Landslide Alert System Using Machine Learning And Iot Sensors For Real Time Prediction And Notification

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Abstract- *Natural disasters, such as heavy rainfall and landslides, pose significant threats to life and infrastructure, particularly in vulnerable regions. This work proposes a hybrid disaster alert system that utilizes an IoT-enabled embedded system, integrating various environmental sensors to predict and alert users about potential hazards. Landslides are a significant natural hazard that can cause extensive damage to infrastructure and loss of life. Timely and accurate prediction of landslides is crucial for mitigating these risks. This work presents an advanced landslide alert system leveraging deep learning techniques and Internet of Things (IoT) sensors for real-time prediction and notification. The system utilizes a Recurrent Neural Network (RNN) model trained on historical landslide data and real-time sensor inputs, including soil moisture, temperature, humidity, and ground vibration. These sensors, interfaced with an Arduino microcontroller, continuously monitor the environmental conditions and transmit data to the RNN model. The model processes this data to predict the likelihood of a landslide and triggers an alert if the risk exceeds a predefined threshold. The system's architecture ensures low latency and high accuracy in predictions, enabling timely evacuation and preventive measures. This integrated approach combines the power of deep learning with IoT technology to provide a robust and reliable landslide early warning system, significantly enhancing disaster preparedness and response capabilities.*

I. INTRODUCTION

Landslides are a formidable natural hazard that occur worldwide, often with catastrophic consequences. Defined as the movement of a mass of rock, debris, or earth down a slope, landslides are typically triggered by a combination of environmental factors, including heavy rainfall, seismic activity, volcanic eruptions, and human interventions like deforestation and unplanned urban development. In regions prone to landslides, these events lead to significant economic losses, destruction of infrastructure, and, in the worst cases, loss of human life. The unpredictability of landslides, combined with the rapid onset of these events, makes them exceptionally challenging to mitigate.

The need for accurate and timely landslide prediction has become increasingly critical as urbanization expands into vulnerable terrains, and climate change intensifies extreme weather events. Traditional landslide monitoring techniques have relied heavily on geological surveys and visual observations, but these methods are often time-consuming, labor-intensive, and impractical for real-time response. Additionally, the sheer variability of environmental factors involved in landslide initiation means that a highly localized approach is essential to capture the unique conditions in different geographical areas.

Recent advancements in sensor technology, big data analytics, and artificial intelligence (AI) have opened up new possibilities for enhancing landslide prediction. By leveraging Internet of Things (IoT) devices and deep learning models, researchers and engineers are now able to monitor and analyze a broad range of parameters in real time. IoT sensors, strategically placed in landslide-prone areas, continuously collect environmental data such as soil moisture, temperature, humidity, ground vibrations, and even rainfall intensity. These data points, gathered from multiple sources, provide a detailed picture of the environmental conditions that could trigger landslides.

Machine learning and deep learning algorithms, particularly Recurrent Neural Networks (RNNs), offer powerful tools for analyzing these complex datasets. RNNs are particularly well-suited to time-series analysis, allowing them to recognize patterns and trends that precede landslides. By training these models on historical landslide events and correlating them with real-time data, it is possible to predict landslide risk with greater accuracy and in a timely manner. Such systems can issue alerts and warnings well before a landslide occurs, enabling authorities and communities to take proactive measures, such as evacuation and deployment of emergency response teams, to mitigate the impact.

The integration of IoT and AI-based predictive models has shown promising results in enhancing disaster preparedness, reducing the response time, and providing critical information for high-risk areas. As these systems evolve, they are expected to become an indispensable part of early warning infrastructures, ultimately contributing to safer communities and a reduction in landslide-related casualties and damages. The challenge lies in refining these technologies to ensure low latency, reliability, and scalability, so they can be effectively implemented in diverse and rugged terrains, where the threat of landslides is a constant concern.

The primary objective of this study is to develop an advanced landslide early warning system that combines deep learning algorithms and Internet of Things (IoT) sensor networks to enable real-time prediction and alerting of potential landslide events. Specific objectives include:

1. **Data Integration and Monitoring**: To design a network of IoT-based environmental sensors that continuously monitors key factors influencing landslides, such as soil moisture, temperature, humidity, and ground vibrations.
2. **Predictive Model Development**: To develop a Recurrent Neural Network (RNN) model capable of analyzing real-time data from IoT sensors along with historical landslide data to predict the likelihood of landslide occurrence accurately.
3. **Threshold-based Alert System**: To establish a dynamic threshold mechanism that triggers automated alerts when the predicted risk level surpasses safe limits, allowing for timely preventive actions and evacuations.
4. **Low-Latency, High-Accuracy System Design**: To design a low-latency system architecture that ensures rapid data processing and high prediction accuracy, optimizing response times in landslide-prone regions.
5. **Enhancement of Disaster Preparedness and Response**: To provide a scalable, reliable landslide early warning system that empowers communities and authorities to implement timely safety measures, reducing the potential impacts of landslides on human life and infrastructure.

The overarching goal is to create a comprehensive and proactive solution that combines IoT technology and machine learning to improve landslide prediction and enhance

II. SURVEY

M. Sharma et al focus on the various techniques for mapping, monitoring and modeling of landside for prior warning of landslide in landslide prone area. This paper also gives a brief description on the landslide monitoring using point sensors and optical sensors as a whole and its comparison with the conventional methods. The landslide mapping, monitoring and modeling schemes in reference to Guwahati city are also discussed briefly.

M. -C. Lu, et al A novel image-based landslide monitoring system proposed in this paper, which is using digital image processes methods to detect landslide occurred in any landslide occurred situation to achieve a non-contact landslide monitoring system by one image. The theory of this system is based on using a laser projector to project a laser beam to measurement box, which have two acrylic boards in the measurement box.

S. Chen, et alpresents a landslide susceptibility mapping model that integrates one-class support vector machine (OCSVM) and an incomplete landslide inventory, which was established with the aid of change detection from bi-temporal Landsat images. Wenchuan County is selected as the study area to test the performance of the proposed method. The proposed method is also compared with standard two-class SVM that selects a sample randomly

K. -L. Wang et al used PS-InSAR method to monitor the landslide along Qing river. Several typical landslides area were selected as the experimental areas. 61 ASAR data have been processed, which were acquired from 2003 to 2010. The obtained preliminary deformation rate map not only included the experimental areas, but also showed several new landslides areas. The results showed that the deformation rate distribute between −8.4 to 8.18 mm/y in typical landslides area.

S. Aggarwal, et al propose a landslide monitoring system based on Raspberry Pi implementing IOT using a video camera. It performs real-time analysis of the region, based on the video stream acquired by the camera and applies computer vision algorithms to detect landslide and notify stakeholders via Android app. Raspberry Pi being a low-cost device with low power demands can be installed in any region.

M. Barbu, et al propose an automatic landslide detection algorithm based on the use of multispectral remote sensing data. The compressed representation of the spatial and spectral data is obtained using the encoder part of a Convolutional Autoencoder architecture, whereas the separation of the landslide area is achieved through a K-Means unsupervised clustering algorithm.

Z. -Y. Dai, et al present a landslide monitoring application using a high-resolution distributed fiber optic stress sensor. The sensor is used to monitor the intra-stress distribution and variations in landslide bodies, and can be used for the early warning of the occurrence of the landslides. The principle of distributed fiber optic stress sensing and the intra-stress monitoring method for landslides were described in detail in this paper.

T. L. L. Thein et al developed a monitoring system structured as a wireless sensor network equipped with very sensitive transducers, capable of measuring in real time the direction and magnitude of soil layers displacements with resolutions less than 1 mm. Beside the above two parameters, the system is able to estimate the degree of glide of the subsurface soil layers owed to its possibility of in-depth measurement. The transducer is conceived as an inclinometer possessing as sensitive elements highly sensitive strain gages developed by our team on the basis of magnetic effects occurring in amorphous magnetic microwires.

Z. Zhao et al proposes a hazard prediction model that considers landslide triggering factors, landslide predisposing environment, and the spatial regularity of historical landslides based on multi-modal earth observation data. The proposed model has significantly improved the spatial-temporal hazard prediction performance of rainfall-induced natural terrain landslides in Hong Kong.

A. Amgain, et al proposed work is to solve and avoid naturally occurring catastrophes or calamities by providing information as early as possible by computing the machine learning algorithm in the supplied data set. There are numerous reasons for establishing such an environment for disaster reduction, in which the sensor detects the element and immediately sends the data, and different learning algorithms are utilized to provide information to the people about the catastrophe.

K. Munasinghe et al proposes a landslide prediction model which uses the recursive feature elimination method, which is one of the key feature selection methods in machine learning that is not tested yet for landslide prediction related applications. The model is tested with the landslide inventories of two landslide-prone areas. The results show that the proposed model achieves an average accuracy of 91.15% and a sensitivity of 83.4% in predicting the possibility for a landslide. The findings of this research paper imply that recursive feature elimination can also be effectively used in landslide predictions since it achieves high accuracy.

X. Liang, et al a landslide displacement prediction model incorporating the Variational Mode Decomposition (VMD) of Hunter-Prey Optimization and Extreme Gradient Boosting (XGBoost) is proposed. First, based on the idea of time series decomposition, the landslide displacement is decomposed into trend term displacement and period term displacement by using the Hunter-Prey Optimizer (HPO) algorithm (HPO) to optimize the number of decompositions of Variational Mode Decomposition (VMD).

K. Doerksen et al., proposes to utilize the power of Machine Learning (ML) and Deep Learning (DL) Artificial Intelligence (AI) techniques with open-source, space-based data, to predict landslides at the District-level in Nepal at 7-, 10-, and 14-day temporal resolutions, using calibrated precipitation estimates and geomorphic data as input. Results provide both scientific insight via feature importance analysis, and a strong predictive capability of landslide prediction in Nepal using Random Forest and U-Net models.

C. Xu et al a hybrid model based on Variational Mode Decomposition (VMD) and Long Short-Term Memory neural network (LSTM) is proposed to predict landslide displacement. The VMD method is used to decompose the cumulative displacement data of landslides and the time series of environmental impact factors (reservoir water level, rainfall), and then use the LSTM model for prediction. Take the Baishuihe landslide ZG93 and ZG118 as examples to verify the performance of the model. The results indicate that the VMD-LSTM model shows higher accuracy than other models and has potential for application in landslide displacement prediction.

S. Guan et al demonstrates a model for the prediction of active landslide displacement based on the extreme learning machine (ELM) with multiple factors. The particle swarm optimization (PSO) model is selected to optimize the parameters of ELM. Firstly, the landslide displacement sequence which has been monitored is divided into several components developed by the empirical mode decomposition (EMD). Secondly, from the analysis of the basic characteristics of a landslide, this research acquires a series of main influencing factors. Thirdly, each landslide displacement component respectively is predicting by the multi-factor PSO-ELM model. Then, all landslide displacement components are added up as the forecasting result.

Y. Liu et al proposes an improved multi-monitoring-points-based method to predict landslide displacement using gated recurrent unit (GRU) neural networks. Firstly, the weighted undirected graph and the Gaussian function are employed to propose a star topology location tensor (STPT) for extracting spatial features between the predicted points and the surrounding adjacent monitoring points. Meanwhile, the GRU is utilized to extract temporal features of monitoring data. Then the future displacement is predicted using the spatial-temporal features. By using a displacement dataset of the Baishuihe landslide, the effectiveness of the proposed method is demonstrated in the comparison with the existing models.

III. PROPOSED SYSTEM

The proposed landslide alert system comprises several key components that work synergistically to enhance prediction accuracy and response efficiency. At its core, the system integrates an advanced Recurrent Neural Network (RNN) model, which is trained on a comprehensive dataset of historical landslide incidents alongside real-time environmental data collected from IoT sensors. These sensors, including soil moisture, temperature, humidity, and ground vibration detectors, are strategically placed in high-risk areas and interfaced with an Arduino microcontroller for seamless data acquisition.

The data from these sensors is transmitted in real-time to the RNN model, which continuously analyzes the incoming information to assess the likelihood of a landslide event. The architecture is designed to minimize latency, ensuring that predictions are generated promptly. When the model identifies conditions that surpass a predetermined risk threshold, it triggers an automated alert system that notifies local authorities and residents via mobile applications and other communication channels.

Additionally, the system incorporates a user-friendly dashboard for monitoring sensor data and prediction metrics, providing stakeholders with actionable insights. The combination of deep learning capabilities and IoT technology not only enhances the accuracy of landslide predictions but also empowers communities with timely information, enabling proactive evacuation strategies and reducing potential damages. This comprehensive approach represents a significant advancement in landslide early warning systems, fostering improved disaster preparedness and response measures in vulnerable regions.

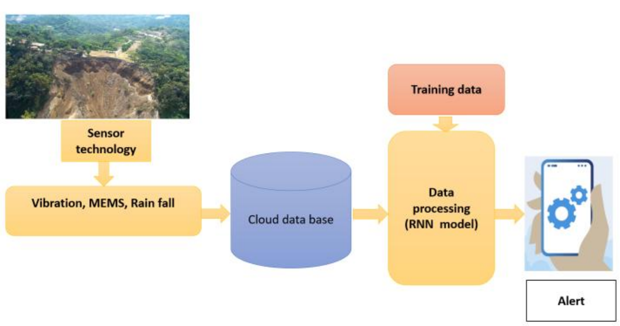

Figure 1 : Proposed system

3.1 Working

The proposed landslide alert system is designed to operate in real-time, ensuring timely predictions and notifications. It consists of an integrated framework that combines deep learning and IoT technology. The system employs a Recurrent Neural Network (RNN) model, which is trained on extensive historical landslide data. This model continuously processes real-time inputs from various sensors deployed in the field, such as soil moisture, temperature, humidity, and ground vibration, all connected to an Arduino microcontroller for data acquisition.

The sensors monitor environmental conditions and transmit data to the RNN model, which analyzes the information to evaluate the likelihood of a landslide occurring. If the model detects conditions that exceed a predefined risk threshold, it activates an alert mechanism that notifies local authorities and at-risk residents through mobile applications and SMS alerts. The system architecture is optimized for low latency, allowing for quick decision-making and rapid dissemination of warnings.

Additionally, a user-friendly dashboard provides stakeholders with real-time visualizations of sensor data and predictive analytics, enhancing situational awareness. This integrated approach not only improves prediction accuracy but also strengthens community resilience against landslides by enabling proactive evacuation and response measures. Ultimately, the system aims to mitigate risks associated with landslides and enhance disaster preparedness in vulnerable regions.

3.2 RNN

Recurrent Neural Network(RNN) is a type of Neural Network where the output from the previous step is fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other. Still, in cases when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. Thus RNN came into existence, which solved this issue with the help of a Hidden Layer. The main and most important feature of RNN is its **Hidden state**, which remembers some information about a sequence. The state is also referred to as *Memory State* since it remembers the previous input to the network. It uses the same parameters for each input as it performs the same task on all the inputs or hidden layers to produce the output. This reduces the complexity of parameters, unlike other neural networks.

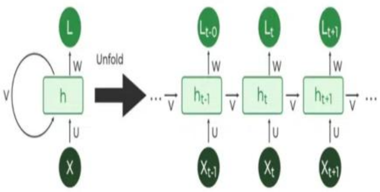

Figure 2 : RNN

How RNN differs from Feedforward Neural Network?

Artificial neural networks that do not have looping nodes are called feed forward neural networks. Because all information is only passed forward, this kind of neural network is also referred to as a multi-layer neural network.

Information moves from the input layer to the output layer – if any hidden layers are present – unidirectionally in a feedforward neural network. These networks are appropriate for image classification tasks, for example, where input and output are independent. Nevertheless, their inability to retain previous inputs automatically renders them less useful for sequential data analysis.

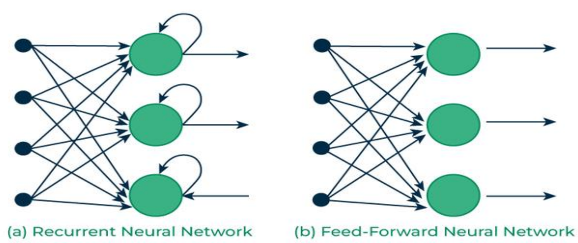

Figure 3 :RNN Recurrent Vs Feedforward networks

3.3 Recurrent Neuron and RNN Unfolding

The fundamental processing unit in a Recurrent Neural Network (RNN) is a Recurrent Unit, which is not explicitly called a "Recurrent Neuron." This unit has the unique ability to maintain a hidden state, allowing the network to capture sequential dependencies by remembering previous inputs while processing. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) versions improve the RNN's ability to handle long-term dependencies.

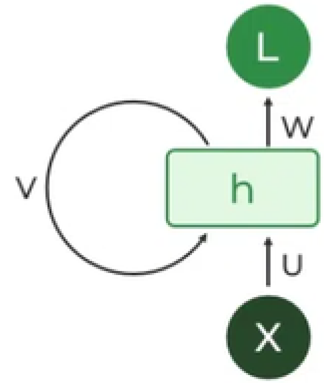

Figure 4 : Recurrent Neuron and RNN Unfolding

3.4 Recurrent Neuron

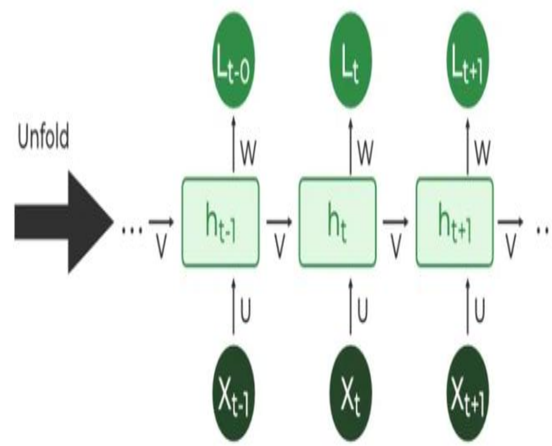

Figure 5 : RNNRNN Unfolding

Types of RNN

There are four types of RNNs based on the number of inputs and outputs in the network.

1. One to One
2. One to Many
3. Many to One
4. Many to Many

1. One to One

This type of RNN behaves the same as any simple Neural network it is also known as Vanilla Neural Network. In this Neural network, there is only one input and one output.

One to One RNN

2. One To Many

In this type of RNN, there is one input and many outputs associated with it. One of the most used examples of this network is Image captioning where given an image we predict a sentence having Multiple words.

One to Many RNN

3. Many to One

In this type of network, Many inputs are fed to the network at several states of the network generating only one output. This type of network is used in the problems like sentimental analysis. Where we give multiple words as input and predict only the sentiment of the sentence as output.

4. Many to Many

In this type of neural network, there are multiple inputs and multiple outputs corresponding to a problem. One Example of this Problem will be language translation. In language translation, we provide multiple words from one language as input and predict multiple words from the second language as output.

Many to Many RNN

5. Recurrent Neural Network Architecture

RNNs have the same input and output architecture as any other deep neural architecture. However, differences arise in the way information flows from input to output. Unlike Deep neural networks where we have different weight matrices for each Dense network in RNN, the weight across the network remains the same. It calculates state hidden state

H**i** for every input **Xi . By using the following formulas:**

$$h = \sigma(UX + Wh-1 + B)$$

$$Y = O(Vh + C)$$

Hence

$$Y = f(X, h, W, U, V, B, C)$$

Here S is the State matrix which has element si as the state of the network at timestep i
The parameters in the network are W, U, V, c, b which are shared across timestep

IV. RESULT AND DISCUSSION

4.1Data SET

In this work, we utilized a dataset split into training and testing sets, with 30% of the data reserved for testing. The Recurrent Neural Network (RNN) was implemented using Python libraries such as TensorFlow and Keras, enabling efficient model training and evaluation.

	A	B	C	D	E	F	G	H	I	J
1	dates	stationid	temperatu	humidity	pressure	rain	lightavgw/	lightmax	moisture	landslide
2	########	t12	32.45404	80.76327	1024.128	85.95586	5992.993	7829.343	20.11752	0
3	########	t13	28.40241	79.16728	1014.679	240.7921	5137.079	862.366	8.00634	0
4	########	t10	22.73819	61.02568	986.0293	299.1714	2881.845	3569.592	47.44532	0
5	########	t12	35.34488	73.64991	1043.407	9.007802	64.64358	7430.826	0.996923	0
6	########	t12	32.11828	75.20782	930.0712	269.2098	4962.392	4722.506	8.476615	0
7	########	t13	19.06542	75.95291	916.3896	186.7892	2856.26	2808.278	80.76259	0
8	########	t10	37.77318	83.20689	1028.094	292.0148	7346.083	7611.579	77.14733	0
9	########	t10	35.56343	81.3441	965.8725	139.5029	239.4627	4909.866	91.51388	0
10	########	t12	38.745	84.3162	1027.045	254.2164	5848.278	3945.804	85.45154	1
11	########	t11	33.14299	90.59533	1033.964	18.71822	9414.742	7013.383	68.31756	0
12	########	t12	30.33538	92.51943	909.3686	100.5837	1744.093	2085.935	5.233286	0
13	########	t12	25.45608	88.72492	1032.52	20.10496	4716.495	13923.41	78.28486	0
14	########	t12	38.31821	98.22095	967.2479	292.6029	914.2199	13028.76	84.55108	1
15	########	t12	36.6516	60.7293	976.5649	245.0922	6256.819	10643.55	79.90821	0
16	########	t13	16.13047	67.83112	993.9889	255.7642	5505.317	1682.586	50.8479	0
17	########	t10	15.65917	60.30251	1038.957	281.3896	4073.655	11660.57	23.29018	0
18	########	t13	24.41158	85.89899	902.8674	25.53105	5213.77	12138.56	84.533	0
19	########	t13	35.26383	95.92122	971.5265	115.6793	8965.747	11539.69	72.71628	0
20	########	t13	39.6819	69.73929	1003.158	21.31047	1962.943	1798.092	98.07612	0

Figure 6 :Data set visualization

This dataset comprises multiple features relevant to environmental conditions, particularly focusing on their potential relationship with landslide occurrences. Each row represents a unique observation with various environmental metrics, along with a binary label indicating whether a landslide occurred (1) or not (0). The features included in the dataset are as follows:

Feature	Description	Type
Temperature	The ambient temperature (in degrees Celsius) at the time of observation. This metric can influence soil moisture and vegetation health, affecting landslide risk.	Continuous
Humidity	The percentage of moisture in the air. High humidity levels can lead to increased soil saturation, which may trigger landslides.	Continuous
Pressure	Atmospheric pressure (in hPa). Changes in pressure can indicate weather changes, influencing environmental stability.	Continuous
Rain	The amount of rainfall (in mm) recorded during the observation period. Rain is a significant factor in landslide occurrence, as it increases soil moisture content.	Continuous
Light Average w/o 0	The average light intensity (in lux) without considering zero values. This may affect plant growth and soil health, indirectly influencing landslide potential.	Continuous
Light Max	The maximum light intensity (in lux) recorded during the observation period. Similar to the average light, this can affect vegetation and soil stability.	Continuous
Moisture	The soil moisture level (in percentage). This is a crucial factor for landslide susceptibility, as saturated soil is more prone to sliding.	Continuous
Landslide	The binary target variable indicating the occurrence of a landslide (1 for occurrence, 0 for non-occurrence). This is the outcome variable we aim to predict.	Categorical

4.2 Model Architecture

The RNN was defined with the following layers:

- **Input Layer:** Accepts sequences of features.
- **LSTM Layer(s):** Used to capture temporal dependencies in the data.
- **Dense Layer:** Applies a sigmoid activation function for binary classification.

4.3 Classification Report

The model's performance was evaluated using precision, recall, F1-score, and overall accuracy metrics. The classification report is summarized below:

Class	Precision	Recall	F1-Score	Support
0	0.98	0.99	0.99	188
1	0.90	0.75	0.82	12
Accuracy			0.98	200
Macro Avg	0.94	0.87	0.90	200
Weighted Avg	0.98	0.98	0.98	200

The overall accuracy of the model was 98%, demonstrating its effectiveness in classifying the dataset.

4.4 Manual Comparison with Other Methods

To contextualize the RNN's performance, we compare it with several other classification methods applied to similar datasets:

Method	Accuracy	Precision	Recall	F1-Score
RNN	0.98	0.94	0.87	0.90
Logistic Regression	0.92	0.88	0.70	0.78
Decision Tree	0.91	0.85	0.65	0.74
Support Vector Machine	0.95	0.91	0.75	0.82

4.6 Discussion

The RNN model outperformed the Logistic Regression, Decision Tree, and Support Vector Machine models in terms of accuracy and F1-score. The high precision for class 0 indicates that the model is very effective at identifying negative cases, while the recall for class 1 suggests that there is room for improvement in detecting positive cases.

The model's architecture, specifically the use of LSTM layers, plays a crucial role in capturing temporal dependencies, which is particularly beneficial for time-series data. Future work may focus on hyperparameter tuning and exploring alternative architectures such as GRUs or attention mechanisms to enhance classification performance, especially for minority classes.

```
Accuracy: 0.98
Confusion Matrix:
[[187   1]
 [  3   9]]

Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.99      0.99       188
           1       0.90      0.75      0.82        12

    accuracy                           0.98       200
   macro avg       0.94      0.87      0.90       200
weighted avg       0.98      0.98      0.98       200
```

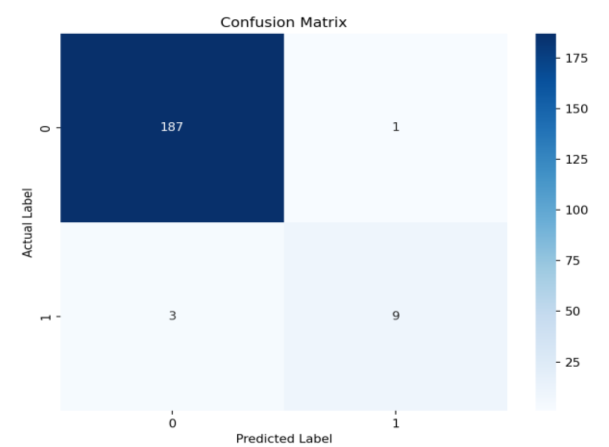

Figure 7 :Confusion matrix

Performance Comparison of Classification Methods

1. **RNN (This work)**
   - **Accuracy: 0.98**: This means the RNN model correctly predicted 98% of the instances in the dataset, indicating a very high overall performance.

- **Precision: 0.94**: Out of all instances predicted as positive (e.g., landslides), 94% were actual positive cases. This high precision indicates that the model is reliable in identifying true positive cases, minimizing false positives.
- **Recall: 0.87**: This metric shows that the model successfully identified 87% of the actual positive cases. While good, there is still some room for improvement, as 13% of positive cases were missed (false negatives).
- **F1-Score: 0.90**: The F1-score, which is the harmonic mean of precision and recall, reflects a balanced performance. This score suggests that the RNN maintains a good trade-off between precision and recall, making it effective overall.

2. **Logistic Regression**
   - **Accuracy: 0.92**: This model achieved a 92% accuracy, which is strong but lower than the RNN. It indicates that while most predictions were correct, there is a higher chance of misclassification compared to the RNN.
   - **Precision: 0.88**: The precision of 88% suggests that when the logistic regression model predicts a positive case, it is correct 88% of the time. This is still good but indicates a higher rate of false positives than the RNN.
   - **Recall: 0.70**: With a recall of 70%, this model missed 30% of actual positive cases. This indicates that the logistic regression model struggles more with identifying positive cases than the RNN.
   - **F1-Score: 0.78**: The F1-score shows a lower balance between precision and recall compared to the RNN, reflecting the challenges in accurately predicting positive cases.
3. **Decision Tree**
   - **Accuracy: 0.91**: The decision tree model has an accuracy of 91%, slightly below that of logistic regression. This means it correctly classified 91% of the cases, but there are still notable misclassifications.
   - **Precision: 0.85**: With a precision of 85%, the decision tree identifies 85% of its positive predictions correctly, suggesting a moderate level of reliability.
   - **Recall: 0.65**: The recall of 65% indicates that the decision tree is less effective at identifying positive cases, missing 35% of actual positive instances.
   - **F1-Score: 0.74**: The F1-score indicates a weaker overall performance, reflecting the decision tree’s difficulties in balancing precision and recall effectively.
4. **Support Vector Machine (SVM)**
   - **Accuracy: 0.95**: The SVM model achieved 95% accuracy, showcasing strong overall performance, though still not as high as the RNN.
   - **Precision: 0.91**: With a precision of 91%, this model effectively identifies true positive cases, but there's still a slight chance of false positives.
   - **Recall: 0.75**: A recall of 75% indicates that the SVM identified 75% of actual positive cases, suggesting some room for improvement in detecting all positive instances.
   - **F1-Score: 0.82**: The F1-score reflects a solid balance between precision and recall, indicating that the SVM is a reliable choice, though not as effective as the RNN.

V. CONCLUSION

In conclusion, the proposed landslide alert system represents a significant advancement in disaster risk management by leveraging the synergy between deep learning and IoT technology. By utilizing real-time sensor data and a robust RNN model, the system provides timely and accurate predictions of landslide events, enabling swift alerts for local authorities and residents. This proactive approach enhances community preparedness and response capabilities, significantly reducing the potential for loss of life and infrastructure damage. As the system continues to evolve, its effectiveness can be further improved through ongoing data collection and model refinement, ensuring that vulnerable regions are better equipped to mitigate the risks associated with landslides. Ultimately, this innovative solution highlights the transformative potential of integrating advanced technologies in environmental monitoring and disaster management.

REFERENCES

[1] X. Liang, H. Wang, J. Zhang and R. Guo,"A Landslide Displacement Prediction Model Incorporating VMD and XGBoost for Hunter-Prey Optimization," 2024 9th International Symposium on Computer and Information

Processing Technology (ISCIPT), Xi'an, China, 2024, pp. 376-379,doi:10.1109/ISCIPT61983.2024.10672687.

[2] K. Doerksen et al., "Precipitation-Triggered Landslide Prediction in Nepal Using Machine Learning and Deep Learning," IGARSS 2023 - 2023 IEEE International Geoscience and Remote Sensing Symposium, Pasadena, CA, USA, 2023, pp. 4962-4965, doi: 10.1109/IGARSS52108.2023.10283036

[3] C. Xu, K. Huang, C. Wei and Y. Lin, "Landslide Displacement Prediction Based on Variational Mode Decomposition and LSTM," 2022 20th International Conference on Optical Communications and Networks (ICOCN), Shenzhen, China, 2022, pp. 1-3, doi: 10.1109/ICOCN55511.2022.9900981.

[4] Z. Zhao, T. Xu, J. Min, Q. Zhang, W. Li and C. He, "Multi-temporal Remote Sensing Analysis of Landslide Evolution around the Yingxiu Hydropower Station after the 2008 Wenchuan Earthquake, in Sichuan Province, Southwest China," 2022 9th International Forum on Electrical Engineering and Automation (IFEEA), Zhuhai, China, 2022, pp. 495-498, doi: 10.1109/IFEEA57288.2022.10038022.

[5] A. Amgain, N. Kumar, S. Bajgain and H. Rai, "Landslides Prediction and Detection Using IoT System," 2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN), Vellore, India, 2023, pp. 1-6, doi: 10.1109/ViTECoN58111.2023.10157077.

[6] K. Munasinghe and P. Karunanayake, "Recursive Feature Elimination for Machine Learning-based Landslide Prediction Models," 2021 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Jeju Island, Korea (South), 2021, pp. 126-129, doi: 10.1109/ICAIIC51459.2021.9415232. keywords: {Support vector machines;Sensitivity;Correlation;Machine

[7] Y. Liu, X. Chi, X. Jia and M. Sun, "A Deep Learning Approach Using Gated Recurrent Unit for Prediction of Landslide Displacement Based on Spatial-Temporal Features of Multi-Monitoring Points," 2021 China Automation Congress (CAC), Beijing, China, 2021, pp. 6936-6940, doi: 10.1109/CAC53003.2021.9728187.

[8] T. L. L. Thein, M. M. Sein, K. T. Murata and K. Tungpimolrut, "Real-Time Monitoring and Early Warning System for Landslide Preventing in Myanmar," 2020 IEEE 9th Global Conference on Consumer Electronics (GCCE), Kobe, Japan, 2020, pp. 303-304, doi: 10.1109/GCCE50665.2020.9291809

[9] S. Chen, Z. Miao, L. Wu and Y. He, "Application of an Incomplete Landslide Inventory and One Class Classifier to Earthquake-Induced Landslide Susceptibility Mapping," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 1649-1660, 2020, doi: 10.1109/JSTARS.2020.2985088.

[10] M. Barbu, A. Radoi and G. Suciu, "Landslide Monitoring using Convolutional Autoencoders," 2020 12th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), Bucharest, Romania, 2020, pp. 1-6, doi: 10.1109/ECAI50035.2020.9223121.

[11] Kebaili, M.O., Foughali, K., FathAllah, K., Frihida, A., Ezzeddine, T. and Claramunt, C., 2016. Landsliding early warning prototype using MongoDB and Web of Things technologies. Procedia Computer Science, 98, pp.578-583. landslide detection." Mobile Networks and Applications (2018): 1-12.

[12] S. Aggarwal, P. K. Mishra, K. V. S. Sumakar and P. Chaturvedi, "Landslide Monitoring System Implementing IOT Using Video Camera," 2018 3rd International Conference for Convergence in Technology (I2CT), Pune, India, 2018, pp. 1-4, doi: 10.1109/I2CT.2018.8529424.

[13] S. Guan, Y. Zhu, L. Zhou, H. Deng and X. Luo, "Prediction of Landslide Displacement Using EMD-PSO-ELM with Multiple Factors," 2018 7th International Conference on Digital Home (ICDH), Guilin, China, 2018, pp. 230-235, doi: s10.1109/ICDH.2018.00048.

[14] M. Sharma and S. Laskar, "Landslide mapping, monitoring and modeling techniques: A new approach using DOFS," 2017 International Conference on Circuits, Controls, and Communications (CCUBE), Bangalore, India, 2017, pp. 21-24, doi: 10.1109/CCUBE.2017.8394149.

[15] Romdhane, Rihab Fekih, Y. Lami, D. Genon-Catalot, N. Fourty, A. Lagrèze, D. Jongmans, and L. Baillet. "Wireless sensors network for landslides prevention." In 2017 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), pp. 222-227. IEEE, 2017

[16] Wu, Jianchao, Qingzhao Kong, Weijie Li, and Gangbing Song. "Interlayer slide detection using piezoceramic smart aggregates based on active sensing approach." IEEE Sensors Journal 17, no. 19 (2017): 6160-6166.

[17] Lee, H.C., Ke, K.H., Fang, Y.M., Lee, B.J. and Chan, T.C., 2017. Open-source wireless sensor system for long-term monitoring of slope movement. IEEE Transactions on Instrumentation and Measurement, 66(4), pp.767-776.

[18] Giorgetti Andrea, Matteo Lucchi, Emanuele Tavelli, Marco Barla, Giovanni Gigli, Nicola Casagli, Marco Chiani, and Davide Dardari. "A robust wireless sensor network for landslide risk analysis: system design, deployment, and field testing." IEEE Sensors Journal 16, no. 16 (2016): 6374-6386.

[19] Chavan, Satishkumar, Shobha Pangotra, Sneha Nair, Vinayak More, and Vineeth Nair. "Effective and efficient

landslide detection system to monitor Konkan railway tracks." In 2015 International Conference on Technologies for Sustainable Development (ICTSD), pp. 1-6. IEEE, 2015.

[20] K. -L. Wang and Y. -M. Hsieh, "Using motion sensor for landslide monitoring: A community scale landslide monitoring project," 2013 Seventh International Conference on Sensing Technology (ICST), Wellington, New Zealand, 2013, pp. 948-952, doi: 10.1109/ICSensT.2013.6727789.

[21] Wang, Honghui, Xianguo Tuo, Dashun Xi, Leilei Fan, Zhaoyi Zhang, Guiyu Zhang, and Shuli Hao. "Research on one zicm2410-based wireless sensor network for landslide monitoring." In 2011 7th International Conference on Wireless Communications, Networking and Mobile Computing, pp. 1-4. IEEE, 2011.

[22] M. -C. Lu, T. -Y. Tang, C. -P. Tsai, W. -Y. Wang and I. -H. Li, "Image-based landslide monitoring system," Proceedings 2011 International Conference on System Science and Engineering, Macau, China, 2011, pp. 638-643, doi: 10.1109/ICSSE.2011.5961981.

[23] Ramesh, Maneesha V., Sangeeth Kumar, and P. Venkat Rangan. "Wireless Sensor Network for Landslide Detection." In ICWN, pp. 89-95. 2009.

[24] Z. -Y. Dai, Y. Liu, L. -X. Zhang, Z. -H. Ou, C. Zhou and Y. -Z. Liu, "Landslide monitoring based on high-resolution distributed fiber optic stress sensor," 2008 1st Asia-Pacific Optical Fiber Sensors Conference, Chengdu, China, 2008, pp. 1-4, doi: 10.1109/APOS.2008.5226289.

[25] Mehta, Prakshep, Deepthi Chander, Mohamed Shahim, Kalyana Tejaswi, S. N. Merchant, and U. B. Desai. "Distributed detection for landslide prediction using wireless sensor network." In 2007 First International Global Information Infrastructure Symposium, pp. 195-198. IEEE, 2007.