Assessing Long-term Impacts of Disaster Using Predictive Data Analytics for Effective Decision Support

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Abstract: Disaster is a big issue that seriously disrupts and affects the community or society. The impact of a disaster causes a short and long period of time. To analyze the impacts of disasters there are lots of available related datasets. Data analytics methods have the potential to assess the impacts of different types of disasters. Collectively data analytics and machine learning techniques play an important role in transforming and being able to make decisions about our social, economic, mental, and psychological things. The objective of this paper is to assess the impacts of disasters from immediate term to long-term, provide crucial help to the emergency management workforce, and policy decisions making based on the latest available datasets. With the help of the various data agencies, extraction of information and activities carried out, we can determine the effects on disaster victims, their community and impacts on society in general. The analysis provides the statistics that can guide our emergency service about the status of facilities that can further support the survivors, and other related information. Detailed assessment i.e., structural survey and hazard mapping provide specific information about reconstruction and mitigation to monitor the situation, needs of the victims, and supporting entities. The assessment is based on the type of disaster that happened and its impact after a few years.

In the current technological advancement of data analytics and machine learning algorithms, the prediction of the long-term effects of a disaster can be performed. Analyzing the impacts over a long period of time is also dependent on the growth of actively cared datasets gathering bodies like agencies, government, NGOs, media, etc., where prediction of short-term and long-term impacts is dependent on the available datasets. Available datasets are preprocessed using data analytics tools and implementation of training and testing for the purpose of predictions and recommendations. As a huge amount of data sets are available through different sources the classification of the datasets can also be performed resulting fast and accurate processing. Model validation techniques play an important role to check the validation, test result, and related outcomes. In this paper advanced machine learning and data analytics tools i.e., XG boost, modified SVM, and modified RF are used for better prediction. The analysis of the short-term effects of disasters has already been suggested and recommended by the various conventional approaches. Here the focus is to analyze and detect the long-term effects of a disaster along with recommendations and models preparing for good decision-making. Therefore, planning should be focused on assessing the impacts from short-term to long-term. The findings of the paper would be helpful to the agencies, local & national authorities, and the government by recommending action plans and their future effects for a longer period in case of disaster.

Keywords: Data analytics, Disaster Management, Long-term Impacts, Machine Learning, Predictive Analytics, XG Boost

I. Introduction

Data plays a crucial role to access reliable information for the prediction of disaster impacts and its effective emergency management. Reliable disaster datasets are having the potential to analyze directly or indirectly the impacts of victims. Disaster datasets are majorly available in three different categories i.e., natural, technological, and hybrid. Geological, hydrological, climatological, meteorological, biological, and space disasters come under the category of natural disasters. Chemical hazards, radiological events, dam failure, power outages, and cyber security come under technological disasters. Terrorism, accidents, epidemic & pandemic, and displaced population, are coming under the category of hybrid disasters. The impact of such categorical disasters can vary from short-term to long-term depending on their types. In most cases, disaster can damage the economy, infrastructure, life, and other human resources. Prediction of disaster impacts is not so easy, because there are several reasons where problems can occur like technological or human error, equipment malfunctioning, disease, biological danger, etc. The impacts of disaster and its duration are also uncertain, and effects can go from short-term to a long period time.

The availability of authentic disaster datasets nowadays to access reliable information for impact prediction and to take effective decisions. Different amounts of data are available on different platforms i.e., social media, volunteer organizations, government official websites, agencies, etc. when any kind of disaster occurs. Nowadays when any kind of disaster occurs, the related type of data i.e., photos, videos, text, audio, etc., can easily be accessed from social media, as social media is a primary mode of instant communication. Organizations like disaster management systems and emergency response systems validate such types of data based on the validation services [1]. Most of the data available on social media is irrelevant and redundant. In such cases, the role of data preprocessing and the use of analytics algorithms are required. Sometimes it also becomes challenging for the organization to predict the impacts of such a disaster due to inappropriate datasets. Taking effective decisions is also difficult in such cases. To reduce the disaster impacts, the emergency response team should be aware of the complete information about the situation based on the previous such type of emergency response systems. Social media and such related organizations have been provided the information about previous events to make sense out of the available information [2]. Further, by analyzing related datasets the emergency response team gains awareness of the situation during disaster response.

Data analytics and Machine learning tools are good to analyze a large amount of available data for identification of unknown patterns in case of enormous quantities of data. It will help the concerned authorities with recent developments and improvements for various tasks handled by disaster management. The objective of this paper is to investigate the impacts of previous disasters and try to predict the future impacts of the disaster. This paper is organized into five sections. Different categorical impacts, majorly physical, social, economic, and psychological have been discussed under the section ‘Impacts of Disaster’. Prediction of disaster and management is discussed in the section ‘Disaster Prediction and Management’. Prediction of the long-term impacts and decision support using data analysis and machine learning models are discussed in the section ‘Related Work’. The algorithms and methods are discussed in the ‘Research Methodology’ section. The proposed results are discussed in the ‘Result and Discussion’ section and finally, the last section ‘conclusion’ concludes the findings.

II. Impacts of Disaster

Disaster affects the physical capital and the infrastructure of an economy in different ways. By predicting the impacts of the disaster, countries have an opportunity to build a system using new technology to analyze the relationship between disaster management systems, the hierarchy of the organization, natural resources, and the political climate. Previous research work has concluded that the analyzed data has shown a positive impact on pre-disaster monitoring and early warning [3]. Some natural disasters have found no statistically significant relationship between technology and the level of disaster in a country. There are several factors that are related to the impact and frequency of disasters like vulnerable natural environments, geographical systems, weak government capabilities, lack of awareness, lack of management, etc.

In the past 20 years, most of the disasters have been caused by natural disasters i.e., floods, storms, heat waves, droughts, and other weather events. India is the top 5 countries hit by the highest number of natural disasters. Every year millions of people get affected by different kinds of disasters. One of the Sendai Framework for Disaster Risk Reduction (SFDRR) 2015–2030, has some targets and priorities to understand the existing risks and priorities [4]. It aims to reduce the impact of losses through the disaster in the next 15 years in the country. The administrative structure of the proposed framework (SFDRR) is extremely important for detecting, handling, and recovering during disaster situations. The targets are clearly defined priorities to prevent new and reduce existing disaster risks [5]. To handle the impacts of disaster, it is necessary to prepare a framework of a particular national disaster management system to reduce vulnerability. In the planned development framework, it should have strategic priorities, critical enablers, and accountability to achieve the vision to lower the impacts of disaster [6].

There are different dimensions like social, economic, infrastructure, health, knowledge, services, etc., where analysis of impacts are required [7]. The following table, table 1 shows the major impacts of disasters affecting human lives physical, psychological, social, and economic along with their types.

Table 1. Impacts of Disasters

Impacts of Disaster			
Physical	Psychological	Social	Economical
Injuries	Distress	Change in individual roles	Loss of life
Death	Flash backs	Disruption of social fabric	Unemployment
Physical disability	Intrusion/ Avoidance	Isolation	Loss of livelihood
Burns	Hatred/ Revenge	Change in marital status	Loss of property
Epidemic	Dependency/ Insecurity	Domestic violence	Loss of crops
Physical illness	Grief/ Isolation	Sexual abuse	Loss of infrastructure
Weakness	Guilt feeling	Single parent children	Loss of household articles
Sanitation	Hyper vigilance	Migration	Loss of income/ Poverty
Miscarriage	Lack of trust	Breakdown of traditional social status	Business Disruption
Fatigue etc.	Hopelessness/ Helplessness etc.	Family and social disorganization etc.	Downturn GDP etc.

To reduce the disruptive impact of the disaster, the proposed model is designed in such a way, that it can help to take prior decisions based on their warning systems. The model is working using a set of principles for prevention & reduction and evaluation the resource degradation. There is flexibility to show positive results, maintain social cohesion and management of natural assets. Intervention programs like training and education about disaster systems are a part of capacity-building treated communities to prepare for future hazards [8].

The impact of disaster is identified in the effective evaluation based on evidence-based decision making and proposed methodology for any kind of emergency at both the levels i.e., victims and organizations. The trained data sets can predict the impacts of the long term based on propensity score matching.

III. Disaster Prediction and Management

Prediction of disaster requires extensive research and reliable information from past disaster data sets to extract the pattern. Using the past records with reliable data, specific trends can be identified to predict future events. Technology is used in the prediction of disaster and its related consequences in current scenarios and long-term aspects. This also predicts the pattern in advance, so that the warning system can be evacuated. This short-term warning may save many lives. The relief program may be planned and effectively carried out. Such a warning system not only helps the victims but also helps the response and recovery team in their efforts on time. The most important thing is the reliability of the warning system in society [9]. The public trust in the system should be considered. Another possible method of disaster prediction is the idea of forecasting. This involves recognizing high-risk areas and adjusting preparation accordingly. Such prediction and warning can also help to reduce the damages and economic losses. Precautionary measures have also been taken to save many lives.

Disaster monitoring systems are using fusion technology of machine learning with sensors to analyze, predict and prevent damages. Decision algorithms and pattern recognition algorithms also help with natural disaster monitoring [10].

The main aim is to reduce the potential losses through disaster, assure appropriate assistance to the victims and try to achieve a fast and efficient recovery. The major tasks to be taken by the disaster management system are safety, security, and protection of life and property. The complete disaster management cycle is broadly categorized into two phases i.e., pre-disaster and post-disaster. Figure 1 shows the major categories of pre and post-disaster phases [11]. The mitigation phase and preparedness phase come under the pre-disaster system, where public education & awareness, hazard & vulnerability assessment, improved infrastructure, training, early warning, communication & response, national emergency, and SOP are recommended. Response and recovery phases come under the post-disaster systems where communication & coordination, saving lives, improving lives, restoring, rehabilitation, and other services are recommended [12]

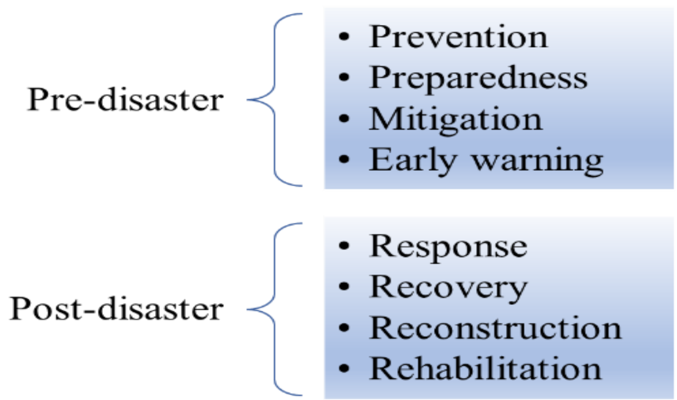

Fig. 1. Pre and post stages of disaster system

To analyze the various impacts of disaster, the datasets are integrated with various spatial decision support systems of disaster management agencies for the prediction and assessment. The data consists of historic data, social media data, concerned agencies data, weather reports, etc., is having the capability to analyze for required changes. According to the disaster management systems, it has four phases i.e., prevention, preparedness, response, and recovery involving different sub-phases for pre and post-disaster coordination and response [13]. Disaster datasets can help in pre and post-assessment like risk assessment, prediction, tracking, estimation, communications, and sentiment analysis. To improve the performance of decision-making systems different data analytic tools and techniques are integrated and trained in the models without human intervention.

IV. Related Work

Based on major data sources which consist of text, video, images, audio, aerial images, research data, government agencies, social media, etc. Disaster management phases consist of four main components: prevention, preparedness, response, and recovery. The main aim of the disaster management system is to reduce the potential losses and try to respond immediately to achieve rapid and effective recovery. The early warning system may help the victims and the team to protect them from different kinds of losses. The stages of disaster management systems also include early warning, monitoring, detection, damage assessment, prediction, post-disaster coordination, reduction, response, and long-term risk assessment. Here the strategy is to predict based on the pattern of such disaster datasets and other related parameters. Based on the data analysis and applying machine learning algorithms we could determine the pattern and solve the problem [14].

To predict long-term impacts like mental health (depression, anxiety, and brain disorder), loss of loved ones, injury or illness, destruction of property, livelihoods, economy/ loss of financial resources, loss of resources, loss of possessions & community, disruption of water, food and communication, epidemics, psychological illness, etc., we must use authentic datasets and the related model/algorithms to train and test the data where an effective decision can be taken [15][16].

The following table 2 shows the different categories and data sources along with models/ techniques that can be used.

Table 2. Data categories, data sources, and model/techniques

Data Categories	Data Source	Model/Techniques
Early warning damage	Satellite imagery	Pixel-based and Feature extraction image analysis methods
Damage assessment	Aerial imagery and videos	Based on the characteristics of aerial photographs like Shape, Size, Color, Shadow, Texture, Pattern, Association, Site, Time, and Resolution.
Monitoring and detection	Simulation, spatial data	Visualizing data through charts helps uncover patterns, trends, relationships, and structure
Forecasting and predicting	Crowdsourcing	Transaction and Analytical processing
Post-disaster coordination and response	Social media	Performance metrics, audience analytics, competitor analytics, Paid social analytics, Influencer analytics, Sentiment analysis
Long-term risk assessment and reduction	Hydrological data	Scale, analog and abstract
Prediction	Meteorological data	Global Forecast System (GFS)
Detection	Twitter	hashtag counting, noun counting, cosine similarity, Jaccard similarity, LDA, and K-means techniques
Disaster management strategies	NGOs, Agencies, radio, television, colleagues	Descriptive, Diagnostic, Predictive, and Prescriptive.

Nowadays, social media is one of the platforms to provide real-time data within a short span of time during crises or emergencies. It is used for communication and coordination with concerned agencies during crises. This helps the agencies with active management, timely help, prioritizing work, services of work, and filtering the data based on requests and needs of the people.

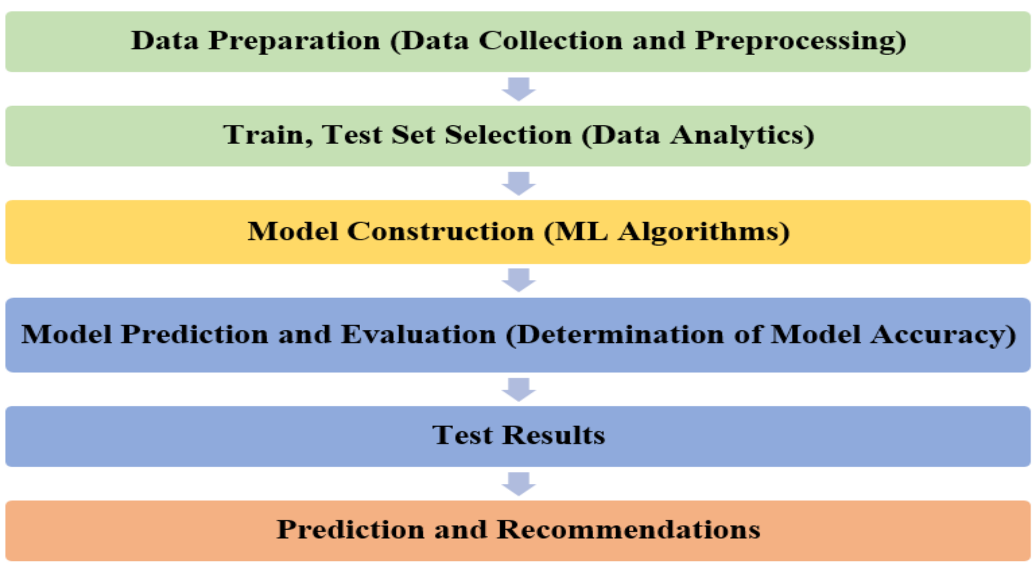

Fig. 2. Process flow model architecture

The proposed model extracts data from various sources, extracted data undergo preprocessing to prune irrelevant and redundant information. After applying preprocessing steps, the relevant data are retained. Next step is to create models using advanced decision tree-based machine learning algorithms like Extreme Gradient Boosting (XG boost), modified Support Vector Machine (SVM), and modified Random Forest (RF) for prediction purposes. After that the model will be evaluated and verified using the testing data. And finally, resulting in the form of prediction & recommendations, and future impacts. After getting the results, the next step will be to test models for the accurate prediction of real-time outcomes [17].

V. Methodology

Technology provides ideas and methods for people to analyze and solve problems. The current technology and trends provide an extremely convenient way for integration, sharing, analysis, mining, and decision making for the reduction of losses and efficient services. New technology includes big data analytics algorithms, cloud computing, AI, wireless communication, drone services, different services models, and deployment services to analyze and solve problems [18]. Currently, there is a huge amount of data available on different platforms in different ways. It is possible to analyze the available data on multidimensional, multilevel, and other factors too. Understanding the property of data is necessary before applying the algorithms, as there are majorly five Vs features (volume, variety, velocity, variability, and value) available in the disaster datasets. As we know that data is generated day by day, it is very difficult to use traditional methods for data visualization, pattern extraction, and decision-making [19]. It is necessary to deal with new machine learning methods like Random Forest, CNN, ANN, SVM, and XG Boost algorithms that are more efficient methods for handling such types of datasets. To process the real-time data, there is an integration of advanced machine learning algorithms where data is used for fast processing with accurate results. As compared with the different parameters of various advanced machine learning algorithms, the result of XG boost algorithms is more accurate and closely predicted [20].

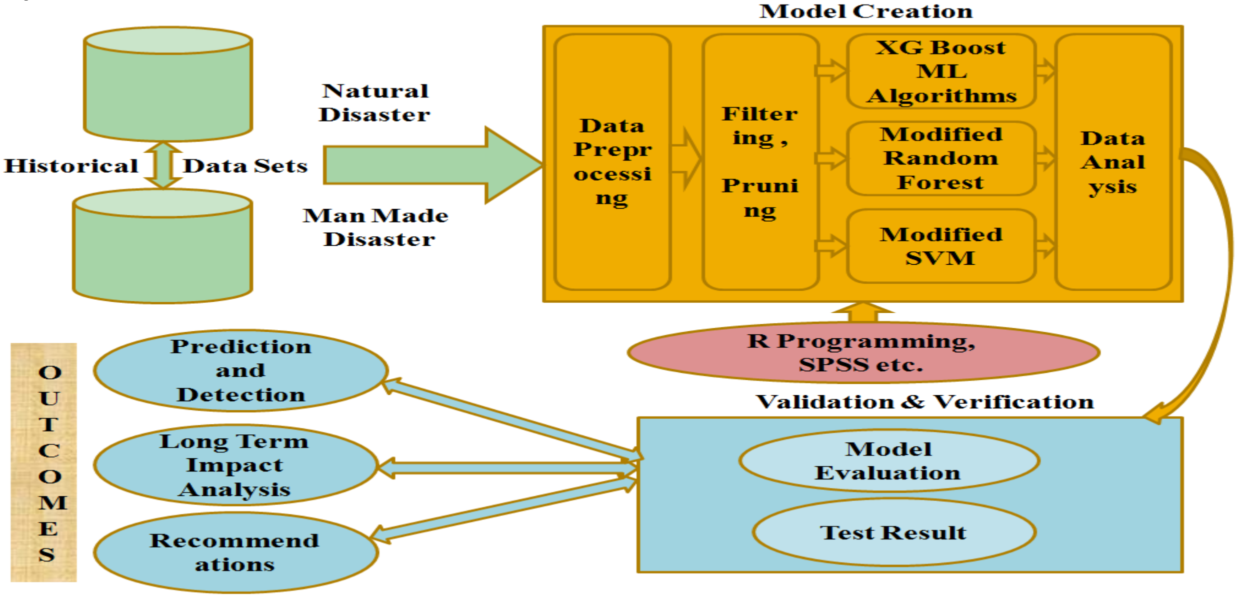

Fig. 3. Proposed solution architecture

Table 3. Comparison of advanced data analytics algorithms with different parameters

Algorithms/ Parameters	XGBoost (eXtreme Gradient Boosting)	SVM/MSVM(Modified SVM)	Random Forest/Modified Random Forest
Tree Pruning	Grows the tree up to max_depth and then prune backward	Stops once a negative loss is encountered	No pruning takes place in random forest
Missing Values	Efficient handling of missing data	Does not perform well with missing data	Good for data set which has missing value attributes
Loss Function	No limit to adds a new dimension to the model	Limit to adds a new dimension to the model	No limit to adds a new dimension to the model
Variance and Bias	High bias, low variance	Low bias and high variance	Low bias, high variance
Flexibility	More stable and efficient	Less efficient	Subset of features are selected at random (collections of decision trees)
Cross Validation	Allows at each iteration	Limited values can be tested	70% data for training and rest for testing
Computation Power	Fast and high Performance, Implement parallel processing	Less than XG Boost	Complex and Time Consuming
Dataset Features	Perform well when we have large data	Doesn't perform well, when we have large data set and noise data	Doesn't perform well, when we have large data set and noise data
Used for	Classification; Regression; Ranking	Classification or regression problems	Classification

To assess the long-term impacts of disaster there are four stages where data can be examined and predicted for decision support. Figure 3 shows the proposed solution to predict the long-term impacts of disaster along with recommendations. In this model, historical datasets/ valid datasets are used for model creation and the outcome of analytics data has been validated for model tests to generate outcomes [21].

Proposed Algorithms and implementation

The proposed project utilizes Extreme Gradient Boosting (XGBoost), a powerful algorithm known for its scalability, ease of use, and robustness. XGBoost assigns weights to all independent variables, which are then input into a decision tree to make predictions. Its advanced system features and algorithmic optimizations make it 10 times faster than other popular machine learning solutions, and it also uses parallel and distributed computing for faster learning and efficient memory usage.

XGBoost is an ensemble learning method, which combines the predictions of multiple models to create a single, more accurate model. This can be done using techniques like bagging and boosting, which are often used with decision trees. Boosting is different from bagging methods like Random Forest, in that it utilizes smaller, less deep trees that are more interpretable. The number of trees or iterations, the learning rate, and the depth of the tree can be optimized through validation techniques like k-fold cross validation. However, it is important to carefully choose the stopping criteria to avoid overfitting.

Below are the three steps used in Boosting Ensemble Technique:

- The process of boosting begins by defining an initial model, F_0, to predict the target variable y. This model is then associated with a residual, which is calculated as the difference between y and F_0.
- A new model, h_1, is then fit to the residuals from the previous step.
- F_0 and h_1 are then combined to create F_1, which is the boosted version of F_0. The mean squared error from F_1 is typically lower than that of F_0.

$$F_1(x) <- F_0(x) + h_1(x)$$

To further enhance the performance of F_1, we can model the residuals of F_1 and create a new model, F_2:

$$F_2(x) <- F_1(x) + h_2(x)$$

This process can be repeated for 'm' iterations, until the residuals have been minimized as much as possible:

$$F_m(x) <- F_{m-1}(x) + h_m(x)$$

During each iteration, additive learners are added to the previous models without altering them, which helps to reduce errors by providing new information.

Optimizing the loss function by means of gradient descent:

In the example discussed earlier, the Mean Squared Error (MSE) was used as the loss function, and the mean was used to minimize the error. However, when using Mean Absolute Error (MAE) as the loss function, the median would be used to initialize the model. Additionally, a unit change in y would cause a unit change in MAE.

For MSE, the change observed is roughly exponential. A more generic approach is to fit $h_m(x)$ on the gradient of the loss function, or the step along which loss occurs, rather than fitting it on the residuals. This makes the process applicable across all loss functions.

Gradient descent is used to minimize any differentiable function. In the case of gradient boosting, instead of predicting the mean residual at each terminal node of the tree as in a regression tree, the average gradient component is computed.

For each node, there is a factor γ which multiplies $h_m(x)$ to account for the difference in impact of each branch of the split. Gradient boosting helps in predicting the optimal gradient for the additive model, unlike classical gradient descent techniques which only reduce error in the output at each iteration.

Gradient boosting algorithm is performed using following steps:

- $F_0(x)$ – By which, initialization of boosting algorithm is defined:

$$F_0(x) = argmin_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma)$$

- Computation of gradient of the loss function:

$$r_{im} = -\alpha\left[\frac{\partial(L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)}, \text{ where } \alpha$$

- $h_m(x)$ is fit on the gradient obtained at each step.
- Multiplicative factor γ_m for each terminal node is calculated and the boosted model $F_m(x)$ is defined:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x)$$

Features of XGBoost

XGBoost is a widely used implementation of gradient boosting. It is known for its interesting features that make it popular among practitioners.
One of the key features of XGBoost is that it follows approach 1 to minimize the objective function. This means that at each iteration, it fits a base learner to the negative gradient of the loss function, and then adds a constant multiplied version of the prediction to the value from the previous iteration.

Input: training set $\{(x_i, y_i)\}_{i=1}^{n}$, a differentiable loss function L(y, F(x)), number of iterations M.

Algorithm:

1. Initialize model with a constant value:
$$F_0(x) = \arg\min_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma).$$
2. For m=1 to M:
   i. Compare so-called pseudo-residuals:
   $$r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \quad \text{for } i = 1, \ldots, n.$$
   ii. Fit a base learner (e.g. tree) h_m (x) to pseudo-residuals, i.e. train it using the training set $\{(x_i, r_{im})\}_{i=1}^{n}$
   iii. Compute multiplier y_m by solving the following one dimensional optimization problem:
   $$\gamma_m = \arg\min_{\gamma} \sum_{i=1}^{n} L\left(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)\right).$$
   iv. Update the model:
   $$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x).$$
3. Output $F_M(x)$.

This approach is based on the intuition that by fitting a base learner to the negative gradient at each iteration, it is essentially performing gradient descent on the loss function. The negative gradients are often referred to as "pseudo residuals" because they help to minimize the objective function indirectly.

VI. Result and Discussion

Following are the Indian data sets of earthquakes having all the possible attributes of the specific disasters from 1990 to 2021:

"[""1990 <= Year >= 2021"",""Country = INDIA""]"
*"Year" "Mo" "Dy" "Hr" "Mn" "Sec" "Location Name" "Latitude" "Longitude" "Focal Depth (km)" "Mag" "MMI Int" "Deaths" "**Death Description**" "Missing" "**Missing Description**" "Injuries" "**Injuries Description**" "Damage ($Mil)" "**Damage Description**" "Houses Destroyed" "**Houses Destroyed Description**" "Houses Damaged" "**Houses Damaged Description**" "Total Deaths" "Total Death Description" "Total Missing" "Total Missing Description" "Total Injuries" "Total Injuries Description" "Total Damage ($Mil)" "Total Damage Description" "Total Houses Destroyed" "Total Houses Destroyed Description" "Total Houses Damaged" "Total Houses Damaged Description"*

In a similar fashion, the datasets are accessed for analytics. Below datasets are having different possible disaster attributes where model/algorithms can apply for future impact analysis [22][23][24]:

Number of deaths from drought, Number of people injured from drought, Number of people affected from drought, Number of people left homeless from drought, Number of total people affected by drought, Reconstruction costs from drought, insured damages against drought, Total economic damages from drought, Death rates from drought, Injury rates from drought, Number of people affected by drought per 100,000, Homelessness rate from drought, Total number of people affected by drought per 100,000

The above possible attributes are described for disasters like drought, earthquakes, volcanic activity, floods, mass movements, storms, landslides, fog, wildfire, extreme temperature, glacial lake outbursts, chemicals, pandemics, etc., to support the outcomes.
Following are the steps to follow:
Steps:

a. Store all possible data sets with all attributes in a csv format.
b. Preprocess the datasets and transform the data into fixed column.
c. Pruning the data if not in use or not necessary for analytics.
d. Prepare the final csv file of the text data and be ready to apply the algorithms.
e. Applying algorithms to calculate the possible combination.
f. Apply advanced ML/data analytics algorithms to predict the impacts of disaster in the long aspects.
g. Based on the prediction decision can be incorporated.
h. Share the data with related agencies for preparedness and mitigation.
i. Applying the result for society and saving people from disasters and possible impacts.
j. Ready for use the modified methods for more accuracy.

Most of the data comes from online for analysis purposes, so data validation is an important factor during analytics. Impacts of disasters are also dependent on various factors interacting with one another, subsequently affecting the others also.
For effective impact and evaluation analysis, the present scenario proposes a methodology for long-term impact evaluation. There are many applications of proposed work in predictive data analytics like crisis mapping, emergency handling strategy, and planning & management [25].

Conclusion

Disaster will occur more frequently. Technological development and population are increasing day by day. The connection of technology with organizations has the capabilities to revolutionize disaster management. The prediction of losses due to disaster is difficult however, based on the advancement of technology can be helping to reduce the impacts. Using data analytics and machine learning techniques can make decisions about social, economic, mental, and psychological things.
Based on the available datasets and using analytical tools it can be done to predict the future impacts of disasters. Scientific and technological advancements in machine learning algorithms can be used to predict long-term impacts of disaster. The predicted data is helpful for the agencies, local & national authorities, and the government by recommending the action plans and effects for a longer period.
Technological advancements can solve humanity's problems. It is also necessary to enhance the

fundamental benefit that helps first responders with recommendations and information. Advanced machine learning tools and algorithms consider all possible hazard scenarios, simulate them, and present the best and alternative decisions for the better management of current as well as future impacts of disaster. For future work, all possible parameters i.e., physical, logical, and IoT frameworks with the proposed decision support system may be considered. The complete framework is comprehensive, flexible, and user-friendly which will support the agencies for planning, policy analysis, and identifying the impacts. It helps inter-departmental coordination in all the phases of disaster systems. The proposed interface may predict the long-term impact of disaster by using a real-time environment. Better planning and strategy may be used for the unknown situation of hazard to reduce the impact of disaster. Study supports the various agencies (Govt./Non-Govt.) working in the field of disaster management.

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