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Comprehensive Study of Rain and Landslide Prediction

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Abstract: A new era in computing history known as the "Internet of Things" (IoT) is about to begin. Machine to machine, machine to infrastructure, machine to environment, Internet of Everything, Internet of Intelligent Things, or the development of intelligent methods—whatever name you give it, it is and has huge potential. Rain and landslide expertise in the field. weather analytics techniques can provide valuable insights into the potential for rain and early warning of these events can help to minimize their negative impacts and reduce the risks associated with infrastructure planning and maintenance, land use planning, and agriculture and forestry management.

I. INTRODUCTION

The major goal of this project is to develop and put into use a system that can forecast the amount of rainfall and landslides. Landslides are one of the most loss of human life and property. A landslide happens when a portion ofa slope abruptly falls due to quick changes in nature like a typhoon, an earthquake, or a heavy downpour. Landslides commonly happen during the rainy season, which lasts from June to September. Recently, there has been an upsurgein fatalities and property damage, as well as periodic localized intense rainstorms with precipitation totals of severalhundred millimetres. Due to the greenhouse gases already released, climate change would continue for several morecenturies. Higher incidence of landslides could result from the unusual weather patterns and localized heavy rain brought on by climate change. With the anticipated rise in landslides caused by climate change, a multilateral, holistic analysis of the causes of landslides is required. By determining landslide vulnerability, damage from landslides can be reduced. The development of scientific techniques for landslide analysis in relation to future climate change is required to avoid and minimise landslide fatalities and property damage brought on by climate change.

The association between past and future rainfall and landslides must be understood in order to forecast the occurrence of landslides induced by future changes in rainfall. Methodologies must also be developed in order to quantitatively predict changes in rainfall as a result of climate change. Advancements in landslide location identification techniques and a system for analysing and verifying the connection between landslides and climate change are also essential. Internal and external factors can both affect the likelihood of a landslide. While exterior variables can be both natural (such as rainfall, river and shoreline erosion, and earthquakes) and artificial (such as cut-embankment, logging, estate development, and quarrying), internal determinants include things like geologicalstructure, topography, soil quality, and forest. When an internally unstable slope is exposed to externally unstable elements, landslides are easily triggered. **O. Matviykiv, et al.,** proposed that there have been several investigationsinto the causes of landslides and climate change. By linking the two, an analysis of landslide occurrence caused byfuture climate change, is still in its early phases and awaiting recognition on a worldwide scale. One of the first attempts to explicitly correlate rainfall analysis with landslide occurrence was this study.

Given the ongoing effectsof climate change and investigations into the analysis of future rainfall prediction based on climatic scenarios, suchas the IPCC A1B scenario, future landslides would occur more frequently. In this study, relationships between landslides and rainfall are examined, and rainfall pattern is examined by relating this data to potential future climatechanges.The design and analysis of the Lab-chip module for the rainwater chemical risks monitoring system receives the most focus. The precise heating of the Lab-chip reaction chambers and the selection of the appropriatepressure to provide the required temperature regime for chemical reactions are the key factors in determining the quantity of dangerous compounds[1]. **T. R. V. Anandharajan, et al.,** suggested that the programme analyse parameters such as the highest and lowest temperatures and rainfall over a sampled number of days. On the basis ofthe information that's accessible, intelligent forecasts are generated using artificial intelligence techniques. Based on linear regression, the analysis and forecast successfully predict the weather for the following day[2]. **Jiang, et al.,** described about the weather monitoring device which will also forecast the likelihood of rain in that location utilising the relationship between relative humidity and rainfall prediction. The NodeMCU ESP8266 Wi-Fi model is employed. Additionally, utilising a cloud server, this data is transmitted in real time to a Blynk app for mobile devices. A

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notification is provided to the mobile app when temperature and relative humidity levels exceed a predetermined threshold, and any connected devices are then turned on or off automatically utilising actuator relays[3]. **Devi, et al.,** described the correlation between predicted rainfall and relative humidity, the device will also predict the possibility of rain in that area. It uses the NodeMCU ESP8266 Wi-Fi model. This data is also sent in real time to a Blynk app for mobile devices using a cloud server. When temperature and relative humidity levelsexceed a predetermined threshold, a notification is sent to the mobile app, and any linked devices are then automatically turned on or off using actuator relays[4]. **B. Ramsay, et al.,** suggested the research, development, andoperating phases of the Radarsat-1 programme, the Canadian Ice Service (CIS) has taken a significant role in the project.

In order to perform operational ice reconnaissance over a seasonal ice cover of roughly 2 million square kilometres, the CIS currently vitally depends on Radarsat-1[5]. **S. T. Thilagam. J, et al.,** Suggested the usage of LabVIEW software to monitor the weather. It measured characteristics like temperature, pressure, and gas detectionusing a variety of sensors. The National Instruments (NI) LabVIEW Platform includes sensors as a data acquisition signal accessory. This system processed the data and acquired the analyses.

When any parameter surpasses the limitpast a certain point, an alert file containing the data is immediately prepared and sent to the concerned parties[6]. **Balakrishnan Sivakumar, et al.,** proposed a better method of weather monitoring employing low-cost IOT deviceswith GPS that are coupled to various sensors. To anticipate weather parameters for any given application region ofinterest, such as temperature, humidity, air pressure, etc., the sensed data is saved in the server[7]. **S. Kothapalli, et al.,** described the construction of a complete system from a real-time data gathering to real-time prediction is themain focus of this effort. The Cloudant NoSQL database service is used to implement the storage system on the IBM cloud computing platform[8]. **Perumal B, et al.,** described an environmental statistical analysis is used in weather forecasting. It is frequently employed to forecast the next weather monitoring report. In terms of temperature, air swing, precipitation, and cloud cover, weather is a climate. Turbidity, as well as the water's acidityand baseness, were used to simultaneously check the quality of the water.

The applications such as agriculture, logistics, transportation, and construction benefit the most from this integration of weather forecasting and water quality management system[9]. **J. C. B. Lopez, et al.,** suggested the Arduino platform is primarily used by the suggested system to process and send data. This technology is less portable because it relies on a typical Ethernet cable connection for stability and reliability of data delivery.

The technology was then put to the test for two weeks.The sensors and microcontroller were consistent in reading the appropriate weather variables and updating the values in the online monitor, according to the data gathered[10]. **J. Mabrouki, et al.,** suggested that by embedded systems and the internet of things as stated. Wireless technology, sensors, and electronic devices are also included in the system. The main objective of this system is to use sensors to detect different climatic factors, such as temperature, humidity, and the existence of specific gases. Following that, remote apps or databases can receive thegathered values. The data can then be examined in graphic and table form [11]. **Deng, et al.,** suggested that the climatic condition standards are based on variables such as temperature, wind, humidity, rainfall, and the size of thedata collection. In this instance, an experiment just considers the variables temperature and humidity.

Theinformation is gathered using the DHT11 temperature and humidity sensor, which is used to determine the temperature and humidity levels in an area or location. The Raspberry Pi is used to upload the data online for cloud storage with the assistance of an Ethernet shield[12]. **A. Munandar, et al.,** proposed the Internet of Things systemfor monitoring the environment. E Sense analyses significant environmental variables such as humidity, temperature, air quality index, CO concentrations, rain, and light. The data gathered from the sensors is sent to Thing Talk using the ESP8266 Wi-Fi module. Speak supports the analysis of the data and the graphical and tabularpresentation of it.

A heat map of the area under surveillance is also produced by E-Sense. Experimentation and testbed installation show that the system is simple to use, affordable, and runs without any requirement for human interaction[13]. **L. Das, et al.,** suggested that by implementing a cutting-edge weather monitoring system and real-time alarm system using IoT is the goal of this project. Arduino UNO is used to monitor temperature (t) and humidityin real-time appliances using a sample size of 10 values and 80% g power[14]. **R. Kavin, et al.,** proposed a systemthat uses sensors to track shifts in the environment, such as temperature, humidity, and CO Level, and sends that information to users for statistical analysis. IoT is a technology that is used to monitor, gather, control, and connect systems globally. It is a more effective and cutting-edge way to access information around the globe[15].

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WEATHER ANALYTICS FOR RAIN PREDICTION:

Indian Institute of Technology & the Institution of Electrical and Electronics Engineering, proposed the usageof Machine Learning for Predicting Rainfall for forecasting, analysis, and prediction of time series. This proposal consists of four ways. Using the statement IDENTIFY, the first stage identifies a set of responses that are utilized to compute time series and autocorrelations, Using the phrase ESTIMATE, the parameters are estimated in this stage, together with the previously indicated variables. Diagnostic evaluation of the variables and parameters gathered in Stage 2 is carried out in this stage. The forecasting values of time series are established at this stage using the ARIMA model for time series and the FORECAST statement. This algorithm's parameters are p, d, and q, where p denotes the number of lag findings, q is the degree of differentiation, and q denotes the order of the moving average[16]. **M. Raval, et al.,** proposed that in addition, many people use data mining techniques to makeweather predictions.

This article classifies numerous weather forecasting methods into two major groups: 1. Synoptic weather forecasting: It is a conventional method for forecasting the weather and involves observing the distinctive weather components over a specific period of time and with regularity. It entails daily data collection and analysis of the vast amount of observable data to discover patterns of evidence. 2. Numerical weather prediction:This method makes use of the analytical capabilities of computers to anticipate the weather and enables the computerprogram to create models rather than relying on human-defined parametric modelling after viewing the data. This frequently goes together with artificial intelligence techniques[17]. **C. M. Liyew, et al.,** suggested by explaining the link between the atmospheric variables that affect the rainfall, the machine learning approach known as linear regression is utilized to predict the rainfall utilizing significant atmospheric features. This study is a correlation conducted and found that a data-driven machine learning algorithm can accurately predict daily rainfall by analyzingsolar radiation, detectable water vapour and diurnal patterns. A larger data set will be used in future work to examinethe effects of employing various atmospheric variables. The studies examine the interaction between independent and dependent characteristics to determine which features influence whether it will rain or not. The investigation did not find or address the amount of daily precipitation, which could affect how well the system works. This was carried out as part of a comparison study using statistical modelling and regression techniques (SVM, RF & DT) toforecast rainfall using environmental variables. Regression techniques performed better in rainfall prediction than statistical modelling, according to the study's findings. The results of the experiment showed that the RF model performed better and produced predictions that were more accurate than the SVM and DT. Rainfall prediction is hence accurate and outperforms traditional approaches in machine learning models. Instead of utilising statistical approaches, this study used a variety of machine learning methods to predict daily rainfall levels[18]. **C. K. Gomathy, et al.,** suggested the description about the Artificial Neural Networks (ANN), regression analysis, and clustering are a few techniques used to forecast rainfall. There are essentially only two ways to predict rainfall.

TheDynamical method is the first, while the Empirical approach is the subsequent one. The empirical approach is based on a review of historical rainfall data and its correlation with different oceanic and atmospheric factors throughout various parts of the earth. The most popular statistical approaches to predict climate include regression, artificial neural networks, fuzzy logic, while participating group data handling techniques. However, a dynamical method uses physical models that utilise collections of equations to make predictions about how the global climate system would evolve in response[19]. **M. Biswas, et al.,** described about the multiple linear regression is the foundation ofthe suggested approach. The data for the prediction is gathered from publicly accessible sources, with 70% of the data being used for training and 30% being used for testing. A statistical technique called multiple regression is usedto forecast values using descriptive variables. The output values and the descriptive variable have a linearrelationship. Regression analysis examines how one variable (referred to as the dependent variable) is influenced by one or more other variables (referred to as the independent variables), and it is useful for estimating and/or predicting the mean or average value of the former in terms of known or fixed values of the latter.

As an illustration,experience is a factor that determines a person's wage, whereas compensation is a dependent variable on experience.Single dependent variable and single independent variable relationships are described by simple linear regression. Regression can generally be expressed as the equation below. Where 0 and 1 are parameters and is a probabilistic error term, we get the expression y = 0 + 1x +1. Modeling and information analysis both rely heavily on regressionanalysis[20]. **M. Biswas, et al.,** suggested that data analysis be performed in order to ensure that future outcomes will be close, allowing for trustworthy and accurate prediction. Only when the raw data has been vetted and checkedfor defects can we be certain that the data has been gathered without error. Additionally, it helps in recognising thedata that contain features that are unrelated to a prediction model. A data mining technique termed data pre-processing turns unstructured, inaccurate input into a form which the model can use and understand. The proposed model pre-processes cleaned meteorological data before organising it. Ultimately, rainfall data is divided into a number of categories based on the standards established by the Indian Meteorological Department. We describe a strategy for

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predicting rainfall in this research that is based on machine learning classification techniques. For testing, 30% of the preprocessed data are used, and for training, 70%. Four different machine learning algorithms are used to process the portioned input, and each output is evaluated before the final[21].

WEATHER ANALYTICS FOR LANDSLIDE PREDICTION:

O.Terzi proposed the DS-LSSVM method to quantify the uncertainties related to predicting landslide displacement.It uses two LSSVMs and the DS method to optimize their parameters. Comparison results show the proposed method's effectiveness and superiority in the construction of high-quality PIs for landslide displacement. It is a promising method for predicting the interval of displacement in areas of the Tree Gorges Reservoir with similar geological conditions[22]. **D. Utomo, et al.,** suggested that land sliding prediction methods fall into three categories:image processing, machine learning, and mathematical assessment models. the comparison of several methods of technique. First, image analysis uses geographic systems of information (GIS), which can collect, store, organise, and analyse geographic information. By examining disaster data, such as landslide history and data on land development for agriculture, the danger of landslides can be anticipated. Depending on how many layers of data were used in the study, different landslip probabilities were found. Second, computational intelligence is employed to evaluate the chance of landslides using machine learning methods such as Bayesian networks, neural networks, and algorithmic evolution.

These techniques include to determine the likelihood that a landslide may occur, variouspotential contributing elements are considered. Due of the lengthy computing times needed for prediction, they arenot real-time. Finally, mathematical evaluation models, like the Factor of Safety, use a single evaluate equation (FS). For the stability of slopes, a hazard model is integrated with hydrographic data, mechanics, and physical ideas.It is simple to simulate and adapts to a variety of situations, but obtaining the whole hydrographic data is challengingsince it is challenging to detect groundwater elevation[23]. **Z. Fang, et al.,** suggested the study of the new AdaPU-RF approach to forecasting landslip susceptibility based on the The Three Gorges Reservoir region in China. The AdaPU-RF technique combines PU learning with an adaptive sampling strategy to fully utilise landslip and unlabeled information and avoid the problem of erroneous label assignment. The key findings are summarised below. First, the AdaPU-RF technique has the potential to provide precise solutions for landslip susceptibility. In terms of the AUC value of the prediction rate curve, the suggested approach outperforms the benchmark methods by an amount of AdaPU-RF method was less subject to the unpredictability of the training/test splitting procedurethan the other methods. Thirdly, the AdaPU-RF method's susceptibility estimation has a realistic and acceptable level of uncertainty. The AdaPU-RF approach is generally more insightful and advised for estimating landslide vulnerability. For the LSP problem, the PU learning offers a fresh application perspective. Meanwhile, we anticipatethat the suggested approach will encourage additional study into the practical uses of PU learning[24]. **E. Collini, et al.,** proposed the issue of landslide event prediction has been discussed in this study in order to provide early warning. When possible, a comparative study of the outcomes of similar studies and solutions put forward in the literature has been done after careful review.

The majority of the research in the literature concentrated on creating susceptibility maps, which is a long-term estimation of landslides with their propensity being primarily based on static land features. The most recent state-of-the-art approaches for early warning (short-term prediction) are basedon machine learning, while state-of-the-art empirical algorithms like SIGMA. These systems primary drawbacks are low reliability (unsatisfactory TSS, OA, and F1) and the fact that they rely on a small set of features that were deemed important a priori. In this study, they gathered static and dynamic information that addressed not only the land description but also the preceding days' worth of rainfall, temperature, wind, and other factors at each site across a vast area and over an extended period of time. Then, many machine learning models were put to the test inorder to find the most accurate predictive model. This paper details the implementation for this purpose, four machine learning techniques based on RF, XGBoost, CNN, and AE have been tested, tuned, and compared with theSIGMA decisional model. Comparison results revealed that the technique based on XGBoost outperformed SIGMAand to, which are the most recent references on predictions, in terms of Sensitivity, MAE, MSE, TSS, OA, and RMSE. Also, a further study using Shapley additive explanation (SHAP), both globally and locally, has been donefor the XGBoost model that produced the best results. This has led to a greater comprehension of the prediction model outputs as well as the value of the attributes and how they interact. The results showed that factors like the amount of rain over the previous three days, the highest temperature recorded the day before, and the level of waterin the river are the most useful predictors, although other predictions on weather and water levels of various kinds may also be helpful. It was also emphasized that while land static features are a precondition for landslides, they are ineffective in developing an early warning system. The short-term prediction should be evaluated every day from a computational standpoint, whereas susceptibility maps are typically calculated once or twice per year[25].**D. Zhang,et al.,** described the focus on the landslide risk prediction problem in this work, specifically landslide risk assessmentand modeling. First, the TOPSIS-Entropy approach is used to calculate the LIMs, which inputs four landslide impactvariables

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and produces the landslide instability margin. The output for landslide risk is the future time series for theLIM via TCN-AttnRNN and RNN-Attn-TCN. A comparison of a vanilla LSTM, a GRU, a TCN, ConvLSTM, andour models is done to determine how effective they are. Our models surpass their competitors in terms of the percentage of metrics reduced, as determined by the analysis of the MAE, RMSE, and MAPE (MRP). The landsliderisk can be predicted using deep learning techniques based on large-scale landslide data thanks to the great accuracyof the models. We use the TOPSIS-Entropy approach to thoroughly examine the landslide risk assessment problem.For assessing landslide risk, there are four landslide effect factors. This method is very simple to use and convenientbecause it can quickly obtain the final LIM used for evaluation from sensor data. Compared to the single-factor evaluation method, this multisensor integrated assessment of landslides is more thorough. Deep learning for temporal prediction is introduced to address the landslide risk prediction problem. The system's architecture consistsof an attention-based TCN and an RNN is better able to handle difficult situations, such modelling landslide data, and optimizes the deep learning model structure[26].

ML MODEL FOR RAIN AND LANDSLIDE PREDICTION:

Z. Liu et al., suggested the study gave a summary of machine learning and ML research on landslide detection and mapping, spatial forecasting, and temporal forecasting in this study. The primary general observations on various elements of ML-based landslide investigations were offered in the final Discussion section of this research, in addition to the three sections of the paper that are specifically devoted to these themes. The complexity of ML algorithms utilized in landslide investigations has matched the rapid progress over time, according to our review that is taking place in the community of AI/ML. In the landslide community, it can be said that ML still has a longway to go. Among of the three landslide subfields examined in this study, it appears that landslide detection researchhas benefited the most from advances in machine learning, whereas it seems that studies on spatial and temporal forecasting have not yet clearly and significantly benefited from ML methods. This is primarily because landslide detection is a computer vision (CV) topic, which has a vibrant community within the artificial intelligence (AI) community where many innovations are carried out. These advancements, along with the fact that landslide detection necessitates less physical comprehension than other landslide study topics, stimulate the use of robust MLtechniques for landslide detection that are more precise. Also, it is anticipated that more and more DL will be usedfor this purpose in the upcoming years, displacing more established techniques like OBIA. It is anticipated that morecutting-edge CV algorithms will take the place of traditional ones in DL techniques. There are predicted to be moreuses for techniques like Graph Neural Networks and different generative modeling techniques like GANs in landslide investigations.

The number of publications using machine learning (ML) algorithms in landslide susceptibility studies has been increasing very quickly in recent years, following a trend that is similar to the growthseen in the previous two decades by multivariate statistical studies carried out for the same purposes. Around the current trend, which focuses on using many machine learning (ML) algorithms and comparing their performance ina similar region, will continue to be the major, not-too-innovative approach in this field at least in the near future, academics will pursue a procedural technique. Given the overlap in these researchs, now we can hold out hope thata new pattern will develop, perhaps combining ML and process-based approaches for a more thorough and comprehensive assessment and understanding of landslide vulnerability at the regional scale. Additionally, it may be anticipated that processes will be created for landslide temporal forecasting that integrate ML algorithms with physically-based approaches, including computational geomechanics models[27]. **D. Utomo, et al.,** proposed a study with a novel approach for landslip prediction to address the challenges of imbalanced data, low true positiverate for learning, determining the forecast horizon, and the time for model re-training. The classification is based onthe factor of safety estimated by the SHALSTAB model, which use the ADASYN technique to balance the stable (no landslip) and unstable (landslip) classes. To address the issue of a low real-positive rate, a BPNN-based event-class predictor was proposed, and two BPNN predictors were built to learn the stable class pattern and the unstableclass pattern. A unique learning-based model re-training strategy as well as a novel predictions horizon alteration method were proposed. As a result, the classifier has a larger percentage of correctly classified objects. This systemmay transition between various predictors in accordance with the projected class to adjust to the environmental state. In order to forecast future errors of this suggested method and account for them during the prediction phase, BPNN is also used to build the error model. Because of this, this method is more accurate than BPNN and ADASYN+BPNN because it has considerably lower MAPE and RMSE. Moreover, the proposed method's NRMSE is higher than that of the competing approaches[28]. **L. Deng, et al.,** described that predicting the geographic distribution of shallow landslides is one of the most difficult issues in landslip risk and danger assessments. The accuracy of a spatial landslip prediction model depends on the strategy used. Physical models (such as centrifuge and model tests, etc.) are limited (at least currently) due to high costs, limitations on the number all tests that can berun, the material used for testing, the number of sites that are eligible for testing, and the small size of the bulk of the tests conducted. Numerical models often have the disadvantage of restricting the representativeness of the casestudy due to idealisation in the computed model, but they can more quickly replicate changing situations.

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The computational models often do not account for three-dimensional impacts. Utilising in-situ observations that have been enhanced by algorithms for learning is a third option. Three "ensemble" machine learning techniques, Random Forest, Gradient Boosted Regression Tree, and Multilayer Perceptron, were examined in order to predict the spatial distribution of landslides in the Kvam region of Norway. The eleven landslip regulating elements included slope angle, aspect, plan curves, profile curves, flow accumulation, flow direction, distance to rivers, water content, saturation, rainfall, plus distance to highways. In this paper, it was shown that machine learning algorithms can predict landslip displacement trends automatically using time-series data, AE and rainfall readings. Using observeddisplacement, AE, and rainfall data gathered from tracking an active landslide over several months, four establishedML models were trained. Up to 60 days after the end of the training session, the top-performing model (LASSO-ELM) was able to predict displacements with a mean absolute percentage error of 2.5%. Comparison of the expectedand measured slope displacements served as evidence of performance. While displacement and rainfall are not synchronized, detected AE is a direct result of the triggering displacement and is therefore synchronous. This is dueto the delay between increasing pore water pressures on the shear surface and rainfall, which can produce instability.Nonetheless, it was demonstrated that the approach could accept the time-lag of less than 24 h in the example studythat was presented, which had a shallow shear surface. This lag will be bigger for deeper shear surfaces and/or soilwith lesser permeability, hence antecedent rainfall conditions should be explicitly taken into account while trainingthe ML model. High prediction accuracy was attained without the use of real-time displacement data for up to 60 days after the training phase ended. If more displacement data are made accessible to update the "trained" model, accuracy could be increased. Instrumentation like in-place inclinometers may be shared amongst numerous slopes due to the relative high expense of generating high resolution displacement time series data[29]. **M. Kuradusenge,et al.,** suggested the two methods, random forest (RF) and logistic regression (LR), were used to analyze the rainfalldata together with other both internal and external elements in order to build a model for forecasting as landslip incidences for an early warning system. ROC-AUC, error rate (TP and FN), and other performance metrics have been used to evaluate the most successful prediction models. The results show that the prediction skills of these twomodels are superior than those found in earlier research studies. The results of the study suggest that considerable daily rainfall (or extended, low-intensity rainfall) may result in landslides, but that these occurrences frequently occur after a few consecutive days (say, two to five) of precipitation. The impact of before rainfall on disaster incidence, as suggested by the prediction models used in this study, served as a good example of this. Both modelsdemonstrated that precipitation that fell five days earlier has a considerable impact on the occurrence of landslide in the subject matter area..[30].

CONCLUSION

Weather analytics for rain and landslide prediction is a critical tool for disaster preparedness, infrastructureplanning and maintenance. It can help to minimize the impacts of natural hazards and improve disaster response planning. Weather analytics can be used to predict the intensity of rain events. This information can be used to plan for flood management and to reduce the risk of landslides. It can be used for real-time monitoring of weatherpatterns, soil moisture, and other factors that can contribute to rain and landslide events. This information can be used to inform emergency responders and help them make informed decisions during disaster response. Accurateprediction and early warning of rain and landslide events can help to save lives, reduce damage to infrastructure, and improve disaster response planning.

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