International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

AI-Based Disaster & Mining Alerts Using Satellite Image and WP Alerts

[1] Lingarasan.G.V, [2] Abishek.G, [3] Loganathan.V, [4] ManojKumar.S

[1 2 3 4] B.tech, Artificial Intelligence & Data Science , Dhirajlal Gandhi College of Technology , Tamilnadu, India.

ABSTRACT :

Disaster management and mining safety require timely detection and alerting mechanisms to mitigate risks and save lives. Traditional systems often rely on manual monitoring, which is slow and error-prone. This paper presents an AI-based system for real-time disaster and mining alerts using satellite imagery and WhatsApp (WP) notifications. By leveraging Convolutional Neural Networks (CNNs) for image processing and Retrieval-Augmented Generation (RAG) for contextual data integration, the system detects natural disasters (e.g., floods, earthquakes) and mining hazards (e.g., landslides, gas leaks) with high accuracy. Alerts are disseminated instantly via WP to stakeholders, ensuring rapid response. The system integrates satellite data from open-source platforms and processes it using cloud-based AI models, achieving a detection accuracy of 91% and an average alert delivery time of under 5 seconds. Future enhancements include multi-hazard classification, voice-based alerts, and integration with IoT sensors for real-time ground data.

Keywords: AI-Based Disaster Detection, Satellite Imagery, Convolutional Neural Networks, Retrieval-Augmented Generation, WhatsApp Alerts, Mining Safety, Real-Time Alert Systems, Disaster Management, Image Processing, Smart Notification Systems.

INTRODUCTION

Natural disasters and mining accidents pose significant threats to human lives and infrastructure, necessitating rapid detection and alerting systems. Conventional approaches rely on ground-based sensors or manual satellite image analysis, which are limited by latency and scalability. The proposed system addresses these challenges by utilizing Artificial Intelligence (AI) to analyze satellite imagery and generate real-time alerts via WhatsApp (WP). By combining Convolutional Neural Networks (CNNs) for image-based hazard detection and Retrieval-Augmented Generation (RAG) for contextual information retrieval, the system ensures accurate and timely notifications.

The system processes high-resolution satellite imagery from sources like NASA's Landsat or Sentinel-2, detecting anomalies such as flood patterns, seismic activity, or mining site instabilities. Alerts are sent to authorities and local communities via WP, enabling swift evacuation or intervention. Evaluations show a 91% detection accuracy and sub-5-second alert delivery, making the system a robust tool for disaster management and mining safety. This paper details the architecture, implementation, and performance of the AI-based alert system, emphasizing its impact on risk mitigation and stakeholder communication.

RELATED WORK

Traditional disaster detection systems use ground-based sensors or manual image analysis, which are slow and resource-intensive. Recent advancements integrate AI with satellite imagery, employing CNNs and deep learning for hazard detection. Studies on RAG and alert dissemination frameworks highlight improved response times in emergency systems. This project builds on these advancements by combining CNN-based image analysis with RAG for contextual data retrieval and WP for scalable alert delivery, tailored to disaster and mining scenarios.

METHODOLOGY

a)DataCollection: The system leverages satellite imagery from open-source platforms (e.g., Sentinel-2, Landsat) and institutional datasets (e.g., disaster logs, mining safety reports). Images are preprocessed using image augmentation techniques and transformed into vector embeddings for efficient retrieval. Hazard-specific datasets (e.g., flood patterns, landslide signatures) are used to train the AI models.

b) Convolutional Neural Networks (CNN): CNNs are employed to analyze satellite imagery and detect disaster or mining hazards. The model identifies patterns such as water inundation (floods), surface cracks (earthquakes), or soil displacement (landslides). Pre-trained models like ResNet-50 are fine-tuned on hazard-specific datasets to achieve high detection accuracy.

c)Whatsapp-alerts : Alerts are disseminated via WhatsApp APIs, enabling real-time notifications to stakeholders. The system formats alerts with hazard details (e.g., location, severity) and sends them to predefined user groups, ensuring rapid communication.

d)Model Training & Evaluation: The system is trained on benchmarked datasets, including satellite imagery and hazard logs. Evaluation metrics include:

- **Detection Accuracy:** Measuring correct hazard identification.
- **Alert Latency:** Ensuring alerts are delivered within 5 seconds.
- **User Feedback:** Stakeholder surveys on alert relevance and timeliness**.**

SYSTEM ARCHITECTURE AND DEPLOYMENT

1. System Overview

The system is an AI-driven platform for disaster and mining alerts, integrating CNNs, RAG, and WP notifications. It processes satellite imagery to detect hazards and sends real-time alerts to stakeholders.

2. Data Processing and Storage

Satellite imagery and hazard logs are processed into vectorized representations for efficient retrieval. A cloud-based database stores indexed data for rapid access.

3. AI Model Framework

- **CNNs**: For hazard detection in satellite imagery.
- **RAG**: For contextual data retrieval and alert enrichment.
- **WP APIs**: For scalable alert dissemination.

4. Deployment Strategy

The system is deployed on a cloud infrastructure (e.g., AWS) for scalability. Key components include:

- Web-based dashboard for monitoring detected hazards.
- API integration with WP for alert delivery.
- Scalable architecture to handle high-volume image processing.

5. Security and Optimization

Data security is ensured through encryption and access controls. Optimization techniques like image caching and query indexing reduce latency.

Figure 1: System architecture diagram (refer to image1.png).

EXPERIMENTAL RESULTS

1. Dataset

The system was evaluated using satellite imagery from Sentinel-2 and disaster/mining hazard datasets. Queries included flood detection, landslide identification, and gas leak alerts.

2. Performance Metrics

- Detection Accuracy: 91% accuracy in identifying hazards.
- Alert Latency: Average delivery time of 4.8 seconds.
- User Satisfaction: Positive feedback from simulated stakeholder tests.

3. Observations

The system effectively detects hazards and delivers timely alerts, with potential for improved accuracy through expanded training data.

DISCUSSION

Advantages:

- Real-time hazard detection using satellite imagery.

- Scalable alert delivery via WhatsApp.
- Contextual insights through RAG integration.

Challenges:

- Handling low-resolution satellite imagery.
- Ensuring alert delivery in low-network areas.
- Expanding multi-hazard detection capabilities.

FUTURE WORK

- **Multi-Hazard Detection**: Enhance CNNs to detect additional hazards (e.g., wildfires, tsunamis).
- **Voice-Based Alerts**: Integrate speech synthesis for voice notifications.
- **IoT Integration:** Combine satellite data with ground-based IoT sensors.
- **Multilingual Alerts:** Support alerts in multiple languages for diverse regions.1. System Configuration

- Processor: NVIDIA GPU for CNN execution.
- Storage: Cloud-based SSD for satellite imagery.
- Software: TensorFlow, RAG, WhatsApp APIs.

2. Sample Queries and Responses

- Query: "Detect flood in region X."
- Response: "Flood detected at coordinates (x, y). Alert sent to local authorities via WP."
- Query: "Monitor mining site for landslides."
- Response: "Landslide risk detected. Safety protocol retrieved and sent via WP."

3. Extended Performance Metrics

- Image Processing Time: 2.5 seconds per image.
- Alert Accuracy: 91%.
- User Feedback: High engagement in test **scenarios.**

4. Hardware Configuration

- Processor: Multi-core GPU.
- Memory: 32 GB RAM.
- Network: Secure cloud infrastructure.

5. Model Training Parameters

- Batch Size: 16
- Epochs: 30
- Learning Rate: 1e-4
- Optimizer: Adam
- Loss Function: Binary Cross-Entropy

6. Model Evaluation

- Accuracy: 91% in hazard detection.
- Alert Latency: <5 seconds.
- User Satisfaction: Positive stakeholder feedback.

ACKNOWLEDGMENT

The authors thank their mentors, faculty, and institutional support for providing resources and guidance. Gratitude is extended to open-source communities for AI and satellite imagery tools that facilitated this project.

CONCLUSION

The AI-based disaster and mining alert system leverages satellite imagery, CNNs, and RAG to detect hazards and deliver real-time WhatsApp alerts. With a 91% detection accuracy and sub-5-second alert latency, it enhances disaster management and mining safety. Future enhancements will focus on multi-hazard detection, IoT integration, and multilingual support, making the system a scalable solution for global risk mitigation.

REFERENCES :

[1] Goodfellow, I., Bengio, Y., & Courville, A., Deep Learning, MIT Press, 2016.
[2] LeCun, Y., Bengio, Y., & Hinton, G., “Deep learning,” Nature, vol. 521, pp. 436–444, 2015.
[3] Vaswani, A., et al., “Attention Is All You Need,” NeurIPS, 2017.
[4] Lewis, P., et al., “Retrieval-Augmented Generation for Knowledge-Intensive NLP Tasks,” NeurIPS, 2020.
[5] Sentinel-2 User Handbook, European Space Agency, 2015.
[6] NASA Landsat Program, [Online]. Available: https://landsat.gsfc.nasa.gov/
[7] WhatsApp Business API Documentation, [Online]. Available: https://developers.facebook.com/docs/whatsapp/
[8] Chen, T., & Guestrin, C., “XGBoost: A Scalable Tree Boosting System,” KDD, 2016.
[9] He, K., et al., “Deep Residual Learning for Image Recognition,” CVPR, 2016.
[10] Devlin, J., et al., “BERT: Pre-training of Deep Bidirectional Transformers,” NAACL, 2019.