International Journal on Emerging Research Areas (IJERA)

DOI:10.5281/zenodo.14760248 *ISSN : 2230-9993*

Advanced Sensor-Based Landslide and Earthquake Detection and Alert System Utilizing Machine Learning and Computer Vision Technologies

Ms. Betzy Babu Thoppil
Dept. of Computer Science
Amal Jyothi College of Engineering
(Autonomous)
Kottayam, India
betzybabuthoppil@amaljyothi.ac.in

Anugrah Premachandran
Dept. of Computer Science
Amal Jyothi College of Engineering
(Autonomous)
Kottayam, India
anugrahpremachandran2025@cs.ajce.in

Annapoorna M
Dept. of Computer Science
Amal Jyothi College of Engineering
(Autonomous)
Kottayam, India
annapoornam2025@cs.ajce.in

Ashwin Mathew Zachariah
Dept. of Computer Science
Amal Jyothi College of Engineering
(Autonomous)
Kottayam, India
ashwinmathewzachariah2025@cs.ajce.in

Bala Susan Jacob
Dept. of Computer Science
Amal Jyothi College of Engineering
(Autonomous)
Kottayam, India
balasusanjacob2025@cs.ajce.in

***Abstract*—This paper presents a comprehensive analysis of the transformative role of the Internet of Things (IoT) and Machine Learning (ML) in advancing landslide monitoring and prediction for enhanced disaster resilience. Landslides, a prevalent natural hazard, pose substantial risks to life, infrastructure, and socio economic stability, particularly in geographically vulnerable regions. The inherent complexity of landslides, triggered by a confluence of geological, hydrological, and meteorological factors, necessitates advanced monitoring and prediction techniques to mitigate their devastating impacts. Traditional monitoring ap proaches, often constrained by limited spatial coverage, data resolution, and real-time analysis capabilities, struggle to provide timely and accurate warnings. The emergence of IoT and ML offers a paradigm shift in landslide monitoring and prediction, enabling real-time data acquisition, sophisticated analysis, and proactive risk management. IoT-enabled sensor networks, com prising diverse sensors strategically deployed across landslide prone areas, provide continuous data streams on critical param eters such as rainfall intensity and duration, soil moisture content, pore-water pressure, ground vibrations (microseismic activity), and slope deformation. These sensors, often low-cost, low-power, and wirelessly interconnected, transmit data to edge computing devices or cloud-based platforms for real-time processing and analysis. ML algorithms, trained on historical landslide data and associated parameters, play a pivotal role in deciphering complex patterns and anomalies within these large datasets. The sources demonstrate the effectiveness of various ML models, including Random Forest, Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Convolutional Neural Networks (CNN), in landslide susceptibility mapping, hazard assessment, and early warning system development.**

***Index Terms*—Landslide, Internet of Things (IoT), Machine Learning (ML), Sensor Networks, Early Warning Systems, Rain fall, Soil Moisture, Ground Vibrations, Slope Stability, Data Analysis, Prediction Models.**

I. Introduction

Landslides, a pervasive natural hazard, pose a significant threat to life, property, and infrastructure globally. They are in fluenced by a complex interplay of meteorological, geological, and anthropogenic factors, leading to various types of slope failures, from rapid rockfalls to slower-moving earthflows. Traditional monitoring approaches, often relying on manual inspections or limited sensor deployments, face challenges in capturing the dynamic nature of landslides and providing timely warnings. However, the convergence of the Internet of Things (IoT) and Machine Learning (ML) presents a transformative opportunity to enhance landslide monitoring, prediction, and risk mitigation strategies. IoT enables the deployment of dense, interconnected sensor networks across landslide-prone areas, collecting real-time data on various parameters indicative of slope stability. These parameters encompass meteorological factors such as rainfall intensity and duration, geological factors like soil moisture content, pore water pressure, and ground vibrations (microseismic activity), and hydrogeological aspects like groundwater levels. This data, transmitted wirelessly through diverse communication protocols (e.g., Zigbee, LoRa, cellular networks), provides unprecedented spatiotemporal insights into slope behaviour.

ML algorithms, with their ability to discern complex pat terns and relationships within large datasets, play a crucial role in analysing the data streams from IoT-enabled sensor networks. By learning from historical landslide events and their associated parameters, ML models can identify precur sory signals, predict landslide likelihood, and even forecast

DOI:10.5281/zenodo.14760248 *ISSN : 2230-9993*

potential runout distances, significantly i mproving t he accu racy and timeliness of early warning systems. This integrated IoT-ML approach empowers stakeholders to make informed decisions, implement timely evacuations, and develop effective mitigation measures, ultimately contributing to saving lives and reducing the socio-economic impacts of landslides. Vari ous ML algorithms, including Random Forest, Support Vector Machines, and Convolutional Neural Networks, have shown promise in landslide susceptibility mapping, hazard assess ment, and early warning system development. The integration of high-resolution topographic data from sources like ALOS PALSAR and optical imagery from satellites like RapidEye further enhances the accuracy and reliability of these models.

II. METHODOLOGY

A. Data Acquisition and Sensor Networks in Landslide Monitoring

This emphasise that effective landslide monitoring hinges on acquiring robust, real-time data from the field u sing a strategically designed network of sensors. This network, often referred to as a Wireless Sensor Network (WSN), serves as the foundation for data-driven decision-making in landslide-prone areas. The selection of specific s ensors i s d riven by the characteristics of the landslides under investigation and the parameters deemed critical for their monitoring. Geotechnical instruments like inclinometers, piezometers, and extensometers offer direct measurements of slope deformation, pore water pressure, and ground movement, respectively. Complementing these, geophysical techniques such as electrical resistivity tomography and seismic refraction tomography provide valuable insights into subsurface conditions and potential slip surfaces without requiring intrusive excavations. The integration of remote sensing technologies like InSAR, LiDAR, and optical imagery analysis further enhances data acquisition by providing large-scale spatial information on ground displacement, rainfall patterns, and land cover changes. The sources highlight the importance of selecting appropriate sensors based on factors like energy efficiency, cost-effectiveness, and the desired spatial and temporal resolution of data. For instance, researchers at Bournemouth University opted for a combination of low-power microprocessors, SigFox and LoRa communication modules, and various sensors for their landslide monitoring pilots, prioritising energy efficiency and data transmission range. This data, collected by the WSN, forms the basis for further processing, analysis, and ultimately, the development of early warning systems and risk assessment models.

Fig. 1. The architectural tiers of the presented framework.

B. Data Processing and Analysis in Landslide Monitoring

This highlight that the large volumes of raw data obtained from landslide monitoring sensors require sophisticated processing and analysis to extract meaningful insights and achieve research objectives. Initially, the data undergoes pre-processing steps, which may include noise reduction, outlier removal, and data normalization, ensuring the data's quality and suitability for further analysis. For instance, in microseismic monitoring, signal processing techniques, such as the Fourier Transform, help differentiate actual landslide activity from ambient noise like traffic vibrations.

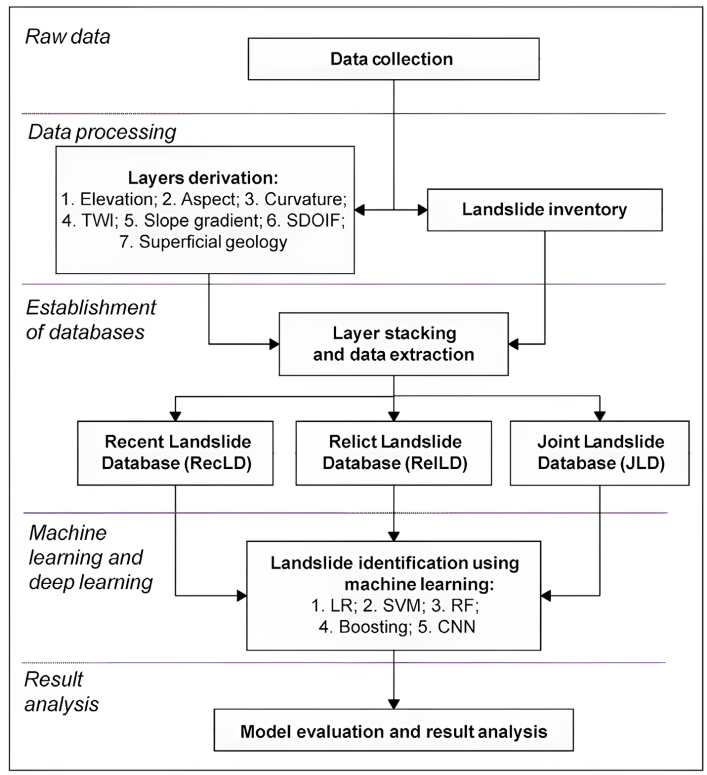

Fig. 2. Proposed landslide identification method using machine learning.

Statistical analysis plays a crucial role in establishing correlations between landslide occurrences and potential triggering factors. Researchers use statistical methods to investigate the relationship between landslide events and parameters like rainfall intensity and duration, soil saturation levels, and seismic activity, as demonstrated in source. The sources emphasise the increasing use of machine learning (ML) for advanced analysis, including landslide susceptibility mapping, prediction, and the development of early warning systems. Various ML algorithms, such as Random Forest, Support Vector Machines (SVMs), and Artificial Neural Networks (ANNs), are employed to analyse complex datasets and identify hidden patterns indicative of landslide activity. This data-driven approach, coupled with expert knowledge and domain understanding, allows for more accurate

International Journal on Emerging Research Areas (IJERA)

DOI:10.5281/zenodo.14760248 *ISSN : 2230-9993*

landslide predictions and the development of effective mitigation strategies.

C. Multi-Level Feature Learning and Extraction

Feature extraction utilizing deep learning computer vision models (VGG, DenseNet, and Inception-V3) constitutes a fundamental component in automated landslide detection systems. These architectures, initially pre-trained on ImageNet's extensive dataset and subsequently fine-tuned with landslide-specific imagery, implement a sophisticated hierarchical feature extraction process. The mechanism operates through multiple processing stages, beginning with initial convolutional layers that extract fundamental visual elements including edges, textures, and color variations from input imagery. Intermediate layers process and combine these basic features to identify more complex patterns characteristic of landslide morphology, while deep layers synthesize learned features to generate high-level representations specific to landslide characteristics. The extracted features culminate in two primary outputs: classification probabilities indicating landslide presence and precise spatial localization of landslide features within analyzed imagery. To enhance model interpretability, Class Relevance Map (CRM) techniques are employed to visualize critical regions influencing the model's decision-making process, providing crucial insights into feature importance and model behavior. Furthermore, ensemble methodologies incorporating multiple deep learning architectures are implemented to optimize feature extraction capabilities. This approach leverages the complementary strengths of different architectures, resulting in robust feature extraction and enhanced prediction accuracy. The comprehensive feature extraction framework has demonstrated significant efficacy in automated landslide detection and prediction from remote sensing imagery, providing a reliable foundation for hazard assessment and monitoring systems.

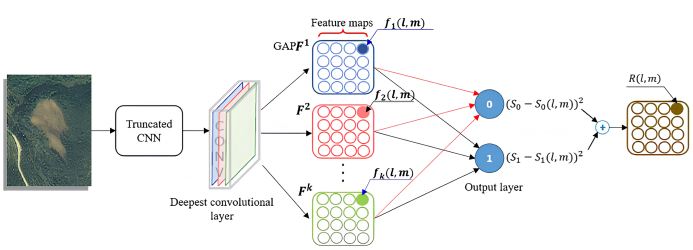

Fig. 3. Class-selective relevance mapping (CRM)

D. Early Warning Systems (EWS) for Landslides

Early warning systems (EWS) represent a crucial application of landslide monitoring, aiming to provide timely alerts to at-risk communities and authorities about imminent landslide threats. The sources emphasise that effective EWS integrate real-time data acquisition from sensor networks with sophisticated data processing, analysis, and prediction models. These systems utilise data from various sources, including rainfall gauges, soil moisture sensors, piezometers, extensometers, geophones, and remote sensing platforms, to monitor critical landslide triggering parameters. Machine learning algorithms play a pivotal role in analysing these data streams, identifying patterns indicative of impending landslides, and generating early warnings based on pre-defined thresholds or risk models. For instance, source describes an EWS that employs Support Vector Regression (SVR) to nowcast and forecast slope stability conditions based on rainfall, soil moisture, and pore water pressure data, issuing alerts at different levels (Early, Intermediate, Immediate) depending on the severity and certainty of the threat. The effectiveness of EWS relies not only on their technical capabilities but also on robust communication channels to disseminate warnings promptly to stakeholders, including government agencies, disaster management authorities, and the general public. Furthermore, the sources underscore the importance of community engagement, education, and preparedness initiatives to ensure timely and appropriate responses to EWS alerts, ultimately minimising the potential impacts of landslides.

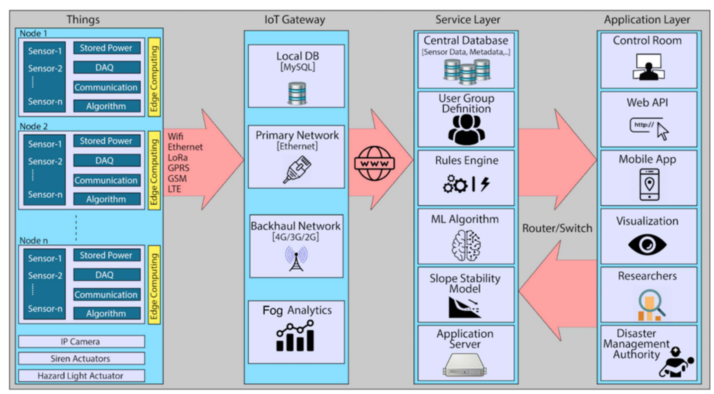

Fig. 4. Architectural diagram of the LEWS

E. Validation and Performance Evaluation of Landslide Detection and Monitoring Systems

The sources emphasise that rigorous validation and performance evaluation are essential for ensuring the reliability and effectiveness of landslide detection, monitoring, and early warning systems. This involves evaluating the accuracy, precision, and overall performance of both the employed sensors and the analytical models used to process the collected data. For sensor validation, researchers often conduct controlled laboratory experiments and field trials to assess their sensitivity, accuracy, and response to various simulated landslide conditions. For instance, in source, researchers validated the performance of a microseismic sensing system using geophone sensors through laboratory simulations of slip surface movements, comparing the recorded signals with expected patterns and time delays. The sources also highlight the importance of differentiating true landslide signals from ambient noise and other environmental factors, such as rainfall or human activity, using signal processing techniques and statistical analysis.

International Journal on Emerging Research Areas (IJERA)

DOI: 10.5281/zenodo.14760248 *ISSN : 2230-9993*

When evaluating the performance of analytical models, especially those based on machine learning, common metrics include precision, recall, F1-score, and the Matthews Correlation Coefficient (MCC). T hese m etrics a ssess t he model's ability to correctly identify true positive (landslide) and true negative (stable slope) cases while minimising false positives and false negatives. Researchers often employ techniques like cross-validation, where the data is split into training and testing sets, to avoid overfitting and obtain a more reliable estimate of the model's performance on unseen data. Additionally, sources stress the importance of comparing the performance of different machine learning algorithms and feature selection methods to identify the most suitable approach for a specific landslide scenario. Visualisation techniques, such as graphs, maps, and dashboards, are also crucial for interpreting and communicating the results of validation and performance evaluations to stakeholders, facilitating informed decision-making and risk mitigation strategies.

III. Existing Systems and Challenges in Landslide Monitoring

Landslide monitoring is crucial for mitigating the risks associated with these natural disasters, which claim thousands of lives annually. Traditional monitoring techniques like remote sensing and geotechnical instrumentation, while useful, have limitations in terms of cost, spatial-temporal resolution, and predictive capabilities. The emergence of the Internet of Things (IoT) has opened up new possibilities for real-time, cost-effective, and scalable landslide monitoring systems. Recent research highlights successful deployments of IoT-based systems that leverage a variety of sensors, including geophones for detecting microseismic events, strain gauges for measuring slope deformation, and hydrogeological sensors for monitoring parameters like rainfall, moisture, and pore water pressure. These systems employ diverse communication technologies, ranging from short-range protocols like Zigbee to long-range options like LoRa and cellular networks, depending on the geographical location and coverage requirements. Data from these sensors is transmitted to central servers for analysis, often using machine learning (ML) algorithms to identify patterns and predict landslide occurrences. Despite these advancements, challenges remain, such as ensuring sensor reliability in harsh environments, handling data quality issues, and developing models that generalize well across diverse geographical locations. Addressing these challenges through ongoing research and collaboration is crucial for enhancing the effectiveness of landslide early warning systems and reducing the socio-economic impacts of these devastating events.

IV. Advancements in Landslide Monitoring through IoT and ML

The convergence of the Internet of Things (IoT) and machine learning (ML) is revolutionising landslide monitoring, offering more precise, timely, and cost-effective solutions compared to traditional methods. This integration empowers researchers and practitioners to gather real-time data on critical landslide-triggering parameters and develop predictive models for more effective early warning systems.

IoT-based systems utilise a diverse array of sensors, each targeting specific i ndicators o f s lope i nstability. Geophones, for example, detect subtle microseismic vibrations that can precede landslides, particularly those triggered by rainfall or earthquakes .Strain gauges provide precise measurements of slope deformation, offering insights into the stability of the terrain .Hydrogeological sensors monitor crucial parameters such as rainfall, soil moisture, and pore-water pressure, which play a significant r ole i n i nfluencing sl ope st ability .T hese sensors, often powered by sustainable energy sources like solar panels , transmit data wirelessly to central servers for analysis. The choice of communication technology depends on factors such as geographical location, coverage requirements, and desired data rates Short-range protocols like Zigbee may be suitable for localised deployments, while long-range options such as LoRa or cellular networks cater to larger, more geographically dispersed monitoring systems.

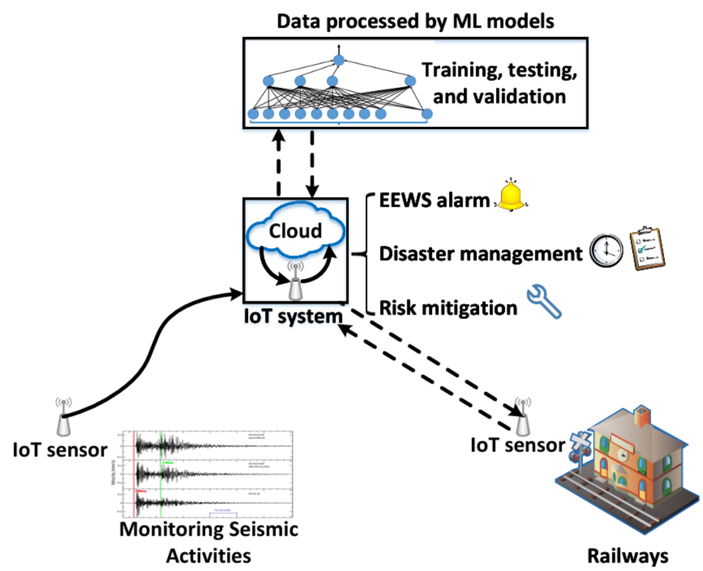

Fig. 5. A sample of IoT-ML interconnection for EEWS

The data collected by these sensors feeds into ML algorithms, enabling the development of predictive models for landslide occurrences. Support Vector Regression (SVR) is one such algorithm that has shown promise in forecasting slope stability .SVR-based algorithms, like "Current-PWP" and "24-PWP", provide nowcast and 24-hour forecasts, respectively, based on real-time sensor data . The ability of these algorithms to identify complex relationships between parameters like antecedent rainfall and pore-water pressure dynamics makes them particularly valuable for landslide prediction .

DOI: 10.5281/zenodo.14760248 *ISSN : 2230-9993*

Furthermore, ML models can differentiate between actual landslide precursors and ambient noise or other environmental factors, reducing the occurrence of false alarms and increasing the reliability of early warning systems .As research progresses, we can expect even more sophisticated ML models that can integrate data from multiple sensor types and sources, offering a more holistic understanding of landslide processes. This, in turn, will lead to more accurate predictions and ultimately contribute to saving lives and protecting infrastructure in landslide-prone areas.

V. Applications of IoT and ML for Landslide Monitoring

The sources highlight several specific applications of IoT and ML technologies working together to create effective landslide early warning systems. Researchers are using geophone sensors in ”Smart Microseismic Sensing” (SM-s) nodes to capture and transmit real-time data on microseismic vibrations, which can be early indicators of landslides, especially those triggered by rainfall or earthquakes. These systems use edge computing to process data locally and transmit only the most important information to the cloud, improving energy efficiency and reducing latency. The data gathered from these networks feeds ML algorithms, such as Support Vector Regression (SVR), to create predictive models. For example, the ”Current-PWP” and ”24-PWP” algorithms provide nowcast and 24-hour forecasts of slope stability based on real-time data from sensors monitoring parameters like pore-water pressure. Furthermore, ML is being used to differentiate between microseismic signals that indicate landslides from background noise like traffic, leading to more accurate alerts. In addition to prediction, researchers are exploring the use of ML for identifying the best locations for sensor placement to maximise the effectiveness of these networks. These applications demonstrate how the combined capabilities of IoT and ML offer a promising approach to mitigating the risks associated with landslides.

VI. Examples of Deployed Models

The sources provide several examples of deployed landslide monitoring systems that utilise IoT and ML technologies to mitigate the risks posed by landslides.

A.

One example is a system deployed in Chandmari, Sikkim, India, a region highly susceptible to landslides due to its location in the North-Eastern Himalayan region, which experiences frequent heavy rainfall and seismic activity . This system utilises ”Smart Microseismic Sensing” (SM-s) nodes equipped with geophone sensors to capture microseismic vibrations in the ground, sampling at a high frequency of 1 kHz. The data is then wirelessly transmitted to data centres for analysis. Crucially, the system uses ML algorithms to differentiate between microseismic signals indicative of landslides and background noise from traffic or pedestrian activity, enhancing the accuracy of early warnings.

B.

Another example is a system in Munnar, Kerala, India, which also experiences frequent heavy rainfall . This system employs a network of diverse sensors that monitor multiple parameters relevant to landslide occurrences, including moisture, pore water pressure, and ground displacement.This system has a proven track record of success, having issued real-time warnings to local authorities during the monsoon seasons of 2009, 2011, 2013, 2018, and 2019, resulting in effective evacuations that underscore the life-saving potential of such technologies .

C.

Another notable system is the one described in a research paper by Somchai Biansoongnerna**, Boonyang Plungkanga ,and Sriwichai Susukb ,researchers from Rajamangala University of Technology Thanyaburi, Thailand,and the Thailand Institute of Scientific and Technological Research .This system focuses on providing early warnings for landslides and rock slides specifically for railways . It uses a combination of sensors, including an accelerometer sensor, soil moisture sensor, laser sensor, and rain gauge,to monitor various parameters relevant to slope stability . The system transmits the sensor data to a control centre using a wireless network ,where it is then uploaded to the cloud-based platform ThingSpeak. ThingSpeak provides data visualisation and analysis capabilities, allowing for real-time monitoring and identification of potential landslide risks . When the system detects that predefined threshold values have been exceeded, it triggers alerts via SMS to end-users, enabling timely responses and potentially mitigating the risks associated with landslides along railway lines .

These examples highlight a global trend of researchers and practitioners moving beyond theoretical frameworks to deploy practical, on-the-ground applications of IoT and ML for landslide monitoring. The successful implementation of these systems in diverse geographical locations with varying landslide triggers demonstrates their adaptability and potential for creating more effective early warning systems. As these technologies continue to develop, we can anticipate more widespread deployment of these life-saving systems, contributing to safer and more resilient communities in landslide-prone areas worldwide.

VII. Future Directions in Landslide Monitoring

This point to several promising future directions for research and development in landslide monitoring through IoT and ML. There is a need for systems that can integrate data from a wider variety of sensor types and sources, including satellite imagery, weather forecasts, and ground-based sensors, to provide a more holistic understanding of landslide processes and improve prediction accuracy . This integration will require robust data fusion techniques and the development of more sophisticated ML models capable of handling heterogeneous data streams. Another area for future exploration is the use of deep learning techniques, such as Convolutional Neural Networks (CNNs) and Vision Transformer (ViT), to automatically extract features

DOI: 10.5281/zenodo.14760248 *ISSN : 2230-9993*

and patterns from sensor data, potentially leading to even more accurate and timely predictions . However, the effective utilisation of deep learning in this domain will require addressing challenges related to data availability, computational complexity, and model interpretability . Researchers also highlight the need for more research into cost-effective and environmentally sustainable IoT solutions, particularly for deployment in remote or resource-limited regions . This includes exploring energy-efficient s ensor d esign, l ow-power c ommunication protocols, and novel approaches to data processing and transmission. Finally, the sources emphasise the importance of developing user-friendly visualisation tools and decision support systems that can effectively communicate landslide risks to stakeholders, including local communities, disaster management authorities, and infrastructure operators .The future of landslide monitoring lies in the continued advancement and integration of these technologies, leading to more reliable, resilient, and widely accessible early warning systems.

VIII. Conclusion

This research proposes an advanced sensor-based landslide and earthquake detection and alert system that integrates IoT, machine learning, and computer vision technologies. This multifaceted approach aims to provide timely and accurate disaster alerts, significantly m itigating r isks i n l andslide-prone regions. The system's strength lies in its comprehensive network of sensors that constantly monitor critical environmental factors. By leveraging both supervised and unsupervised machine learning, the system analyzes real-time data and historical patterns to predict the likelihood of landslides and earthquakes. This predictive capability is further enhanced by incorporating computer vision techniques that assess terrain features and changes.

The system's effectiveness is amplified b y i ts multi-channel alert dissemination, ensuring that warnings reach residents, authorities, and emergency services through SMS, mobile applications, email, and social media. Moreover, the system goes beyond just issuing alerts by providing valuable insights into the factors contributing to these natural disasters. Through data visualization and predictive analytics, local authorities gain access to actionable information, empowering them to make informed decisions regarding disaster mitigation, resource allocation, and evacuation planning. By integrating cutting-edge technologies with robust data analysis and dissemination strategies, this project contributes to developing safer, more resilient communities in the face of natural disasters.

References

[1] M. J. Froude and D. N. Petley, "Global fatal landslide occurrence from 2004 to 2016," Natural Hazards Earth Syst. Sci., vol. 18, no. 8, pp. 2161–2181, Aug. 2018.

[2] X.-Q. Xu, L.-J. Su, and C. Liu, "The spatial distribution characteristics of shallow fissures of a landslide in the Wenchuan earthquake area," J. Mountain Sci., vol. 13, no. 9, pp. 1544–1557, Sep. 2016.

[3] R. M. Iverson, M. E. Reid, M. Logan, R. G. LaHusen, J. W. Godt, and J. P. Griswold, "Positive feedback and momentum growth during debris-flow entrainment of wet bed sediment," Nature Geosci., vol. 4, no. 2, pp. 116–121, Feb. 2011.

[4] B. G. Chae, H. J. Park, F. Catani, A. Simoni, and M. Berti, "Landslide prediction, monitoring and early warning: A concise review of state-of-the-art," Geosci. J., vol. 21, no. 6, pp. 1033–1070, 2017.

[5] L. M. Highland and P. Bobrowsky, "The landslide handbook—A guide to understanding landslides: Reston Virginia," U.S. Geol. Surv. Circular 1325, p. 129, 2008.

[6] O. Hungr, S. Leroueil, and L. Picarelli, "The Varnes classification of landslide types, an update," Landslides, vol. 11, no. 2, pp. 167–194, Apr. 2014.

[7] A. Askarinejad, "A method to locate the slip surface and measuring subsurface deformations in slopes," in Proc. 4th Int. Young Geotechnical Eng. Conf., Alexandria, Egypt: The Egyptian Geotechnical Society, 2009, pp. 171–174.

[8] C. Fosalau, C. Zet, and D. Petrisor, "A new landslide inclinometer using highly sensitive gauges," Int. J. Smart Sens. Intell. Syst., vol. 7, no. 5, pp. 1–5, Jan. 2020.

[9] D. Petrisor, C. Fosalau, C. Zet, and C. Damian, "Measurement of landslide displacement and orientation using strain gauges based on amorphous magnetic microwires," in Proc. 19th Symp. Adv. Instrum. Sensors Interoperability (IMEKO), Barcelona, Spain, 2013, pp. 655–660

[10] B. Swathi, M. N. Kumar, D. Pullarkatt, and M. V. Ramesh, "Wireless movement sensor network for real-time monitoring of slope instability," in Proc. Int. Conf. Wireless Commun., Signal Process. Netw. (WiSPNET), Mar. 2017, pp. 1518–1523.

[11] Tai-Lin Chin, Shih-Hung Shen, Chia-Yu Huang, Yu-Che Tsai, Yih-Min Wu, "Learning-Based Seismic Detection Using a High-Density Seismic Network", IEEE Sensors Journal, vol. 19, no. 15, pp. 6372-6381, Aug. 2019.

[12] Hosmer, D.W., Lemeshow, S., "Applied Logistic Regression". Wiley, New York, 1989.

[13] Hsu, C., Chang, C., Lin, C., "A practical guide to support vector classification". National Taiwan University. Technical Report, 2010.

[14] A.L. Achu, C.D. Aju, Mariano Di Napoli, Pranav Prakash, Girish Gopinath, E. Shaji, Vinod Chandra, "Machine-learning based landslide susceptibility modelling with emphasis on uncertainty analysis", Geoscience Frontiers, vol. 14, 2023.

[15] Nicola Casagli, Emanuele Intrieri, Giacomo Gigli, Veronica Tofani, Francesco Raspini, "Landslide detection, monitoring and prediction with remote-sensing techniques", Nature Reviews Earth and Environment, vol. 4, pp. 29–44, 2023.

[16] Ruilong Wei, Chengming Ye, Tianbo Sui, Huajun Zhang, Yonggang Ge, Yao Li, "An Adaptive Multi-Scale Attention U-Net for Automated Landslide Mapping From High-Resolution Remote Sensing Imagery", Remote Sensing, vol. 15, no. 16, 2023.

[17] Kemal Haciefendioglu, Nehir Varol, Vedat Togan, Umit Bahadır, Murat Emre Kartal, "Automatic landslide detection and visualization by using deep ensemble learning method", Neural Computing and Applications, vol. 36, 2024.

[18] Byron Guerrero-Rodriguez, Jose Garcia-Rodriguez, Jaime Salvador, Christian Mejia-Escobar, Shirley Cadena and Jairo Cepeda, "Improving landslide prediction by Computer Vision and Deep Learning", IOS Press, vol. 1, no. 5, 2023.

[19] Haojie Cai, Tao Chen, Ruiqing Niu and Antonio Plaza, "Landslide Detection Using Densely Connected Convolutional Networks and Environmental Conditions", Remote Sensing, vol. 14, 2021.

[20] Tong Liu, Tao Chen, Ruiqing Niu and Antonio Plaza, "Landslide Detection Mapping Employing CNN, ResNet, and DenseNet in the Three Gorges Reservoir, China", Remote Sensing, vol. 14, 2021.

[21] Qing Liu, Tingting Wu, Yahong Deng and Zhiheng Liu, "SE-YOLOv7 Landslide Detection Algorithm Based on Attention Mechanism and Improved Loss Function", MDPI Journals, vol. 12, 2023.