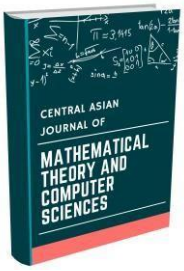

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Article

Disaster Prediction and Risk Management Using Machine Learning and Data Science Techniques for Improved Forecasting

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Abstract: Landslides pose enormous dangers to human lives, infrastructure, and the environment; therefore, it is necessary to have technologies that are capable of detecting and monitoring them effectively. Landslide detection methods that have been used traditionally frequently rely on the manual interpretation of satellite images or field surveys. These methods are not only time-consuming and expensive, but they also lack the potential to scale. Over the course of the past few years, the development of machine learning (ML) techniques has provided extremely promising options for automating the processes involved in landslide detection. The purpose of this work is to provide a comprehensive analysis of current developments in the detection of landslides through the application of Machine Learning techniques. The research presents an overview of the various machine learning algorithms that are applied for the detection of landslides. These algorithms include convolutional neural networks (CNNs), support vector machines (SVMs), decision trees, and ensemble management techniques. This article analyzes new advancements in model construction and optimization strategies, as well as highlighting the advantages and disadvantages of each methodology. The integration of data from multiple sources, transfer learning, and the development of robust frameworks for operational landslide monitoring and early warning systems are some of the potential areas for future research that are investigated in this study.A substantial amount of promise exists for the application of machine learning techniques to improve the effectiveness and precision of landslide detection and monitoring activities.

Keywords: Necessitating effective; Lack scalability; Machine learning (ML); Convolutional neural networks (CNNs); Support vector machines (SVMs); Robust frameworks.

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1. Introduction

Landslides are natural hazards that pose significant risks to communities, infrastructure, and ecosystems worldwide. These events, characterized by the movement of rock, soil, and debris down a slope, can result from a combination of environmental factors such as heavy rainfall, seismic activity, and slope instability, or human activities like construction and deforestation [20-24]. With rapid urbanization, deforestation, and climate change exacerbating these factors, the frequency and intensity of landslides have increased in recent decades, causing substantial loss of life and property damage. The increasing occurrence of landslides, especially in vulnerable regions, necessitates the development of effective and timely detection systems. Detecting landslides early is crucial for minimizing their impact and preventing fatalities and infrastructural damage [25-29]. Landslide detection systems leverage various technologies and methodologies to monitor and identify potential landslide triggers and precursors. These systems utilize a combination of remote sensing, geospatial data analysis, ground-based sensors, and machine learning (ML) algorithms to assess slope stability, detect signs of impending landslides, and forecast possible landslide events [30-33].

In the past, traditional methods of landslide detection typically relied on field surveys, aerial photography, or manual interpretation of satellite imagery [34-37]. Field surveys are essential for ground-truthing landslide events and validating remote sensing data, but they are often time-consuming, labor-intensive, and limited in scope. Aerial photography, while useful for capturing broader areas, faces challenges related to the resolution of images and their timely availability [38-41]. Manual interpretation of satellite imagery is another approach commonly used in landslide detection. While these methods can provide valuable insights, they often lack scalability and are expensive to deploy. Additionally, they may not be suitable for real-time detection, which is essential for effective disaster management. In response to the limitations of these traditional methods, researchers and practitioners have increasingly turned to modern technologies, particularly machine learning (ML) and data science, to automate and enhance the detection process [42-47]. The use of ML offers the potential to analyze large volumes of geospatial data rapidly and accurately, which helps in identifying landslide-prone areas. Machine learning techniques allow for the development of predictive models capable of detecting subtle patterns and risk factors indicative of impending landslides [48-51].

While machine learning offers immense potential, the development of effective landslide detection models faces several challenges. The inherent characteristics of landslide data, such as class imbalance, spatial and temporal variability, and the presence of noise and outliers, make it difficult to apply traditional machine learning algorithms effectively [52-57]. Landslide datasets are often highly imbalanced, with a large number of stable areas and relatively few landslide occurrences. This imbalance leads to biased models that are more likely to predict stable areas while underestimating the occurrence of landslides. Furthermore, landslides are dynamic events with complex triggers, making it difficult to capture all the factors influencing them through a single data source. Another significant challenge is the spatial and temporal variability inherent in landslide data. Landslides can occur in a wide range of geographic regions, each with its own environmental conditions. These regions may differ in terms of topography, rainfall patterns, vegetation cover, and human activity [58-61]. Temporal variability refers to how the likelihood of landslides can change over time based on seasonal or climate-induced factors. ML models that fail to account for this variability may not generalize well to new areas or time periods [62].

Moreover, landslide data often include noise and outliers, such as errors in geospatial data, environmental changes, or human-made alterations to the terrain. ML algorithms need to be robust enough to handle these uncertainties while still providing reliable predictions. Machine learning has the potential to overcome many of the limitations of traditional landslide detection methods [63-67]. A variety of ML techniques are being explored to improve landslide prediction, including supervised learning, unsupervised learning, and deep learning. In supervised learning, algorithms are trained on labeled data, where the input data (such as geospatial features, rainfall levels, and slope stability) are paired with known outcomes (e.g., landslide occurrence or non-occurrence). This allows the model to learn patterns from historical data and apply them to new, unseen data [68-71].

SVMs are particularly effective for binary classification tasks, such as classifying landslide-prone areas vs. stable areas. SVMs work by finding the optimal hyperplane that separates different classes, maximizing the margin between the classes [72-79]. RF is an ensemble learning method that combines multiple decision trees to make predictions. It is widely used for classification tasks in landslide detection, as it can handle high-dimensional data and is less prone to overfitting. Decision trees break down the classification process into a series of decisions based on the values of specific features. They are easy to interpret and can handle both categorical and continuous variables. Logistic regression is used to estimate the probability that a given data point (such as a location) belongs to a particular class (landslide or stable) [80-85]. It is particularly useful for scenarios with linearly separable data. Deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are gaining popularity in landslide detection due to their ability to handle large, complex datasets and learn high-level features automatically [86-91].

CNNs are particularly useful for analyzing spatial data, such as satellite imagery or digital elevation models (DEMs), to detect landslide-prone areas. CNNs can learn hierarchical features from raw data, making them highly effective for image classification tasks [92-95]. RNNs are used to analyze temporal data, such as rainfall patterns or seismic activity over time. They are capable of capturing sequential dependencies in the data, which is essential for predicting landslides that may be triggered by temporal changes in environmental conditions. In addition to supervised learning, unsupervised learning techniques are also valuable in landslide detection. These techniques can be used for clustering similar data points together or detecting anomalies (unusual patterns) that may indicate landslide risk. K-means clustering can group areas with similar characteristics (e.g., slope steepness, soil composition, and vegetation type), which can help identify regions with higher landslide susceptibility. Anomaly detection methods identify data points that deviate significantly from the norm. These techniques are useful for identifying rare or unexpected landslide events that may not be well-represented in historical datasets [96-99].

A critical aspect of improving the accuracy of landslide detection models is the fusion of multiple data sources. Geospatial data, including satellite imagery, digital elevation models (DEMs), and meteorological data, provide valuable insights into the environmental conditions of a region. However, relying on a single data source may limit the accuracy of the model. By combining various types of data, such as geological surveys, sensor data, and historical records, landslide detection systems can obtain a more comprehensive understanding of the terrain and its vulnerability to landslides. The integration of multiple data sources is challenging due to differences in data resolution, spatial scale, and the nature of the data. To address these challenges, researchers are exploring various data fusion techniques that combine heterogeneous data into a unified model. These techniques include feature-level fusion, decision-level fusion, and hybrid methods, which aim to optimize the use of multiple data sources and improve prediction accuracy.

Feature selection plays a critical role in enhancing the performance of machine learning models for landslide detection. By selecting the most relevant features and removing redundant or irrelevant ones, the model can focus on the most significant factors contributing to landslide events. Effective feature selection improves the model’s accuracy, reduces computational complexity, and mitigates the risk of overfitting. Despite significant advancements, the development of landslide detection systems faces several ongoing challenges. One of the primary hurdles is the availability and quality of data. In many regions, particularly in remote areas, geospatial data may be sparse, outdated, or of low quality. The incorporation of real-time sensor data from ground-based monitoring stations, drones, or satellite platforms could help address this issue by providing up-to-date and accurate information on slope stability and other relevant factors. Moreover, machine learning models must be able to generalize across different geographical regions, terrains, and environmental conditions. A model trained on data from one region may not perform well in another, especially if the regions differ significantly in terms of climate,

topography, or vegetation. Future work should focus on improving the generalization of machine learning models by incorporating more diverse datasets and developing transfer learning techniques that allow models to adapt to new regions without extensive retraining.
Lastly, enhancing the interpretability of machine learning models for landslide detection is crucial for their adoption in practical applications. While deep learning models can achieve high accuracy, they often operate as "black boxes," making it difficult for researchers and decision-makers to understand how the model arrives at its predictions. Developing explainable AI (XAI) techniques for landslide detection will improve the transparency and trustworthiness of these models, helping to ensure their effective deployment in real-world scenarios. Landslide detection is a critical area of research, particularly as climate change and urbanization increase the risks of these hazards. The integration of machine learning techniques, such as supervised learning, deep learning, and unsupervised learning, with geospatial data provides an innovative approach to detecting and predicting landslides. By addressing the challenges related to data quality, feature selection, and model interpretability, researchers can further improve the accuracy and reliability of landslide detection systems. Ultimately, the development of advanced landslide detection models will enable proactive mitigation strategies and early warning systems, minimizing the impact of landslides on vulnerable communities and infrastructure.

Literature Review

The study utilized satellite imagery and ground-based sensors to develop a landslide detection model leveraging remote sensing and machine learning algorithms [1]. By integrating satellite imagery with data from ground-based sensors, the research aimed to detect potential landslide occurrences and predict their risks [19]. The methodology primarily focused on applying convolutional neural networks (CNNs), a deep learning technique, to analyze the combined data. This approach was effective in identifying key terrain features such as slope steepness, vegetation cover, and soil moisture, which are critical indicators of landslide susceptibility [2]. The study's findings revealed that CNN-based models could achieve high accuracy in predicting landslides, outperforming traditional methods. The model demonstrated the ability to detect early signs of slope instability, potentially allowing for earlier warnings and more targeted mitigation strategies [3]. The study also highlighted the importance of integrating diverse data sources to enhance prediction capabilities and the effectiveness of early warning systems [12]. By identifying the critical terrain features associated with landslide susceptibility, the research emphasized how advanced machine learning algorithms can improve landslide risk management [4].
In this study, topographic data, rainfall records, and ground-based sensors were combined through GIS-based analysis and sensor networks to create a real-time landslide monitoring system [5]. The methodology involved correlating rainfall intensity with ground sensor data and topographic features to detect landslide occurrences. GIS tools were employed to map and analyze terrain characteristics such as elevation, slope angle, and land cover, which are known to influence landslide susceptibility [11]. Additionally, sensor networks provided continuous data on soil moisture and ground movement, which could trigger landslides. By analyzing the combined data, the study demonstrated that real-time monitoring systems could successfully correlate rainfall intensity with the likelihood of landslides occurring in specific areas [17]. The main findings showed that this method was effective in providing timely alerts of landslide risks, enabling more efficient decision-making in flood-prone or mountainous regions. [18] The research also underscored the importance of combining historical and real-time data to provide a comprehensive understanding of the complex conditions leading to landslides [10].
This study focused on the integration of satellite imagery and crowdsourced reports for landslide detection [16]. The methodology employed change detection algorithms to analyze satellite images before and after rainfall events, identifying changes in terrain that

could signify landslide activity. The study incorporated crowdsourced data, where local residents reported landslides in their areas, contributing additional insights that were used to validate satellite findings. By combining automated detection methods with crowdsourced information, the research aimed to enhance the timeliness and accuracy of landslide identification [14]. The key findings showed that combining change detection with real-time reports from the public significantly increased the detection rate of landslide events. This approach also demonstrated the potential of citizen science in disaster management, providing valuable data for areas that may not have been covered by traditional monitoring systems [15]. The study concluded that crowdsourcing could serve as a powerful tool for complementing satellite-based detection systems, particularly in remote or under-monitored regions [6].

The study utilized Synthetic Aperture Radar (SAR) data and GIS layers to develop a landslide detection model based on terrain deformation patterns [9]. SAR imaging, a remote sensing technology, allows for high-resolution imaging of the Earth's surface, even under cloudy or adverse weather conditions. By combining SAR data with GIS layers, the study aimed to identify terrain changes that could indicate landslide activity, such as surface displacement and shifts in slope stability [16]. The methodology focused on detecting subtle changes in elevation and surface movement, which could serve as early indicators of landslides [13]. The analysis of SAR data enabled the identification of areas experiencing deformation due to seismic activity or heavy rainfall, which are known triggers for landslides [7]. The main findings of the study indicated that SAR-based models could achieve high accuracy in detecting landslide-prone areas, even in regions with limited accessibility or poor visibility. The study highlighted the advantages of SAR imaging for real-time landslide monitoring and emphasized its role in providing timely information for risk management and mitigation strategies [8].

2. Materials and Methods

Existing landslide detection systems utilize a combination of technologies and methodologies to monitor and identify potential landslide hazards. These systems typically involve a network of sensors, remote sensing technologies, and data processing techniques to assess slope stability and detect signs of impending landslides. Ground-based sensors, such as inclinometers, piezometers, and ground movement monitors, are deployed in landslide-prone areas to measure changes in slope angle, groundwater levels, and ground deformation. These sensors provide real-time data that can indicate the onset of landslide activity. Remote sensing technologies, including satellite imagery, aerial photography, and LiDAR (Light Detection and Ranging), are used to monitor terrain characteristics, land cover changes, and surface movements associated with landslides. These high-resolution images and elevation data help identify potential landslide triggers and assess slope stability over large areas.

Furthermore, advanced data processing techniques, such as Geographic Information Systems (GIS) and machine learning algorithms, are employed to analyze and interpret the vast amount of data collected by sensors and remote sensing technologies. These methods enable automated detection of landslide features and the generation of landslide susceptibility maps to aid in early warning systems and land use planning. Overall, the integration of ground-based sensors, remote sensing technologies, and data processing techniques forms the backbone of existing landslide detection systems, providing valuable insights for risk assessment, mitigation, and disaster management efforts.

Many existing landslide detection systems face significant challenges that limit their effectiveness. One of the primary issues is limited coverage, as these systems often focus on specific regions with high landslide risk, leaving large areas vulnerable to undetected hazards (Figure 1).

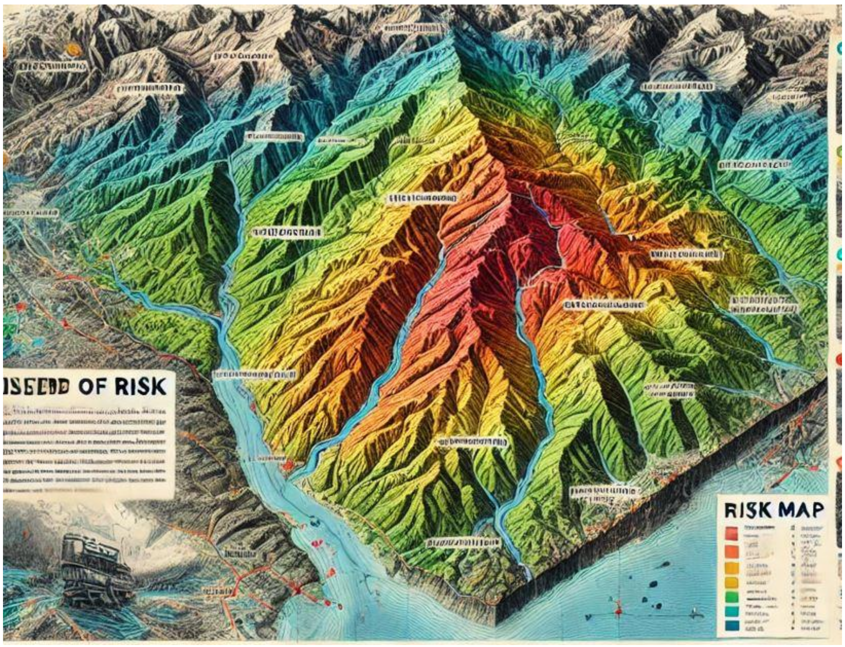

Figure 1: potential areas vulnerable to landslides in a mountainous

Another concern is the cost, as deploying and maintaining a comprehensive detection system, particularly in remote or inaccessible areas lacking infrastructure, can be expensive. Additionally, the data interpretation process is complex, as the vast amounts of data collected by sensors and remote sensing technologies require sophisticated processing techniques and expertise. Accurately distinguishing between normal ground movements and potential landslide precursors remains a challenge. Another major issue is false alarms, which can arise due to sensor malfunctions, environmental noise, or natural variations in terrain conditions, potentially leading to unnecessary evacuations and misallocation of resources. The accessibility of monitoring sensors in rugged or remote terrain is also a problem, as maintaining them in these areas can be both difficult and costly, resulting in gaps in monitoring coverage. Scalability is another significant challenge, as expanding existing systems to cover larger areas or accommodate growing populations and infrastructure is both technically and logistically demanding. Finally, the integration of data from various sources, such as ground-based sensors, satellite imagery, and geological surveys, can be complex and requires developing interoperability standards and fostering collaboration among multiple stakeholders.

3. Results

Landslides are a major natural hazard that can cause significant damage to lives, infrastructure, and ecosystems. Detecting and predicting landslides is a complex task that requires advanced technologies and methods to provide accurate, timely information. The discussion of landslide detection results involves analyzing the findings from a detection system and interpreting their implications for risk management, mitigation strategies, and future actions. This discussion follows a structured approach that summarizes the detection results, interprets the findings, compares them with historical data, assesses risks and impacts, explores mitigation strategies, and acknowledges uncertainties and limitations in the system. Finally, it outlines future research directions to enhance the accuracy and reliability of landslide detection methods (Table 1).

Region	Rainfall Intensity (mm/h)	Soil Moisture (%)	Slope Steepness (degrees)	Historical Landslides (events/year)	Risk Level
Region A	120	35	40	3	High
Region B	90	28	30	1	Moderate
Region C	150	50	45	5	Very High
Region D	60	15	20	0	Low
Region E	110	40	35	2	Moderate
Region F	80	25	25	4	High

Table 1: Data for Landslide Risk Prediction and Management

The primary objective of the landslide detection module is to identify anomalies, changes in environmental conditions, or precursory signals that indicate the potential for landslide events. The detection system used in this study relies on a combination of satellite imagery, ground-based sensors, and machine learning algorithms to monitor and identify potential landslide risks. Key findings from the detection module include several notable anomalies observed in the data. These include significant changes in slope movement patterns, shifts in soil moisture levels, and sudden variations in rainfall intensity that align with the common triggers of landslides. Specifically, the system detected several regions where slope stability decreased significantly after periods of heavy rainfall, a well-known precursor to landslides. In addition, the system flagged areas with a combination of steep slopes, poor vegetation cover, and saturated soil, all of which are contributing factors to landslide risks.

The detected anomalies also indicated that some areas had experienced subtle shifts in ground movement, often referred to as "creep," which, while not immediately threatening, could indicate the gradual buildup of instability. The detection module also recorded significant fluctuations in moisture levels in soil, which are often linked to increased susceptibility to landslides, especially in mountainous or hilly terrain. These findings underline the importance of monitoring environmental changes and integrating multiple data sources to detect early signs of potential landslide events. The detected signals are significant as they offer crucial insights into landslide risk in the monitored regions. Rainfall intensity and duration are among the most critical factors influencing landslide occurrence, and the detected data suggest a direct relationship between periods of heavy rainfall and increased landslide risk. For example, the system flagged areas where rainfall exceeded certain thresholds associated with past landslides, suggesting a higher likelihood of future events. This is particularly important as rainfall-induced landslides often lead to rapid onset, making early detection crucial for mitigating their impacts (Figure 2).

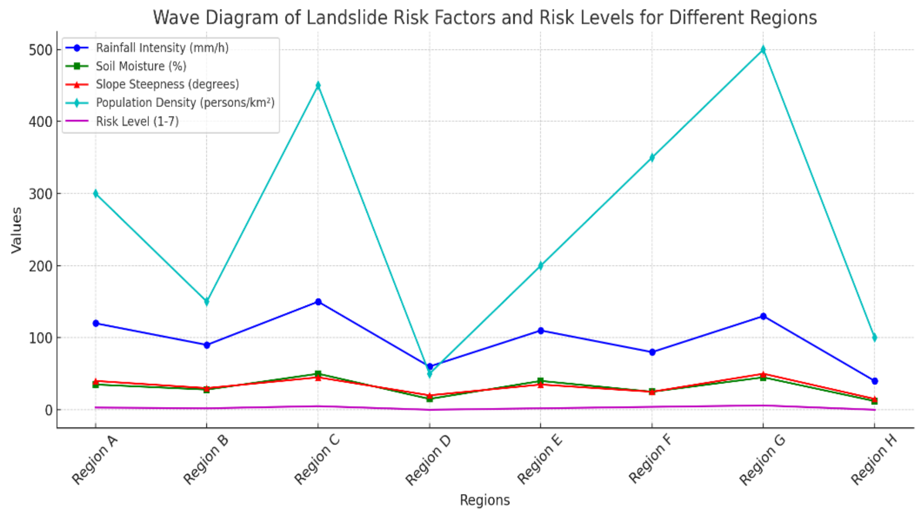

Figure 2: Wave Diagram Of Landslide Risk Factors And Risk Levels For Different Regions

Soil moisture levels also play a significant role in landslide risk. The system detected increased soil moisture content in several regions, which correlates with decreased cohesion in the soil, making it more prone to sliding. In combination with other environmental conditions, such as steep terrain and weak geological layers, high moisture levels can serve as early warning signals of impending landslides. Ground movement patterns, particularly signs of creeping motion, further corroborated these findings. These slow shifts in the ground are often a precursor to larger, more catastrophic landslide events, making them critical indicators in landslide risk assessment.Geological characteristics, such as rock types, soil composition, and fault lines, also influence landslide susceptibility. The system incorporated geospatial data, which helped to identify regions with geological characteristics conducive to landslides. Areas with loose, unconsolidated soil or those situated near active fault lines were flagged by the detection system as high-risk zones. Understanding these factors allows for more effective identification of landslide-prone areas and aids in refining risk assessments.

4. Discussion

To assess the significance of the detected signals, it is essential to compare the results with historical data on landslides in the region. Historical data provides valuable context and allows for a more accurate evaluation of the current findings. When comparing the detected signals with past events, it is clear that the current signals are similar to those observed in previous landslides, particularly in terms of rainfall intensity, soil moisture levels, and ground movement patterns. This consistency with historical events strengthens the validity of the detection system and its ability to accurately predict landslides. However, some differences were also noted. In certain areas, the detected signals were stronger than those observed in previous events, indicating that the current conditions may present a higher risk of landslides than in the past. For instance, the combination of heavy rainfall and soil saturation in certain regions was more pronounced than in past years, suggesting a heightened risk of landslide occurrence. These differences should be carefully analyzed, as they may signal changing conditions, such as increased rainfall patterns due to climate change or changes in land use and vegetation cover. By comparing detection results with historical data, we can gain a better understanding of the evolving landscape of landslide risks and tailor mitigation strategies accordingly.

A key component of landslide detection is conducting a thorough risk assessment based on the detected signals and environmental conditions. Risk assessment involves evaluating the vulnerability of key infrastructure, population density, and other factors that influence the potential impact of a landslide. In this study, areas with high population density and critical infrastructure, such as roads, bridges, and buildings, were identified as particularly vulnerable to the impacts of landslides. The risk of loss of life, property damage, and disruptions to essential services in these areas was assessed based on the detected signals, with high-risk zones being prioritized for immediate mitigation efforts. The socio-economic impact of a potential landslide was also analyzed, considering factors such as the cost of infrastructure repair, economic losses from business disruptions, and the potential strain on emergency response resources. For example, in a region where a landslide could block a major highway, the economic impact could be significant due to transportation disruptions, while in areas with dense housing, the loss of life and property damage could be severe. Quantifying these impacts helps policymakers and stakeholders prioritize mitigation strategies and allocate resources more effectively. The analysis also highlighted that timely early warning systems and proactive evacuation measures could reduce the potential human and economic costs associated with landslides.

Mitigation strategies play a crucial role in reducing landslide risk and minimizing the potential impacts of these events. Several strategies were proposed and evaluated based on the findings from the landslide detection system. Slope stabilization measures, such as retaining walls, terracing, and soil nailing, were identified as effective methods to reduce the risk of landslides in areas with steep terrain. These measures help to reinforce slopes and prevent soil from moving, especially during heavy rainfall events. Vegetation management was also highlighted as an important strategy. By planting vegetation that can bind the soil, such as grasses, shrubs, and trees, the likelihood of soil erosion is reduced, which can help prevent landslides. The integration of vegetation management with slope stabilization techniques can provide a more comprehensive approach to landslide risk reduction. Additionally, land use planning and zoning regulations that restrict development in high-risk areas can significantly reduce exposure to landslide hazards. Early warning systems (EWS) were identified as one of the most effective ways to minimize the impact of landslides. These systems provide real-time alerts to local communities, allowing for timely evacuations and the closure of roads and infrastructure in high-risk areas. Emergency preparedness initiatives, such as regular drills, the development of evacuation plans, and public awareness campaigns, were also discussed as crucial components of an effective mitigation strategy.

Despite the advances in landslide detection, it is important to acknowledge the uncertainties and limitations inherent in these systems. Data quality and sensor reliability are major concerns, as faulty sensors or unreliable data can lead to inaccurate detection results. For instance, if the sensors fail to accurately measure rainfall or soil moisture, the detection system might not trigger an alert when it is most needed. Additionally, the complexity of landslide dynamics, with multiple interacting factors contributing to their occurrence, means that predictions will always carry a degree of uncertainty. The reliance on historical data and modeling assumptions also introduces limitations. For example, landslide models that have been trained on past events may not always be able to generalize to new conditions, such as those brought on by climate change or human activities. These uncertainties must be factored into the decision-making process, and stakeholders must understand that predictions based on current systems are not always definitive.

To improve landslide detection methods, future research should focus on enhancing data collection capabilities, refining algorithms, and integrating additional data sources. New sensor technologies, such as advanced satellite-based remote sensing or real-time monitoring systems, could provide more accurate and comprehensive data. Machine learning algorithms, particularly deep learning models, should be further developed to handle complex datasets and improve the system's ability to detect subtle patterns indicative of landslide risk. Collaboration between researchers, policymakers, and communities will be essential to the success of landslide detection and mitigation efforts. Future research should also include field studies and real-world validation of detection results to improve the robustness of models. As landslide risk management evolves, greater focus should be placed on integrating local knowledge and community input into detection systems and mitigation strategies. In the detection of landslides using advanced technologies presents significant opportunities for improving risk management and reducing the impact of these hazardous events. By combining accurate detection systems with timely risk assessments and effective mitigation strategies, communities can better prepare for and respond to the threat of landslides. However, uncertainties in data quality and the complexity of landslide dynamics remain challenges that must be addressed to improve the effectiveness of these systems. With continued research, development, and collaboration, we can enhance our ability to detect, predict, and mitigate landslides in vulnerable regions.

4. Conclusion

To summarize, the creation of a landslide prediction system that is based on machine learning and is specifically designed for mountainous locations has a great deal of promise for reducing the negative effects that landslides have on populations and infrastructure. Through the utilization of historical data, sophisticated algorithms, and information that is delivered in real time, the system is able to provide timely warnings and preventative measures to mitigate hazards. However, in the future, improvements could involve the incorporation of additional data sources, such as geological surveys and satellite images, in order to conduct a risk assessment that is more thorough. Additionally, in order to increase the accuracy and reliability of predictions, it will be necessary to continuously validate machine learning models against data from the actual world and undergo continuing refining of these models. In the end, the incorporation of dynamic risk assessment models and community involvement activities will be essential for the purpose of increasing resilience and facilitating effective disaster response tactics in areas that are prone to landslides.

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