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Supervised Approach for Natural Calematy Detection:

Landslide

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Abstract : The landslide susceptibility assessment was estimated using various methods. This proposed work predicted the region to be susceptible to landslides based on the available data, including conditional factors, we can employ the method ML algorithms. Heavy rainfall can trigger landslides, posing a significant risk to the stability of the land. The earthquake caused significant damage, resulting in the loss of vegetation and support structures in high areas. Elevation and a lack of sufficient soil moisture . In-depth investigation. It is important to consider the factors that influence a landslide in order to assess its occurrence. Predictors of Landslide Occurrence. In order to provide real-time situational insights and responsive capabilities AI tools are advanced platform for disaster management, where it can get an advantage if combines machine learning edge computing and geographic information systems (GIS). Proposed System aims to enhance detection of Natural Calamities area of Land Sliding. In this paper modular design facilitates easy scalability and customization are explained. System has user-friendly interface which facilitates visualization alert notifications and response coordination. High performance algorithms for accurate forecasting such as Support Vector Machines (SVM) and Recurrent Neural Networks (RNN) are selected and evaluate performance. At the Initial stage small set of image dataset (Existed) is used as test case and Live dataset is collected from Pune region is used in implementation. We achieved 95% detection accuracy with our database. Communities may improve their preparedness and recovery efforts with this or by selection of another uncover Calamities for Pune region.

***IndexTerms* - Natural Calamities, Landslide Detection, Support Vector Machine(SVM),Recurrent NN(RCN), Detection and Classification.**

I. INTRODUCTION

The world natural disasters pose serious risks to infrastructure human life and ecosystems. These events which are the result of natural processes can happen suddenly and cause great destruction. Wildfires floods earthquakes tsunamis and landslides are examples of common natural disasters. Despite the fact that every variety has its own special qualities they can all quickly cause significant harm. Disaster management strategies must be effective in order to lessen their effects and enable timely responses [1].

For instance, landslides happen when rock dirt and other debris tumble down a slope, they are frequently brought on by volcanic eruptions intense rains or seismic activity. These catastrophes have the potential to bury communities seriously harm infrastructure and interfere with transportation networks. Another serious risk is earthquakes which occur when energy in the Earth's crust is suddenly released and causes severe shaking. Structural collapses tsunamis and fatalities may result from them and they may happen suddenly [2][3].

Massive ocean waves known as tsunamis are caused by seismic activity that occurs underwater such as earthquakes or volcanic eruptions. Increasing in height as they approach land and submerge coastal areas these waves can travel great distances at a high speed. Given their sudden onset and strong currents that have the potential to cause extensive damage tsunamis present a special threat. On the other hand, floods happen when rivers and lakes overflow due to heavy rains or abrupt releases of water from reservoirs. In addition to harming agricultural land and submerging entire cities flooding can cause long-lasting disruptions in the affected areas [4][5].

Because of their interdependence earthquakes and floods can both set off secondary disasters like landslides or infrastructure failures. Factors like deforestation urbanization and climate change are contributing to the increasing frequency and severity of these types of disasters which emphasizes the critical need for effective disaster preparedness and management systems [6][7].

particularly in regions prone to heavy rainfall, seismic activity, or human-induced changes. The need for effective landslide detection tools is critical for several reasons like By identifying high-risk areas, authorities can focus their resources on regions that require immediate attention, thereby enhancing overall safety and efficiency. We can use resource allocation for monitoring and response efforts.

II. Literature Review

India is among the top four countries with highest landslide risk, where for every year the estimated loss of life per 100 km2 is greater than one. Approximately 0.42 million sq. km or 12.6% of land area, excluding snow covered area, is prone to landslide hazard. Out of this, 0.18 million sq. km falls in North East Himalaya, including Darjeeling and Sikkim Himalaya; 0.14 million sq. km falls in North West Himalaya, 0.09 million sq. km in Western Ghats and Konkan hills, and 0.01 million sq. km in Eastern Ghats of Aruku area in Andhra Pradesh [1]

Emergency managers are using machine learning algorithms more often to support decision-makers and first responders in the planning preparation response and recovery phases of a disaster. These algorithms offer useful tools for use in emergency management applications since they are well-suited to handle the massive volumes of spatiotemporal data generated during emergency situations. In order to provide a consistent operational framework for applying machine learning in emergency management machine learning finds applications across a variety of emergency events and highlights commonalities worth examining. In spite of recent developments more work is required to earn the confidence of emergency management staff and put these algorithms to practical use in order to realize their potential advantages [9].

In order to identify efficient disaster management techniques and technologies this research paper conducts a thorough analysis of numerous studies pertaining to earthquake management systems. High-quality studies that made a substantial contribution to the advancement of knowledge in this field were given priority during a comprehensive literature search that was carried out using academic databases and online libraries. In order to comprehend the state-of-the-art in earthquake management systems at the time the analysis comprised grouping pertinent studies into four categories: keyword output type of earthquake detector and seismic effect. In order to effectively mitigate the effects of earthquakes and other natural disasters the findings emphasize the significance of making investments in robust disaster management systems involving communities in preparedness efforts and addressing issues like resource allocation communication and information dissemination [10].

In the paper WATERSensing: A Smart Warning System for Natural Disasters in Spain a system based on social sensing techniques is presented for the early detection and management of water-related disasters like floods. The system created as part of the WATERoT project uses natural language processing (NLP) techniques to analyse posts about water issues in real-time. It leverages data from social media platforms such as Twitter and Telegram. A case study on Storm Gloria in January 2020 shows how well the system works to link social media activity with real-world disaster events providing information that can be used to enhance emergency response protocols. With the help of the architectures modules for data gathering semantic analysis and visualization authorities can quickly identify possible threats [11].

For disaster management systems that use Wireless Sensor Networks (WSNs) an energy-efficient modified metaheuristic inspired algorithm called ModifyGA is proposed. This algorithm creates a fitness function that maximizes network lifetime by integrating criteria and dynamic sensing range. By optimizing intra-cluster distance systematically using node energy within the cluster lowering hop-count and encouraging the selection of highly capable nodes for cluster-heads the ModifyGA addresses the problems of cluster overlapping electing lower-energy nodes as cluster-heads highly dense clusters and hot spot issues in the network. The usefulness of ModifyGA with a single static sink several static sinks and movable sinks is demonstrated by simulation analysis highlighting the technology's potential as a cost-effective option for WSN-based disaster management systems [12].

In order to estimate the damages caused by natural disasters like wildfires this research study presents a machine learning-based method that makes use of geographical data and satellite radar images (SAR). By evaluating SAR images and categorizing the state of damage to individual buildings the system generates damage proxy maps. After making the required modifications the model which was trained on historical data can be used to predict the path of different natural disasters such as hurricanes and floods. Through the ability to quickly and accurately assess damages following disaster events this approach has a high potential to improve social resilience by facilitating timely relief efforts and well-informed decision-making [13].

A thorough overview of machine learning (ML) applications in disaster and pandemic management can be found in the research paper Disaster and Pandemic Management Using Machine Learning: A Survey. Modern machine learning algorithms that are utilized to forecast disasters plan evacuation routes for large crowds examine social media posts and support post-disaster scenarios are reviewed. Challenges unresolved issues and future research directions for ML-based disaster and pandemic management are highlighted by the authors as they discuss how various ML models integrated with other technologies such as IoT object sensing 5G networks smartphones and satellites can be deployed at different phases of disaster management [14].

In the context of major natural disasters this paper discusses disaster recovery for edge computing (EC) emphasizing the prevention of data loss and the mitigation of network congestion. Due to the massive volume of data especially from video IoT devices EC faces difficulties like network congestion in contrast to traditional cloud computing (CC) where data is backed up to geographically disparate locations. The suggested approach uses network hops between distributed telephone central offices (TCOs) storage capacity and disaster prediction data to choose TCOs as backup locations. The approach is more effective than conventional methods according to simulations as it lessens network congestion and boosts data backup efficiency while retaining resilience against disaster prediction underestimation[15].

The application of artificial intelligence (AI) models in various stages of natural disaster management (NDM) is systematically reviewed in the research paper titled Can we detect trends in natural disaster management with artificial intelligence? A review of modelling practices. The review examines the application of AI techniques such as neural networks support vector machines and fuzzy logic in NDM for disaster preparedness response and recovery drawing on 278 studies. In order to facilitate tasks like risk assessment early warning systems and emergency management it emphasizes how effective AI is at processing complex data. The study highlights patterns knowledge gaps and prospective avenues for future investigation including the necessity of more multidisciplinary methods and improved integration of resilience and climate change factors. All things considered artificial intelligence holds great promise for raising the precision and efficiency of decision-making in the context of disasters[16].

Table 1. The classification of landslides.

Table 1 Methodological Summary from Review

Sr No.	Title	Methodologies	Advantages	Future Scope
1.	RescueAid: Smartphone-Aided Situational Awareness [8]	Utilized smartphones and ML-based object/event detection tools.	Provides real-time sensory data to responders and command centers.	Integrate with existing emergency response systems and expand sensor capabilities.
2.	Machine Learning for Emergency Management [9]	Conducted a survey and analysis of existing ML applications.	Highlights potential of ML for real-time response, data analysis, and prediction.	Develop more robust and accurate ML models for specific disaster scenarios.
3.	A Systematic Review of Disaster Management Systems Approaches, Challenges, and Future Directions [10]	Comprehensive review of big data, cloud computing, IoT, GIS, and ML.	Highlights need for a holistic approach combining multiple technologies for improved effectiveness.	Emphasize technology integration, system resilience, community engagement, and ethical considerations in future research.
4.	WATER Sensing: A Smart Warning System for Natural Disasters in Spain [11]	Data collection from social media platforms (Twitter, Telegram), NLP processing for topic categorization, and visualization with geolocation.	Real-time detection, crowd-sourced data utilization, and cost-effectiveness.	Expansion to other disasters, multi-language support, and integration with additional social media platforms like YouTube and Instagram.
5.	An Energy-efficient Modified Metaheuristic Inspired Algorithm for Disaster Management System Using WSNs [12]	Utilized a metaheuristic algorithm for optimizing resource allocation and energy use.	Contributes to operational efficiency by minimizing energy consumption during disasters.	Explore application of the algorithm in diverse WSN-based disaster management scenarios.
6.	Machine Learning on Satellite Radar Images to Estimate Damages After Natural Disasters	Data collection from Sentinel-1 A/B satellites, feature engineering, modelling with various ML models, and validation with 5-fold cross-	High resolution of SAR data, efficient and scalable damage assessment across large areas.	Broader applications to other disasters like floods and hurricanes, incorporating real-time data, and improving model accuracy with additional data

	[13]	validation.		sources.
7.	Disaster and Pandemic Management Using Machine Learning: A Survey [14]	Detailed literature review on ML algorithms and their integration with technologies like IoT, UAVs, and satellite systems.	Enhanced accuracy in predicting disasters and pandemics, better resource utilization, and reduced human intervention through automation.	Integration with 5G and blockchain, improving algorithms, and enhancing scalability of ML models.
8.	Effective Disaster Recovery for Edge Computing Against Large-Scale Natural Disasters [15]	Backup TCO selection based on disaster prediction, storage capacity, and network information.	Reduces network hops and mitigates data loss compared to conventional methods.	Optimize backup strategies for various disaster scenarios and integrate with advanced prediction models.
9.	Can We Detect Trends in Natural Disaster Management with Artificial Intelligence? [16]	Systematic review of AI models across various stages of disaster management.	Identifies gaps in accuracy and efficiency, emphasizes the need for generalization.	Develop more accurate and efficient AI models that generalize across diverse disasters.
10.	The SENSE-ME Platform [17]	Decentralized phone-sensing network, opportunistic networking, mobile sensing, and distributed information processing.	Enables spontaneous data collection in emergencies without fixed infrastructure.	Enhance scalability and robustness of the platform.

III. Proposed System Design

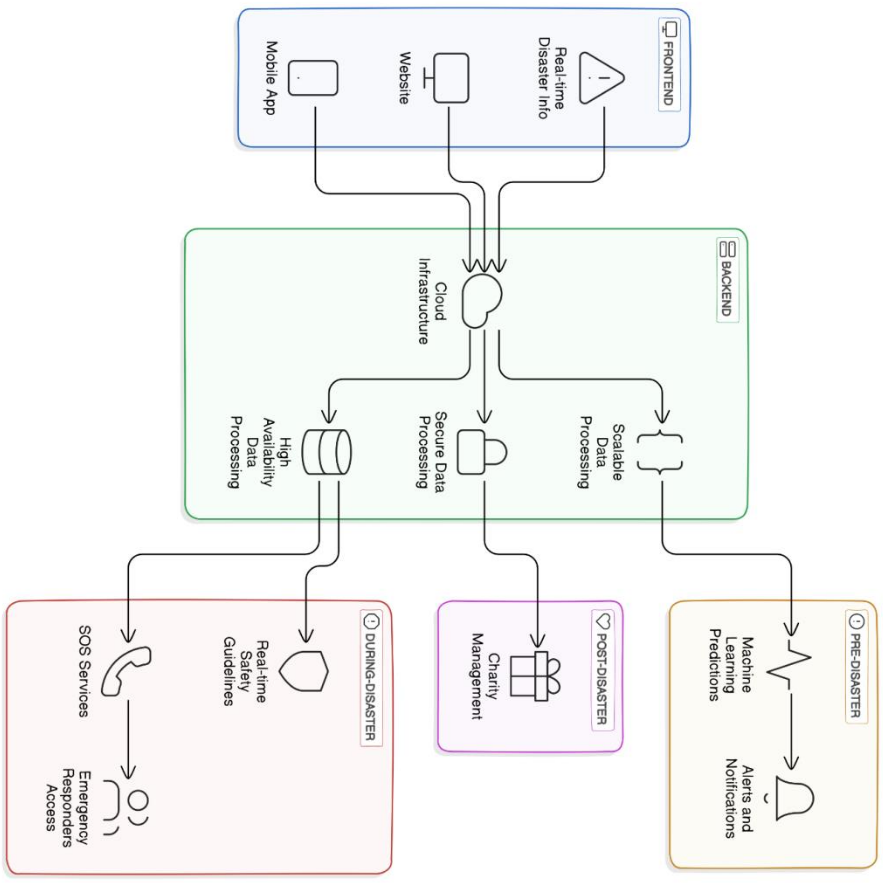

Figure 1: Proposed System Architecture

Use of machine learning algorithms and AI technologies proposed system aims to provide a complete Landslide management solution. System uses predictive algorithms to anticipate possible calmeties events in addition to monitoring real-time data facilitating more precise and prompt responses. In order to help communities reduce the risk of disaster get ready for impending threats and recover more quickly the platform offers an intuitive interface for real-time visualization alert generation and emergency response coordination.

Figure 1 of proposed system depicted in the system architecture diagram that is provided. The frontend includes a mobile app and website with real-time alerts and information about disasters. For secure data storage and scalable data processing the backend is dependent on AWS cloud infrastructure. Users receive alerts and notifications as well as analysis and prediction from machine learning algorithms. During calamities the platform provides real-time safety guidelines post-disaster charity management and pre-disaster preparedness features. Furthermore, SOS services and emergency responder access are combined to guarantee efficient reaction and recuperation. This architecture exemplifies how Smart system can offer management capabilities by utilizing machine learning/ AI and cloud computing through intuitive user interfaces.

IV. Methodology:

The Konkan region and the Western Ghats – districts of Raigad, Ratnagiri, and Sindhudurg. And parts of Thane, Satara, and Pune areas are susceptible to landslides. The foothills of the mountain range were a popular destination for hikers and nature enthusiasts. The Sahyadris are filled with numerous small and large villages, scattered throughout the konkan region. Are susceptible to mass movements. On July 30, 2014, a landslide took place in the village of Malin. In the Ambegaon taluka of the Pune district. It happened due to the heavy rainfall, and. Claimed the lives of over 60 individuals. From 25th July 2005, there was continuous rainfall, leading to a series of floods. In the districts of Jujur, Rohan, Dasgaon, and Kondivate, there were significant landslides that occurred in the village of Mahad. Raigad district and claimed over 100 lives and severely impacted four villages. A landslide took place in the ghatkopar suburbs of Mumbai in July 2000, following heavy rainfall. The heavy rainfall resulted in the unfortunate loss of 67 lives and caused injuries to numerous individuals. In a devastating landslide accident in Saka, on. On July 26, 2005, in Mumbai, over 74 people lost their lives, and a significant number of tin sheds were destroyed. Devastated when mud and rocks tumbled down from the surrounding hillsides [20].

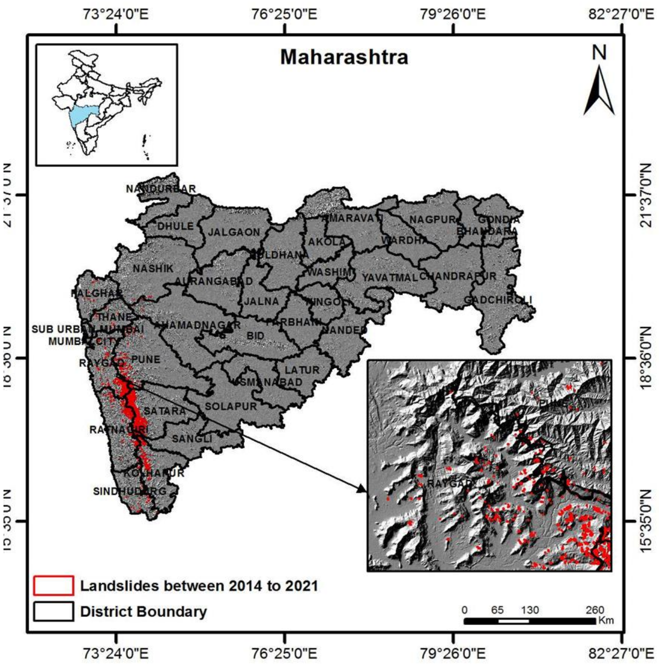

Figure 2: Konkan Region of maharstra Affected by Landslide

In Figure 2 , RED color shows : Konkan Region of maharstra Affected by Landslide.The main objective of this paper is to propose a landslide likelihood identification method using machine learning algorithms.

Table 2 District of Maharashtra(Konkan) Ranking for Landslide

District	Rank
80	Thane
107	Pune
109	Raygarh
114	Sindhudurg
128	Nashik
129	Ratnagiri
131	Ahmadnagar
133	Kolhapur
134	Satara
139	MumbaiSuburban
140	Mumbai

CNN is one of the most influential and significant algorithms in deep learning with multiple network architectures[60]. In this work CNN architectures, consisting of one convolution layer, pooling layer , flattening layer, and fully connected dense layers [61], were used. The dropout layer was also connected to avoid over fitting. The random search method of the Keras tuner library was used to select the number of filters, kernel size, activation function, number of neurons in fully connected layers [62]. The hyper-parameters were used for random search for number of convolution filters, kernel size, activation function, learning rate, and number of neurons[21].

Linear Regression: The linear regression is utilized to understand the linear relationship between the dependant variable (landslide probability) and the independent variable (various predictors). In the study, the multiple linear regression is employed as a single predictor is not enough to explain the landslide probability. The linear function is shown in equation 1.

$$Y=\beta0+\beta1X1+\beta2X2+\ldots\ldots\ldots\beta nXn$$

where:

Y is the dependent variable

X1, X2, …, Xn are the independent variables

β0 is the intercept

β1, β2, …, βn are the slopes

Our primary objective while using linear regression is to locate the best-fit line, which implies that the error between the predicted and actual values should be kept to a minimum. There will be the least error in the best-fit line.

The best Fit Line equation provides a straight line that represents the relationship between the dependent and independent variables. The slope of the line indicates how much the dependent variable changes for a unit change in the independent variable(s)

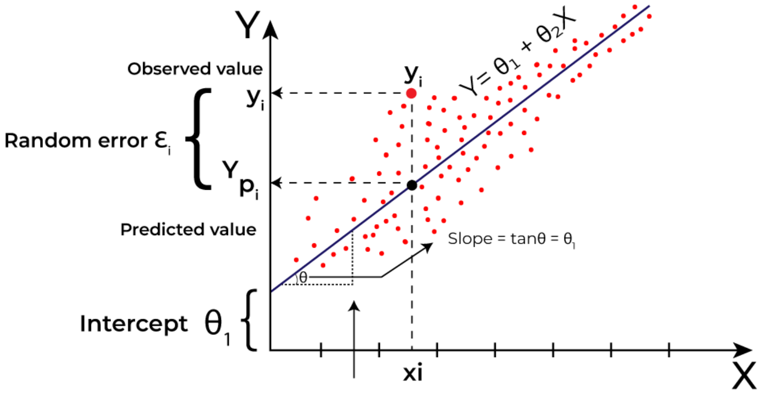

Figure 3 Linear Regression

Here Y is called a dependent or target variable and X is called an independent variable also known as the predictor of Y. There are many types of functions or modules that can be used for regression. A linear function is the simplest type of function. Here, X may be a single feature or multiple features representing the problem.

The standard frequency ratio (FR) was used to measure the difference between the ground event and the impact. An advantage of the FR model is that it can reveal the relationship between the occurrence of earthquakes and any type of disturbance based on the simple data collection principle, thus distributing the effects of the ground.

$$x + y = z \qquad (1)$$

In the proposed study, standard statistical measures namely: mean squared error (MSE), Mean Squared Error represents the average of the squared difference between the original and predicted values in the data set. It measures the variance of the residuals.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y})^2$$

The root mean squared error (RMSE) is a metric used to evaluate the performance of a regression model. It is defined as the square root of the mean squared error (MSE), which is the average squared difference between the predicted values of the model and the true values of the data

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y})^2}$$

The Mean absolute error represents the average of the absolute difference between the actual and predicted values in the dataset. It measures the average of the residuals in the dataset.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_i - \hat{Y}\right|$$

3.1Population and Sample

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