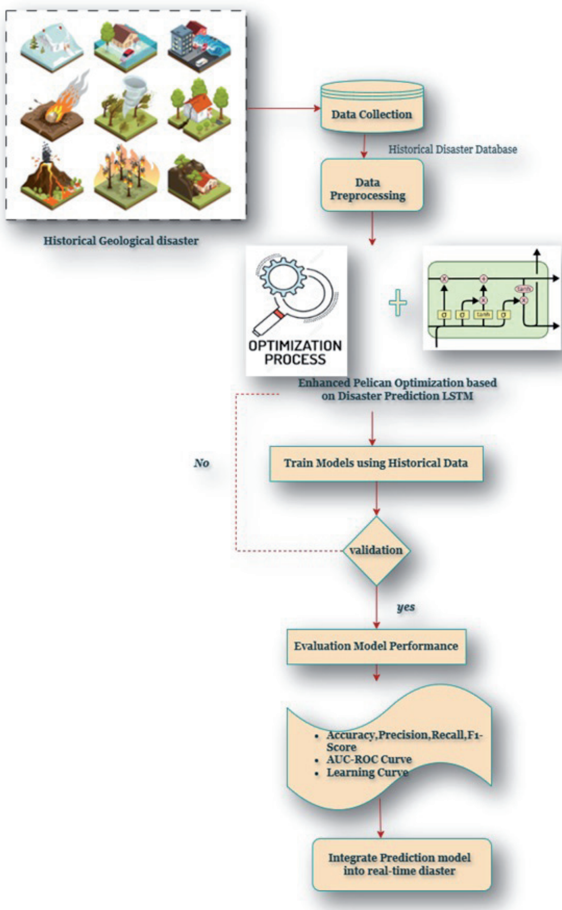

Fig. 4 - Proposed model

This workflow of the proposed method (shown in Fig. 4) is the overall attempt towards creating a disaster-prediction model based on historical geological disaster information. It starts with the step of data collection of the past disaster events, then preprocessing of the data to clean, normalize and structure the data. That processed data is then inputted into two aspects, an optimization mechanism that improves the feature selection and parameter adjustment, and an LSTM-based prediction model that trains temporal patterns in the occurrence of disasters. These optimized results are summed up to provide historical data on the model. The model is then checked through validation to determine whether the model has achieved the desired standards after training. The system is then validated and proceeds to model evaluation where the system is assessed based on accuracy, precision, recall, F1-score, AUC-ROC and learning curves. Lastly, as soon as the model achieves good performance it is incorporated into a real-time disaster prediction system to facilitate early warning and decision making.

RESULTS

Historical Geological disaster data in China

Disasters are defined as any geophysical, meteorological, or climatic event, including volcanic eruptions, earthquakes, flooding, fires, droughts, storms, and landslides. The annual average for the past few years is used to calculate decadal figures. In Fig. 5 represent quantifies the number of individuals who die every year because of natural calamities like earthquakes, floods, storms, heatwave, and landslides. It shows the magnitude of disaster events and preparedness as well as effectiveness of early warning systems, preparedness and emergency response. The more it is higher, the more vulnerable it is, the reduced the disaster mitigation ability.

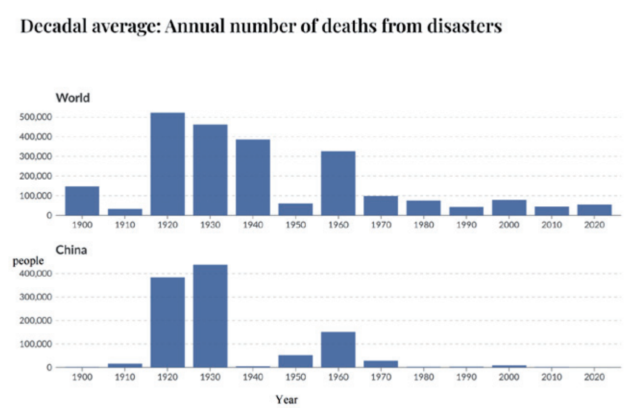

Fig. 5 - Number of disaster-related deaths per year

In Fig. 6 metric is used to describe the number of people who get injured in a year due to their exposure to disaster events. Structural collapses, debris, flooding, landslides or secondary hazards result in injury. Monitoring this can be used to comprehend the magnitude of human damages, and

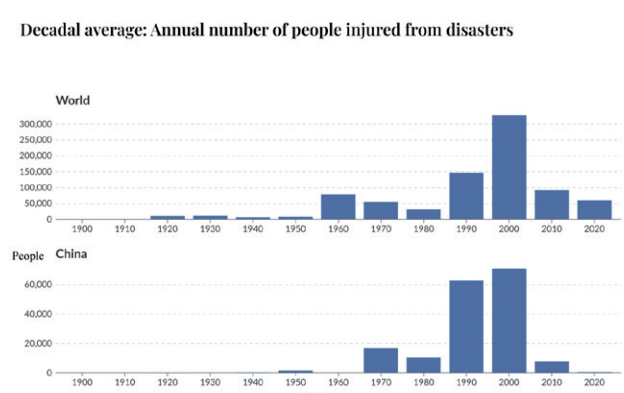

Fig. 6 - The annual number of disaster-related injuries

the strain imposed in healthcare systems both during disasters and following disasters.

Figure 7 reflects the same as the former indicator, but pays attention to those injuries which, according to the reporting agencies, should be discussed as disaster-related ones. It comprises both direct physical injuries and collateral injuries. (e.g. when evacuation is undertaken). It assists in quantifying the non-fatal human impact and it is frequently employed to determine the efficacy and safety procedures of emergency responses.

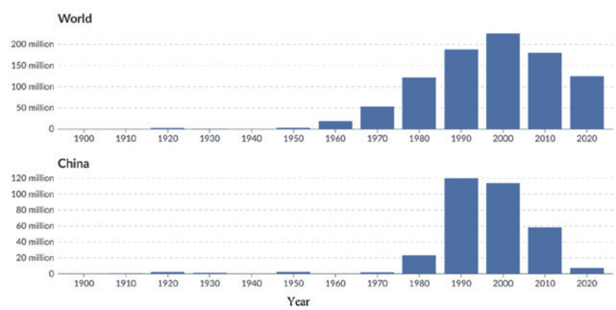

Fig. 7 - The number of individuals impacted by disasters per year

In Fig. 8 indicator an annual percentage of the GDP of a nation or the globe reflects economic losses that are due to disasters in terms of infrastructure, crops, and buildings that are damaged as well as the economic disruption. Comparing China to the global averages reveals that the impact of disasters on the national economy is so high in comparison to the scale. When the share is higher, it indicates more economic effect of disasters which may slow down the development process and it might need more investment on resilience and adaptation measures.

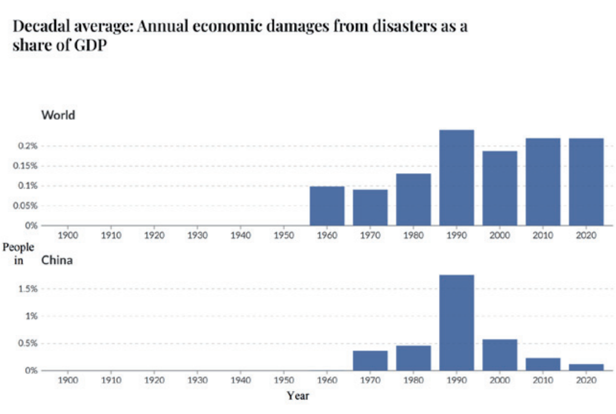

Fig. 8 - Annual disaster-related economic damages as a percentage of GDP

Compared to the average over the preceding 30 years (1991-2020), the global frequency of natural catastrophes in 2021 was 13% higher, resulting in 81% fewer deaths, 48% fewer affected individuals, and 82% greater economic losses. Strong earthquakes were less frequent and caused comparatively little damage; wildfires killed fewer people but impacted a 219% rise in population, and direct financial losses were 109% more than in the past. With 48% more occurrences than in the previous and 4393 fatalities - more than the total number of deaths from all natural disasters but 35% lower than the previous average of flood - related deaths-flood disasters were the most prevalent in 2021. Asia had the highest frequency of regional natural disasters in 2021, followed by North America; Asia also had the greatest amount of fatalities from catastrophic events of any continent, accompanied by North America; North America had the greatest revenue losses from disasters, accompanied by Europe; and natural disasters, particularly floods, storms, and extreme temperatures, had a greater impact on developing nations than on developed ones.

The entire amount of money lost to disasters as a percentage of GDP

Disasters are defined as all geophysical, meteorological, and climatic events that occur between 1960 and 2022, including quakes, eruptions of volcanoes, slides, droughts, wildfires, storms, and floods.

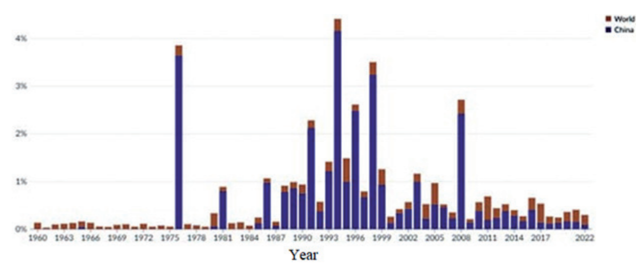

Fig. 9 - Financial disaster as a percentage in GDP

Financial disaster as a percentage of GDP in Fig. 9 is a measure of the percentage of loss of economy due to disasters like floods, earthquakes, storms, droughts or other major occurrences in a country on the overall economy of the country. It quantifies damages associated with disasters in terms of the proportion of the total economic output in the country. The increase in percentage indicates that disasters are more influential on the economic stability, recovery expenses, and sustainable growth. This indicator allows the comparison of vulnerability between countries and demonstrates the degree to which an economy is resilient to large-scale shocks.

Performance Evaluation

Experimental setup: The proposed EPO-DPLSTM is evaluated through explorations that are performed on MatlabR2024a platform and the results of which are presented in the subsequent sections together with other relevant analysis. The Performance of the proposed EPO-DPLSTM method is confirmed using the original classification algorithms, such as

Decision Tree (DT) (Senthilnayaki *et alii*, 2023), Random Forest (RF) (Zhang *et alii*, 2023), Support Vector Machine (SVM) (Priyadharshini *et alii*, 2024), Naïve Bayes (NB) (Tang *et alii*, 2020). The effectiveness of disaster prediction on geological disaster data should be measured using different metrics like precision, accuracy, recall, and F1-score.

A machine learning model's evaluation accuracy and capacity for generalization determine its quality. The following are a few typical parameters for model evaluation:

1. metrics for Evaluation: Accuracy (ACC), which represents the accuracy of the model evaluation. The count of samples that the model's accurately predicted values divided by the total number of sample accuracy. Metrics like F1 value, recall, and precision are also included;
2. AUC-ROC CURVE: the model's capacity for generalization is expressed by the ROC curve and AUC value. The ROC curve, also known as the operating characteristic of the receiver curve in minimum, is a thorough index that takes into account the continuous variables of sensitivity and specificity. The AUC value typically ranges from 0.5 to 1.0, and the higher the AUC number, the best the model performs.
3. CURVE OF LEARNING: the model fitting problem is described by the learning curve, which also determines whether the model is over- or under-fitting.

Evaluation Metrics

- Accuracy

In order to evaluate disaster prediction effect based on Machine Learning, we use a range of measure, such as recall, F1-Score, precision and accuracy. We compare these performance measures with the existing methods such as DT, RF, SVM and NB.

Classification Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DT	80.2	77.8	77.1	79.5
RF	88.6	85.2	84.5	87.2
SVM	90.8	88.9	89.9	89.5
NB	82.1	80.3	79.9	81.3
EPO-DPLSTM[Proposed]	99.5	95.6	96.1	98.5

Tab. 2 - Performance comparison of different baselines with suggested method

The percentage of incidents that are reliably and effectively classified is analyzed by accuracy. Table 1 and Fig. 10 show the accuracy outcome. Our suggested approach achieved a higher EPO-DPLSTM (99.5%) than the current methods: DT (80.2%), RF (88.6%), SVM (90.8%), and NB (82.1%). When compared to existing approaches, the proposed approach, EPO-DPLSTM, has significantly improved prediction in forecasting geological disaster effectiveness.

- Precision

The efficiency of the disaster prediction is measured by this

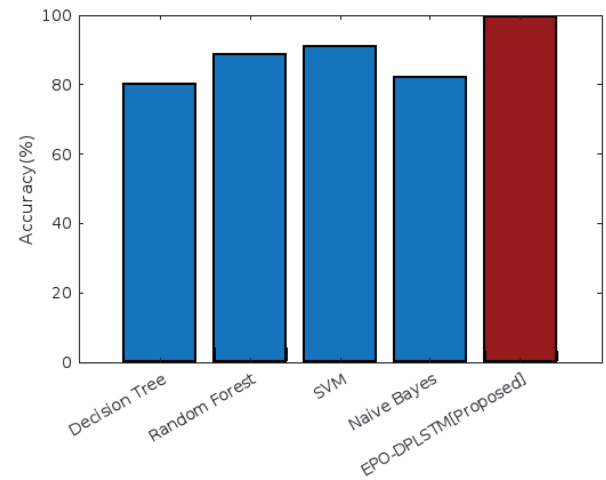

Fig. 10 - Outcome of accuracy

statistic. In this paper, we utilize web crawler dataset. Figure 11 shows that while the precision of the current techniques (DT, RF, SVM and NB) has been demonstrated to be less than 90%, the precision of our suggested approach, EPO-DPLSTM, has been demonstrated to be 95.6% higher than that of the previous techniques. Table 2 and Fig. 11 show the precision's outcome. When compared to existing approaches, the proposed approach, EPO-DPLSTM, has significantly improved disaster prediction effectiveness in historical geological data.

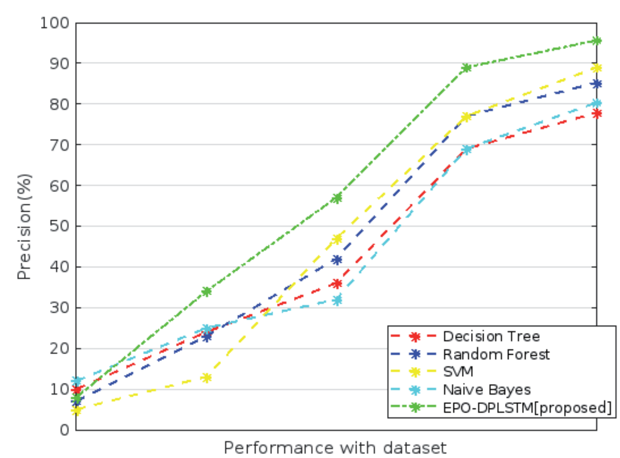

Fig. 11 - Outcome of precision

- Recall and F1-Score

Recalls show the percentage of true positives that are effectively acknowledged out of all real positives. Compared to the existing method DT(77.1%) RF (84.5%), SVM (89.9%), NB (79.9%) Our proposed method was higher EPO-DPLSTM (96.1%). The proposed approach, EPO-DPLSTM, has significantly improved the prediction when compared to current methods.

The efficiency of the disaster prediction is measured by this statistic dataset. Fig. 12 and Table 2 show a comparison of the present classification methods and the suggested classification methods in terms of F1-score. Compared to the existing method DT (79.5%), RF (87.2%), SVM (89.5%), and NB (81.3%) Our proposed method was higher EPO-DPLSTM (98.5%).

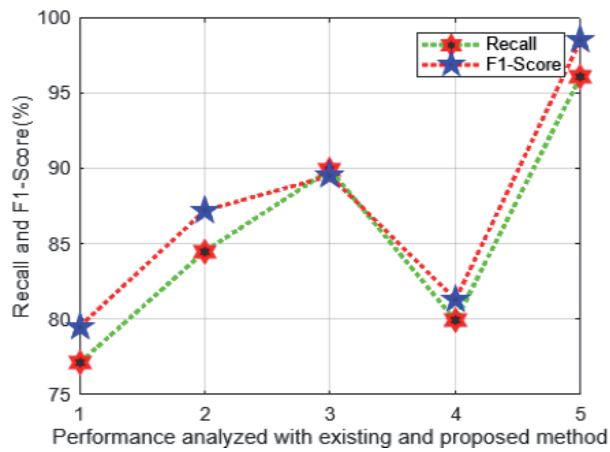

Fig. 12 - Outcome of Recall and F1 Score

Figure 13 shows the Overall performance of existing and suggested model performance.

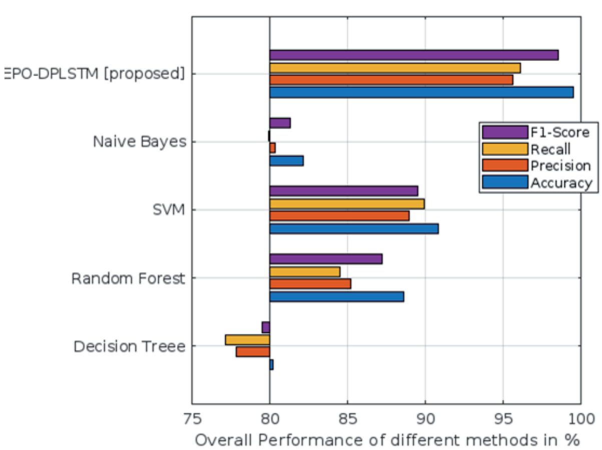

Fig. 13 - Overall performance of existing and proposed method

AUC-ROC Curve

The overall distribution of point samples (30% disaster points and non-disaster points) in each catastrophe location is evaluated statistically the evaluation results' accuracy may be objectively confirmed, offering a more reliable confirmation of the susceptibility zoning findings. In geological catastrophe susceptibility investigations, the ROC-AUC curve is frequently used to evaluate the evaluation model's accuracy. The percentage of geological disasters that were accurately anticipated is plotted versus the percentage of disasters that were poorly predicted. The susceptibility assessment findings test and ROC curve in Fig. 14 are used in this study to confirm the precision of the assessment findings. The evaluation model's AUC value in this study is 0.989, which is nearer 1 and higher than 0.5. This shows that the method accuracy satisfies the necessary standards and offers a fair and accurate depiction of the historical geological disaster-prediction scenario in the research region.

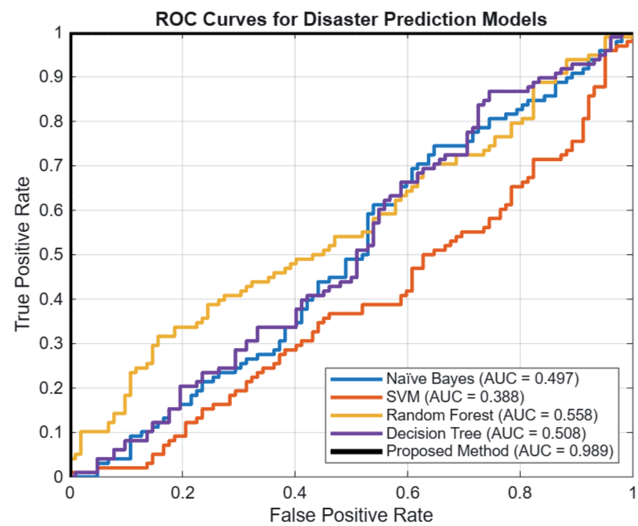

Fig. 14 - AUC-ROC Curve for the Existing and suggested method

The ROC graph in Fig. 14 is used to compare the classification performance of the current approach and the suggested approach depending on whether they can classify disaster and non-disaster events. The curves that are nearer to the top-right side show higher predictive ability. The proposed method has the steepest and the highest ROC curve and an AUC of 0.989 and this is an excellent discrimination model when compared to the other four models. Random Forest and SVM have an intermediate predictive ability and Naive Bayes and the Decision Tree perform relatively poorly. On balance, it can be concluded that the ROC plot puts into a prominent place the high level of robustness and reliability of the suggested method of predicting geological disasters.

Learning Curve

When a proposed model is trained too well on the training data, it is said to be overfit. It consequently performs badly on fresh, untested data. Fig. 15 shows several indicators that a model might be overfitting: After a certain point in the training process, the model's performance flattens or begins to decline; The model performs noticeably better on training data than on validation or test data.The complexity of the model is substantially higher than the problem's complexity.

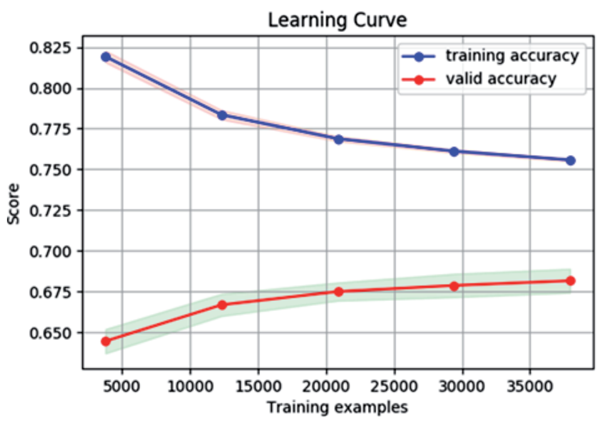

Fig. 15 - Learning curve for the suggested training and cross-validation

Table 3 compares the advantages and disadvantages of methods with existing methods of Decision tree, Random Forest, Support Vector Machine, Naïve Bayes with suggested method.

Algorithm	Advantages	Disadvantages
Decision Tree	Capable of capturing non-linear interactions, easily comprehensible and interpretable	May not generalize well to fresh data and is prone to overfitting.
Random Forest	High Accuracy, less prone to overfitting than decision trees, and the ability to handle big, high-dimensional datasets	computationally costly, challenging to understand and interpret
Support Vector Machine	High dimensionality and accuracy in handling nonlinear data	computationally costly and sensitive to the parameters and kernel function selection
Naïve Bayes	Computationally efficient, easy to build, and capable of handling high-dimensional data	Assuming feature independence could miss intricate relationships.
EPO-DPLSTM	long-term dependencies in sequential data are captured with high precision.high seismic activity prediction, forecasting few occurrences.	extended time for development, interpretability

Tab. 3 - Comparison of advantages and disadvantages of methods

DISCUSSIONS

The result of this research proves that the proposed EPO-DPLSTM model is capable of learning complicated time series using historical geological disaster records and provides very precise early-warning forecasts. The input data, which consisted of web-crawled information on disaster events, environmental indicators, time-varying characteristics, and geospatial characteristics in the region, allowed the model to scope the dynamics of events as well as the spatial-temporal changes necessary to provide sufficient forecasts. The DPLSTM network supported two types of tuned parameters, including the best number of hidden units, learning rate, dropout percentage, and batch size, as advanced in the Enhanced Pelican Optimization algorithm, which has greatly enhanced the convergence and generalization. Although these are the strengths, there are a number of limitations. First, historical disaster data could be of different quality and completeness across locations, which could impact the consistency of the prediction. Second, external influencing factors (i.e., land-use change, hydrological alteration of the ground, or unmonitored micro-seismic events) were not considered in totality and might restrict the ability of the model to generalize to unobservable extreme events. Moreover, in spite of EPO boosting optimization, it is a more expensive method of computation than less complex methods of optimization. Future studies are needed to combine multi-source real-time streams of data, i.e., remote sensing images, Internet of Things sensor systems, rainfall radar, and soil deformation monitors, which can enhance the forecasting accuracy. Also, the hybrid deep learning models (e.g., Transformers, CNN-BiLSTM, or graph neural networks) could enhance the spatial-temporal feature extraction. The real-time deployment model expansion, creation of interpretable AI elements, and verification of performance through different regions with various geological characteristics are all necessary directions in order to give more practical information to policymakers and stakeholders.

Recent knowledge in sensor fusion and deep architectures is an indication of extensions in our approach. To do flood mapping, the capsule-network fusion pipeline, where the SAR (Sentinel-1) and optical (Sentinel-2) data are first combined and then covered by capsule layers, was recently demonstrated in improving the inundation delineation when compared to the normal CNN ensembles, especially the ability to retain the geometric relationships and the part-whole relationships in the imagery that we can incorporate in our model to enhance the extraction of spatial features (Ahmadi *et alii*, 2025). More recently, CNN-based P-wave detectors have shown significantly superior P-wave detection in noisy environments compared with classical STA/LTA algorithms; a combination of such detectors as a quick seismic-flag signal into our LSTM network will potentially provide very-short-lead seismic warnings associated with earthquakes (Zhexebay *et alii*, 2025). Taken together, these studies indicate a future, multi-modal EPO-DPLSTM that integrates capsule-learned spatial embedding, CNN seismic flags, and environmental time series- whilst accounting for both uncertainty quantification and cross-region validation- to increase the mapping fidelity and operational early-warning utility.

CONCLUSIONS

This essay emphasizes that effective preparation for and response to disaster activities depend on precise forecasts of weather and natural catastrophes. Its global effects underscore the necessity of using advanced technology globally. Because machine learning algorithms enable effective resource allocation and early warnings, they have a revolutionary impact on catastrophe management, lowering socioeconomic effects and saving lives. The global significance of our research stems from the widespread use of machine learning techniques. EPO-DPLSTM algorithms offer insights necessary for knowledgeable reaction operations across several geographies and climatic circumstances since they can evaluate a wide range of data sources. They serve as a pillar in the fight against natural disasters worldwide, emphasizing the necessity of an organized, climate and geographical-technologically advanced approach to global issues. Despite persistent problems with accuracy and data quality, our analysis highlights the subject's dynamic nature. These problems are addressed by constant innovation and research, which guarantees continued progress and resilience to unforeseen setbacks. By acknowledging the limitations of the current, we pave the way for a future where technology evolves and adapts to meet the demands of a dynamic environment. Machine learning algorithms have a wide and exciting variety of potential applications in catastrophe preparedness and response in the future. Prioritizing innovation, promoting collaboration, and engaging with communities are essential elements. By doing this, we can use this technology's revolutionary potential to protect communities affected by natural disasters and eventually save lives. Further study by combining machine learning with IoT sensors and real-time data analytics for enhanced prediction capabilities.

The main goal of this research was to create an intelligent and highly precise framework of disaster prediction based on historical geological data of disasters to enhance early warning and improve supportive disaster management. In order to do that, we have suggested the EPO-DPLSTM model, which is aimed at maximizing the learning of temporal features and enhancing the generalization and the reliability of predictions.

The paper has a number of contributions. First, it presents a more advanced metaheuristic-deep learning hybrid model, in which the global optimization approach is combined with the LSTM-based sequence prediction, taking the field of disaster prediction a step further. Second, it has been proven after years of experimentation that the suggested EPO-DPLSTM model is significantly more effective than the conventional machine learning methods, such as Naïve Bayes, SVM, Random Forest, and Decision Tree. The model had an accuracy of 99.5% and an AUC of 0.989, which reflects that the model has very good discriminatory power and a high level of robustness in the identification of early disaster patterns. Third, the model takes into consideration historical geospatial, hydrological, and environmental variables, and this enables the model to have a more comprehensive perspective of disaster hazards and facilitate the formulation of accurate and dependable early alarm systems.

Even though it has been performing strongly, there are a number of limitations. The efficiency of this model is determined by the quality and completeness of historical disaster records, which might differ in different areas as a result of the lack of data or errors in reporting. Also, the existing structure is mainly based on fixed historical characteristics and has not yet embraced real-time sensor information or multi-source remote sensing stimuli. Certain hyperparameter values, even after having been optimized in the Enhanced Pelican Optimization algorithm, might need additional training to generalize to a wider region. Further, the model is yet to be clearly tested in a wide variety of territorial geographies, where this could affect transferability.

Future directions of the research should emphasize the combination of real-time IoT sensor streams, high-resolution remote sensing imagery, and advanced data fusion methods in order to record the dynamic changes in the environment. Future insights can include the introduction of more up-to-date architectures, including capsule networks, transformer-based sequence models, multimodal spatiotemporal fusion networks, and so on, which can further improve the accuracy of disaster detection and early warnings. Also, cross-regional transfer learning and scaling the sample to other regions would be useful in assessing model resilience in other climatic and geological conditions. Creating easy-to-use decision support tools that are built on this framework would also be helpful to policymakers, emergency planners, and disaster-risk management authorities.

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Received July 2025 - Accepted November 2025