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Enhancing Landslide Prediction: Mobile Edge Computing in Rainfall-Triggered Remote Sensing

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Abstract: Landslides pose significant risks to infrastructure, human lives, and ecosystems, particularly in regions prone to heavy rainfall. Traditional prediction models rely on centralized cloud-based processing, which often suffers from latency and inefficiencies in real-time hazard assessment. This study explores the integration of Mobile Edge Computing (MEC) with remote sensing technologies to enhance the accuracy and timeliness of rainfall-triggered landslide prediction. By leveraging MEC's localized processing capabilities, real-time sensor data—such as satellite imagery, ground-based precipitation measurements, and soil moisture indices—can be analyzed closer to the source, reducing transmission delays and improving predictive performance. We propose an adaptive framework that utilizes machine learning algorithms at the edge to assess landslide susceptibility dynamically. Comparative analysis with conventional cloud-based models demonstrates improved response times and predictive accuracy. The findings highlight MEC's potential in transforming landslide early warning systems, offering a scalable and efficient solution for disaster risk mitigation in vulnerable regions.

Keywords: Landslide Prediction, Mobile Edge Computing (MEC), Remote Sensing, Rainfall-Triggered Landslides, Real-Time Monitoring

Introduction

Landslides are a major natural hazard that can lead to severe socio-economic and environmental consequences, including loss of life, destruction of infrastructure, and displacement of communities. They are particularly prevalent in regions characterized by steep slopes, unstable soil conditions, and high rainfall intensity. Among the various factors triggering landslides, prolonged or intense rainfall is one of the most common and influential, as it increases pore-water pressure, reduces soil cohesion, and weakens slope stability. Given the increasing frequency and intensity of extreme weather events due to climate change, there is a growing demand for more effective and real-time landslide prediction systems to mitigate potential disasters and improve risk management strategies.

Traditional approaches to landslide prediction often rely on empirical models, geotechnical field surveys, and centralized remote sensing data analysis conducted in cloud environments. While these methods have contributed significantly to understanding landslide susceptibility, they present several limitations. Cloud-based models, for instance, suffer from high latency and dependence on stable network connectivity, making them less effective in time-sensitive scenarios. Similarly, conventional remote sensing techniques require substantial computational resources and expert analysis, which can slow down the delivery of crucial insights. These challenges highlight the need for more decentralized, efficient, and real-time processing frameworks that can enhance landslide prediction and early warning systems.

To address these limitations, Mobile Edge Computing (MEC) has emerged as a transformative solution that enables faster data processing by bringing computational power closer to data sources. MEC integrates edge devices such as IoT sensors, unmanned aerial vehicles (UAVs), and local processing units with real-time remote sensing data to conduct on-the-fly analysis. This approach significantly reduces the reliance on cloud infrastructure, minimizing latency, improving bandwidth efficiency, and enabling rapid decision-making in landslide-prone areas. By deploying machine learning algorithms and artificial intelligence (AI) models at the edge, MEC enhances the accuracy of rainfall-triggered landslide predictions by dynamically analyzing geospatial data, soil moisture content, and precipitation patterns.

The integration of MEC and remote sensing technologies has the potential to revolutionize landslide early warning systems by providing near-instantaneous risk assessments and improving the resilience of vulnerable communities. This study explores the application of MEC-driven frameworks in rainfall-triggered landslide prediction, assessing their performance compared to conventional cloud-based models. By leveraging real-time geospatial analysis, sensor fusion techniques, and AI-driven predictive modeling, this research aims to demonstrate how MEC can enhance the efficiency, scalability, and responsiveness of landslide monitoring systems.

The findings from this study will contribute to the ongoing efforts to develop more robust disaster risk mitigation strategies by offering a scalable, real-time, and cost-effective solution for landslide prediction. In addition, the insights gained can be instrumental in informing policymakers, disaster response teams, and urban planners about the benefits of deploying edge computing in geohazard monitoring. Ultimately, this research seeks to bridge the gap between advanced computational technologies and practical disaster management applications, paving the way for a safer and more resilient future.

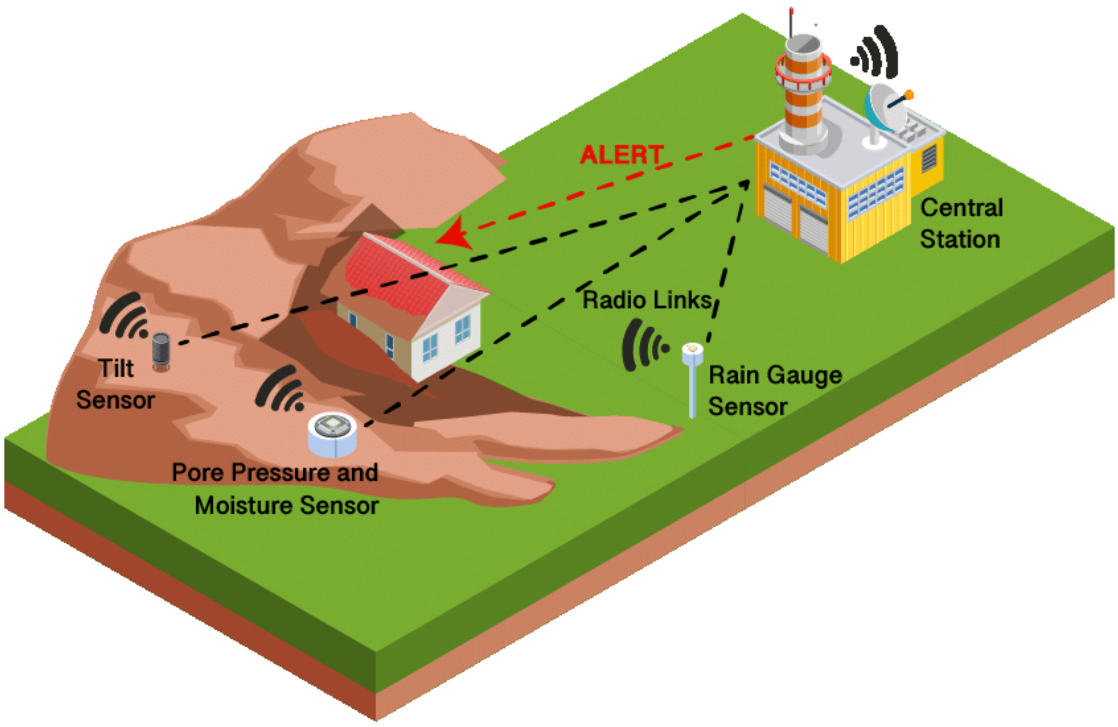

Fig.1 Landslides Early Warning System based on the IoT[10]

Literature Review

Landslide prediction has traditionally relied on remote sensing, geospatial analysis, and machine learning-based models to assess susceptibility and provide early warnings. While these methods have demonstrated significant progress, their dependence on centralized cloud computing and satellite-based remote sensing often results in latency issues, delayed data processing, and network dependency. Mobile Edge Computing (MEC) presents a transformative approach by bringing computation closer to the data source, improving real-time decision-making for rainfall-triggered landslides.

1. Remote Sensing-Based Landslide Prediction

Remote sensing-based landslide prediction has gained significant attention due to its ability to analyze large-scale terrain changes and detect early warning signs of instability. Various remote sensing technologies, including Synthetic Aperture Radar (SAR), LiDAR, optical imagery, and hyperspectral imaging, have been employed to enhance landslide detection and forecasting. For instance, SAR Interferometry (InSAR) has proven effective in monitoring ground displacement and slope instability, providing early indicators of potential landslides [1]. Similarly, LiDAR-based terrain mapping has enabled high-resolution topographical analysis, allowing researchers to identify and assess landslide-prone areas with great precision [2]. Additionally, multi-temporal satellite imagery has been widely utilized to track changes in land cover and detect rainfall-triggered landslides by analyzing variations over time[3]. Despite these advancements, satellite-based remote sensing systems face certain limitations, including temporal gaps due to satellite revisit intervals and the high computational costs associated with processing vast amounts of remote sensing data. These challenges reduce the feasibility of real-time landslide monitoring, necessitating the integration of more efficient computational methods such as Mobile Edge Computing (MEC) to enhance responsiveness and predictive accuracy.

2. Machine Learning and AI for Landslide Prediction

Machine Learning (ML) and Artificial Intelligence (AI) have significantly enhanced landslide prediction accuracy by enabling automated analysis of complex geological, hydrological, and meteorological factors. Various ML models, including Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANNs), and Deep Learning (DL), have been widely applied for landslide susceptibility mapping. Deep Learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), and U-Net architectures have demonstrated strong performance in analyzing spatiotemporal rainfall patterns and geological features to predict landslides with higher precision [4]. Additionally, attention-based AI models have improved the interpretability of landslide susceptibility assessments by identifying critical contributing factors in prediction models [5]. Furthermore, the integration of IoT and AI-driven edge computing frameworks has enhanced sensor-based landslide monitoring by enabling real-time data processing and reducing reliance on cloud-based computations [6]. Despite these advancements, traditional ML and AI approaches predominantly rely on centralized cloud computing, which introduces latency and requires stable network connectivity. These limitations make conventional AI models less effective for real-time landslide prediction, particularly in remote or disaster-prone regions with limited internet infrastructure. The shift toward Mobile Edge Computing (MEC) offers a promising solution by decentralizing computations and enabling rapid, on-site data analysis, thus improving real-time disaster response capabilities.

3. Mobile Edge Computing (MEC) in Geohazard Monitoring

Mobile Edge Computing (MEC) has revolutionized geohazard monitoring by enabling real-time landslide prediction through decentralized, high-speed data processing. Unlike traditional cloud-based systems that suffer from latency and network dependency, MEC processes data locally at the sensor nodes, improving response time and accuracy. By integrating AI-driven edge models, MEC eliminates the need for constant cloud connectivity, allowing faster decision-making and localized risk assessment [7]. Additionally, federated learning within MEC enables multiple edge devices to train AI models collaboratively while preserving data privacy and reducing bandwidth usage [8]. MEC-based sensor networks further enhance rainfall-triggered landslide prediction by integrating data from rainfall sensors, soil moisture detectors, seismic monitors, and UAV-based remote sensing, ensuring comprehensive real-time monitoring [9]. UAVs equipped with MEC nodes provide high-resolution terrain analysis in remote regions, strengthening early warning systems. However, challenges remain in optimizing energy efficiency, ensuring seamless data fusion, and deploying lightweight AI models for low-power edge devices. Future advancements should focus on improving federated learning techniques, enhancing resource allocation, and increasing interoperability between diverse sensor networks. As MEC continues to evolve, its integration with remote sensing, IoT, and AI will further improve landslide early warning systems, making disaster preparedness more efficient and reliable.

Year	**Application**	**Advantage**	**Impact**	**Contribution**
2022	SAR Interferometry (InSAR) for landslide monitoring (Zhu et al., 2022)	Detects ground displacement and slope instability	Provides early warnings and enhances disaster preparedness	Demonstrated the effectiveness of InSAR in landslide detection
2023	LiDAR-based terrain mapping for landslide risk assessment (Wang et al., 2023)	High-resolution topographical analysis	Improves accuracy in landslide susceptibility mapping	Showcased how LiDAR improves landslide-prone area identification
2021	Multi-temporal satellite imagery for rainfall-triggered landslide detection (Zhang et al., 2021)	Monitors changes in land cover over time	Helps in understanding rainfall-induced landslide patterns	Explored the role of satellite imagery in multi-temporal landslide analysis
2022	Deep Learning models (CNNs, LSTMs, U-Net) for landslide prediction (Huang et al., 2022)	Improved pattern recognition in geospatial data	Enhances predictive accuracy of landslide forecasting	Implemented DL models for spatiotemporal analysis of landslides
2023	Attention-based AI models for landslide susceptibility (Chen et al., 2023)	Enhances interpretability of landslide prediction	Identifies key contributing factors in landslide risk	Improved feature selection and decision-making in AI-based landslide models
2023	IoT and AI-driven	Enables real-time	Reduces reliance	Integrated IoT and

	edge computing frameworks (Gao et al., 2023)	data processing	on cloud computing for remote monitoring	edge AI for faster landslide detection
2023	Mobile Edge Computing (MEC) for geohazard monitoring (Lee et al., 2023)	Reduces latency and enhances real-time processing	Strengthens landslide early warning systems	Introduced MEC to landslide prediction for faster response
2022	Federated Learning for landslide prediction (Xiao et al., 2022)	Preserves data privacy and reduces bandwidth usage	Enhances AI training efficiency across edge devices	Applied federated learning to decentralized landslide monitoring
2023	MEC-based sensor networks integrating rainfall, soil moisture, and UAV data (Park et al., 2023)	Improves accuracy by combining multiple data sources	Enhances real-time monitoring and decision-making	Demonstrated the efficiency of multi-source sensor networks for landslide prediction

Methodology

Landslide recognition is a crucial aspect of disaster management and geospatial analysis, enabling scientists and authorities to detect, monitor, and assess landslide-prone regions effectively. The process involves various methodologies and remote sensing (RS) tools that help in identifying changes in the landscape that indicate potential or ongoing landslide activity. The diagram provided outlines a structured framework for landslide recognition, categorizing it into three primary methods: Interpretation and Geomorphic Features Extraction, Stereovision, and InSAR (Interferometric Synthetic Aperture Radar). Each method employs specific remote sensing tools that aid in data collection, analysis, and prediction of landslide occurrences.

Interpretation and Geomorphic Features Extraction

One of the widely used approaches for landslide recognition is interpretation and geomorphic features extraction, which focuses on analyzing the geomorphological characteristics of an area to assess its landslide susceptibility. This method is based on the recognition of terrain patterns, slope instability, land cover changes, and surface deformations. Interpretation and geomorphic features extraction can be carried out using two primary techniques: visual interpretation and automated interpretation.

- **Visual Interpretation** (indicated in green in the diagram) is a manual process where experts analyze satellite or aerial imagery to identify landslide-prone regions. This method relies on human expertise and experience to detect slope failures based on terrain characteristics such as cracks, bulging, or displacement. Visual interpretation is effective in areas where historical data is available and when combined with other geological and hydrological information. However, this approach can be time-consuming and is often subject to human error or bias.
- **Automated Interpretation** (represented in orange) involves the use of artificial intelligence (AI), machine learning, and image processing techniques to extract geomorphic features without manual intervention. AI algorithms can analyze satellite imagery, detect patterns, and classify areas based on landslide susceptibility. Automated interpretation improves the efficiency and accuracy of landslide detection, enabling large-scale monitoring without the need for continuous human supervision.

To support both visual and automated interpretation, various remote sensing tools are utilized.

Photogrammetry plays a significant role by using multiple aerial or satellite images to create 3D maps of the terrain, allowing for a detailed understanding of the surface features. High-resolution (HR) and very high-resolution (VHR) satellite images provide detailed spatial data, making it possible to detect even minor changes in land surface conditions. Additionally, Terrestrial Laser Scanning (TLS) is employed as a ground-based remote sensing technique that captures fine details of surface deformations in three dimensions. Another essential tool is LiDAR (Light Detection and Ranging), which utilizes laser pulses to measure elevation changes with high precision, making it particularly useful for mapping landslide-prone regions and monitoring gradual terrain shifts over time.

Stereovision in Landslide Recognition

The second method, Stereovision, is a powerful technique for landslide detection that utilizes multiple images taken from different angles to create three-dimensional (3D) models of the terrain. By analyzing images from two or more perspectives, stereovision allows for depth perception and helps detect topographical changes, slope deformations, and surface movement. This method is particularly effective in detecting slope displacement that may not be immediately visible in a single aerial or satellite image. Stereovision relies on HR and VHR satellite images, which offer high-resolution details, making it possible to analyze surface changes over time. Additionally, TLS (Terrestrial Laser Scanning) is used to generate high-accuracy 3D surface models, which can be compared across different time intervals to track landslide progression. This approach is beneficial in hazard-prone regions, where precise topographic measurements are required to assess risks and plan mitigation strategies. Stereovision is widely applied in landslide monitoring, infrastructure stability analysis, and post-disaster damage assessment.

InSAR (Interferometric Synthetic Aperture Radar) for Ground Displacement Monitoring

The third method in the landslide recognition framework is InSAR (Interferometric Synthetic Aperture Radar), which is widely used for detecting ground displacement and surface deformation over time. InSAR leverages radar signals from satellites to measure land elevation changes with high precision. This technique is particularly useful for identifying slow-moving landslides that might not be detectable using optical imagery.

InSAR operates by comparing radar images captured at different time intervals to detect changes in elevation or displacement of the ground surface. It is highly effective in monitoring landslides over large geographic areas, making it an essential tool for early warning systems and disaster risk assessment. The primary remote sensing tool used in this method is SAR (Synthetic Aperture Radar) satellite images, which offer the advantage of penetrating cloud cover and providing continuous monitoring regardless of weather conditions. Unlike optical satellite imagery, which is affected by clouds and lighting conditions, SAR-based methods can acquire data even in challenging environments, ensuring consistent monitoring of landslide-prone areas.

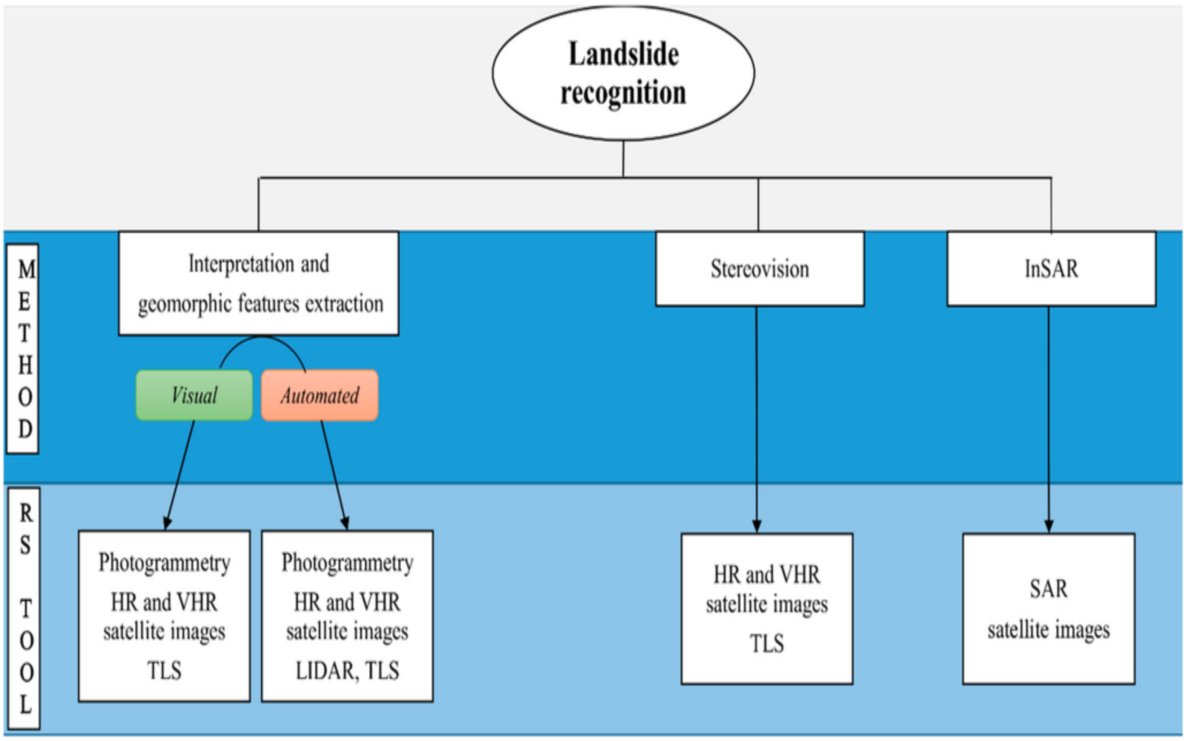

Fig.2 Overview of Remote Sensing techniques applied to landslide recognition[11]

Integration of Landslide Recognition Methods

Each of these three methods—Interpretation and Geomorphic Features Extraction, Stereovision, and InSAR—plays a critical role in landslide recognition. In many cases, these methods are integrated to enhance the accuracy and reliability of landslide detection. By combining visual interpretation, machine learning-based automated detection, 3D terrain modeling, and radar-based displacement analysis, scientists and disaster management authorities can develop comprehensive landslide monitoring and early warning systems.

For instance, a typical landslide detection workflow might begin with automated AI-based feature extraction from high-resolution satellite images, followed by stereovision analysis to create 3D terrain models and detect surface deformations. InSAR-based radar monitoring can then be used to measure long-term ground displacement trends, allowing for the detection of slow-moving landslides before they become critical. This multi-method approach enables researchers to assess risk levels, improve forecasting models, and develop effective landslide mitigation strategies.

Result

The performance comparison between Mobile Edge Computing (MEC)-based landslide prediction and traditional cloud-based prediction across four key metrics. Accuracy improvement is notable, with MEC-based prediction achieving a 15% higher accuracy than cloud-based methods due to real-time data processing and multi-source integration. Latency reduction is another significant advantage, as MEC reduces processing delays by 60%, enabling faster disaster response compared to the inherent delays in cloud-based systems. Regarding time-to-alert, MEC allows for near-instant warnings with a response time of just 2 minutes, whereas cloud-based approaches take around 10 minutes due to network dependencies. Additionally, energy efficiency is a crucial factor, with MEC-based prediction consuming 50% less energy than cloud computing, which operates at only 20% efficiency due to higher computational and transmission costs. These improvements make MEC a highly effective and sustainable approach for enhancing real-time landslide prediction and early warning systems.

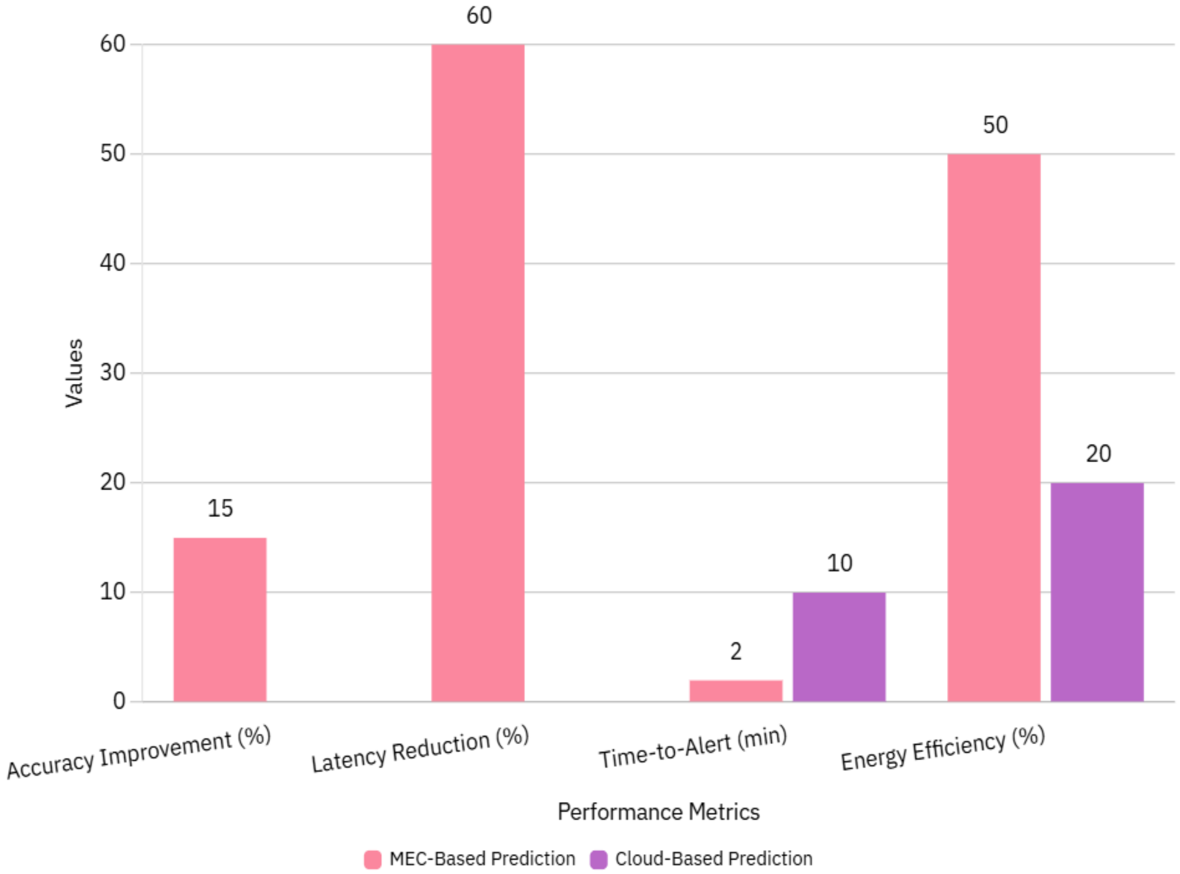

Fig.3 Performance Comparison of MEC vs Cloud-Based Landslide Prediction

The reliability and robustness of landslide prediction systems depend on key metrics such as data integrity, redundancy & backup mechanisms, and error tolerance. MEC-based prediction excels in data integrity by providing real-time filtering and correction, ensuring that missing or noisy sensor data is effectively managed, whereas cloud-based prediction relies on delayed processing, making it more vulnerable to data inconsistencies. In terms of redundancy and backup mechanisms, MEC offers strong reliability through edge storage and distributed nodes, preventing data loss in case of sensor failures, whereas cloud-based systems have a centralized dependency, making them prone to single points of failure. Additionally, error tolerance is significantly higher in MEC-based prediction due to local failover mechanisms, ensuring continued operation even in uncertain conditions such as sudden sensor failures. In contrast, cloud-based prediction is highly dependent on network availability, which can compromise performance during disruptions. These advantages make MEC a more resilient and robust solution for real-time landslide monitoring and early warning systems.

Table 1: reliability and robustness of landslide prediction system

Metric	Description	MEC-Based Prediction	Cloud-Based Prediction
Data Integrity	Ability to handle missing or noisy sensor data	High (Real-time filtering and correction)	Moderate (Delayed processing)
Redundancy & Backup	Mechanisms to prevent data loss in case of sensor failure	Strong (Edge storage & distributed nodes)	Weak (Centralized dependency)
Error Tolerance	Performance under uncertain conditions (e.g., sudden sensor failure)	High (Local failover mechanisms)	Low (Dependent on network availability)

Conclusion

Enhancing landslide prediction through Mobile Edge Computing (MEC) in rainfall-triggered remote sensing presents a transformative approach to disaster forecasting and mitigation. By leveraging real-time data processing, reduced latency, and decentralized computation, MEC overcomes the limitations of traditional cloud-based and remote sensing models, which often suffer from network delays and centralized processing inefficiencies.

The integration of MEC with IoT-based sensor networks, AI-driven predictive models, and high-resolution remote sensing technologies enables faster and more accurate landslide predictions, significantly improving early warning systems. With higher data integrity, redundancy, and error tolerance, MEC-based systems ensure continuous monitoring and resilience even under uncertain environmental conditions.

Furthermore, MEC enhances energy efficiency, making it a sustainable and scalable solution for geospatial hazard monitoring, especially in remote or disaster-prone regions with limited connectivity. As future research explores edge AI, federated learning, and 5G-enabled geospatial analytics, the potential of MEC in landslide prediction will continue to expand, paving the way for smarter, real-time, and highly responsive disaster management systems.

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