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SS Chinchorkar
Associate Professor, Polytechnic in
Agricultural Engineering, AAU,
Muvaliya Farm, Dahod, Gujarat,
India

Satellite remote sensing and artificial intelligence for disaster risk reduction

SS Chinchorkar

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Abstract

Reduction of disaster risk (DRR) turned out to be a paramount global concern in reaction to the growing rate and severity of natural disasters like floods, earthquakes, wildfire, cyclones, and landslides. The use of traditional disaster monitoring and management systems is usually limited due to the inability to experience real-time data processing, coverage, and prediction. Disaster monitoring has been greatly developed through satellite remote sensing given its capability to give continuous, large scale and multi-temporal observations of the surface of the earth. But, the increasing amount and volume of satellite data require sophisticated tools of analysis. Machine learning and deep learning, as well as Artificial Intelligence (AI), have transformed the disaster risk assessment process by making it possible to extract features, identify patterns, and predict using algorithms. In the described paper, the author will examine the possibilities of integrating satellite remote sensing and AI in disaster risk reduction, provide a thorough methodology, analysis framework, and a performance assessment. It emphasizes the role of AI-oriented models in enhancing early warning frameworks, damage estimate, and disaster management efficiency. Issues like heterogeneity of data, computational needs and interpretability of models are also addressed. This paper shows that AI-satellite imagery synergy also serves as a scalable, accurate, and real-time tool in disaster preparedness and mitigation, therefore, playing a major role in resilient and sustainable development.

Keywords: Disaster risk reduction, remote sensing, artificial intelligence, machine learning, deep learning, satellite imagery, hazard detection, early warning systems, geospatial analysis

1. Introduction

The reduction of the disaster risk (DRR) is becoming a critical international concern in the midst of the growing number of natural disasters like floods, cyclones, fires, earthquakes, and landslides that are being exacerbated by global warming, urbanization, and other causes of environmental degradation. The increasing occurrence, scale, and uncertainty of these types of disasters have demonstrated the constraints of antiquated disaster management frameworks that abide by physical surfaces, past-based data and conventional study. Such traditional methods in most cases are not sufficient in terms of space coverage, predictability in time and ability to react with unpredictability and large scale disaster incidents. In this regard, the satellite remote sensing has become a revolutionary technology and has made it possible to continuously observe the surface of the earth on a large scale in a variety of environmental conditions. The use of modern satellite systems with multispectral, hyperspectral and radar sensors has been able to offer useful information on the state of the atmosphere, surface alteration of terrestrial and ocean quality and vegetation well-being and hydrology. Such data sets will play a key role in detecting early warning, monitoring hazard development, and estimating the impacts of disasters in near real-time. An example of this is the essential role played by remote sensing in observation of flood inundation, cyclone pathways, hot spots of wild fires and earthquake induced land movement. Granting an insight into the sudden and gradual change of the environment, the use of multi-temporal satellite data also increases the available opportunities to evaluate trends and patterns. Nevertheless, the proliferation in satellite data volumes, its types, and speed has raised tremendous difficulties when it comes to processing, reviewing, and interpreting the data. Conventional analytical approaches do not have the ability to work with the large-dimensional datasets and frequently cannot recognize intricate spatial and temporal connections involved in

Corresponding Author:
SS Chinchorkar
Associate Professor, Polytechnic in
Agricultural Engineering, AAU,
Muvaliya Farm, Dahod, Gujarat,
India

the disaster phenomena, which restricts their support of predictive modeling and decision-making.

Machine learning (ML) and deep learning (DL) are the aspects of Artificial Intelligence (AI) that have become one of the key tools to deal with these constraints and revolutionize the discipline of disaster risk reduction through the utilization of intelligent, automated, and scalable methods of analyzing satellite data. The AI-based models can handle vast volumes of heterogeneous geospatial data, extract meaningful features and identify concealed patterns that cannot be easily identified using standard methods. Random Forest, Support Vector machine and gradient boosting machine learning algorithms have been shown to perform well in the task of disaster susceptibility mapping and classification because they are capable of addressing non-linear relationships and high-dimensional feature space. More complex deep-learning architectures, such as the Convolutional Neural Networks (CNNs), demonstrated their outstanding potential in detecting the disaster on the images, e.g., flood regions, burnt areas, and infrastructure failures through the high-resolution satellite images. Moreover, time-series networks such as Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks allow exploring time-series data and predicting a disaster according to historical patterns and environmental factors. Combined with satellite remote sensing, AI deployment also is supportive of real-time analytics, improving early warning systems and making it possible to respond rapidly to disasters. Also, the combination of multi-source information, such as meteorological or topographical data and socio-economic factors, enhances the accuracy and strength of AI-directed disaster models, even further. Regardless of these developments, there are still a number of difficulties such as the large labelled dataset required, the high computation costs and the absence of transparency in complicated AI models. However, satellite remote sensing synergy with artificial intelligence is a paradigm shift in disaster management, which allows to assess the risks beforehand, allocating resources efficiently, and making informed decisions. This combination has great potential in creating resilient communities, reducing losses in disasters and even in enabling sustainable development amid a more uncertain and more hazardous world.

2. Related Works

In disaster risk reduction, the use of satellite remote sensing has been changing tremendously during the past decades due to the development of the Earth observation technologies and geospatial analytics. Initial studies largely concentrated on the application of satellite images to post-disaster recovery, in which optical observations were used to determine impacted areas and estimate damages following occurrences of floodwaters, quakes and cyclones. These methods were locally optimistic and dependent on manual interpretation and simple image processing algorithms, which were restrictive of scalability, speed, and precision. First experiments revealed that satellite imagery of the early Earth observation campaigns had the potential to yield useful data on disaster-impacted areas especially in the mapping of flood areas and the area of earthquake damage^[1]. Technology has improved, and scientists started to use indices and spectral analysis methods to detect in a more accurate way to identify water bodies, vegetation stress and burnt lands^[2]. It was further enhanced by the introduction of hardcore radar sensing especially Synthetic Aperture Radar (SAR) which brought more effective case of disaster monitoring since data would still be obtained even in unfavorable weather conditions such as in

cloud cover and at night^[3]. Moreover, the application of multi-temporal satellite datasets provided the opportunity to investigate the changes with time and help reveal the gradual and abrupt alterations in the environment that occur due to disasters^[4]. In spite of these advancements, conventional remote sensing continued to rely on its limitation in dealing with large-scale datasets effectively and in being able to resolve intricate spatial-temporal interactions inherent in disaster processes and thus requiring the incorporation of additional sophisticated computational strategies.

The development of Artificial Intelligence (AI) made a big change in reducing the risks of disasters, as it allowed automated analysis of satellite images based on data. The first AI method in the disaster-related remote sensing included the Support Vector Machines (SVM), Random Forests (RF), and Decision Trees. These models performed better in classification and prediction of processes especially in the areas of flood susceptibility mapping and landslide risk assessment because of their capacity to deal with high-dimensional data and non-linear relationships^[5]. In particular, Random Forest models were popular due to their strength and capacity to handle noisy data, which explains their use in the modeling of the environment and in predicting disasters^[6]. On the same note, Support Vector Machines demonstrated high generalization in the task of hazard classification, particularly where there was a dense terrain of hazardous terrain^[7]. As deep learning developed, Convolutional Neural Networks (CNNs) have become a formidable tool to examine high-resolution satellite imagery, vastly better at accurately detecting disasters and mapping^[8]. The use of CNN based models allowed a automatic extraction of the features and hierarchically based representations were learned hence allowing less manual feature engineering. Moreover, historic deep learning networks, like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, helped analyze time-series data and forecast a disaster occurrence according to historical trends and environmental forecasts^[9]. The fusion of CNN and LSTM models has also been studied to learn both spatial and temporal features, which show great effectiveness in forecasting multifaceted hazards such as floods and landslides^[10]. Such improvements emphasize the revolutionary approach of AI in optimizing efficiency, accuracy, and scale of systems of disaster risk reduction.

Research in recent years has been moving towards the direction of combining multi-source data and developing sophisticated AI methods and enhancing disaster risk reduction capabilities. The usage of data fusion technique that uses optical satellite images in addition to radar, thermal, and LiDAR images has made disaster detection more reliable and robust especially in harsh weather conditions^[11]. The use of meteorological information, topographical data, and socio-economic signals in the creation of AI further increased predictive accuracy and situational awareness^[12]. Moreover, the cloud computing systems and the concept of big data have allowed the processing of massive volumes of satellite-based data within seconds and effects prompt business disaster monitoring and response^[13]. More advanced deep learning models, such as transformer, attention, and self-supervised learning models have been proposed to learn complex spatial-temporal relationships and enhance the generalization of models^[14]. In addition, recent research has highlighted the significance of explainable AI (XAI) to deal with the absence of transparency in deep learning models, especially in sensitive systems like disaster management, where transparency and, therefore, intelligibility are critical to decision-making^[15]. Irrespective of these innovations, issues

like lack of data, computational complexity, and transparency of models in different geographical areas are also a major concern. However, the history or incorporation of satellite remote sensing and artificial intelligence further advances the limits of disaster risk reduction by providing new options towards enhancing resiliency, as well as improving the early warning systems and maintaining sustainable development in disaster-affected areas.

3. Methodology
3.1 Research Design

The methodology of the research proposed in this study follows a systematic and integrative approach that is intended to create a smart framework of disaster risk reduction that would be based on satellite remote sensing and Artificial Intelligence (AI). The design aims at closing the gap between big-scale satellite data collection and real-time disaster prediction, detection, and assessment. The methodology is divided into several

consecutive steps, such as data acquisition, preprocessing, feature extraction, model development, disaster detection, and evaluation. First, reliable satellite based Earth observation tools are used to obtain multi-temporal data on the environment in the pre-disaster period, during, and in the post-disaster period. These data sets are subsequently pre-processed to bring about uniformity between various sensors, resolutions and time intervals. The use of feature extraction techniques provides relevant and meaningful spatial, spectral and temporal characteristics to disaster identification. The essence of the methodology is to educate machine learning and deep learning models to discern patterns related to various types of disasters that include floods, wildfires, and landslides. The framework is geographically and disaster-universally scalable and adaptable, making it applicable in the real-life disaster management processes ^[16, 17].

Table 1: Research Design Overview

Research Stage	Description	Purpose
Data Acquisition	Collection of multi-temporal satellite imagery	Capture environmental and hazard variations
Preprocessing	Data cleaning, normalization, correction	Ensure consistency and accuracy
Feature Extraction	Deriving spatial, spectral, temporal features	Prepare structured input for models
AI Model Development	Training ML/DL algorithms	Enable automated disaster detection
Disaster Detection	Identification of hazard-prone and affected areas	Monitor and predict disasters
Evaluation	Performance assessment using metrics	Validate model effectiveness

3.2 Data Collection and Source Evaluation

To provide diversity in spatial, spectral and temporal aspects, the study involves the use of secondary data sample comprising of various satellite based Earth observation systems. The datasets consist of optical imagery, multispectral bands, and radar data, which collectively present the holistic picture of the environmental conditions, pertinent to the disaster events. The data sources are chosen to include many characteristics related to a disaster (including water bodies, vegetation cover, soil moisture, and land deformation). Radiometric, atmospheric, geometric alignment, and cloud masking are all preprocessing steps that help to filter out noise and discrepancies in the data. The temporal normalization is also undertaken so as to make images acquired within different time periods comparable. The data is classified as training, validation and testing partitions to facilitate the use of the supervised learning models. Particular consideration is made to data quality, resolution and frequency to prevent incorrect identification of the sudden catastrophes such as flood and the gradual hazards such as droughts. Such an elaborate data collection approach augments the accuracy and strength of the analytical structure ^[18, 19].

3.3 Analytical Framework

This analytical framework is constructed as a multi-layered

system which combines spatial, spectral and temporal analysis to efficiently determine disaster risk. On the pixel scale, AI models designate each pixel as belonging to one of these categories: water, vegetation, urban area, or burned area to facilitate the accurate identification of the areas of the disaster. On the feature level, more sophisticated features like texture, vegetation indices (e.g., NDVI), and water indices (e.g., NDWI) are used to improve classification accuracy. Multi-date satellite images are used to analyse the temporal changes to identify any disaster progress and damage and their localization. Random Forest and Support Vector Machines machine learning models are utilised in the baseline classification, whereas deep learning models, like Convolutional Neural Networks (CNNs), are used in high-resolution image processing and features detection. Deep learning models such as Recurrent Neural Networks (RNNs): RNNs are created with the purpose to capture sequential relationships and forecast future disasters. Long Short-Term Memory (LSTM) networks: LSTMs are designed to capture sequential relationships and forecast future disasters. Ensemble techniques are also used to use the results of several different models to enhance the overall prediction quality and strength ^[20, 21].

Table 2: Analytical Framework Components

Framework Layer	Evaluated Parameters	Expected Outcomes
Pixel-Level Classification	Spectral values, pixel intensity	Accurate hazard mapping
Feature-Level Analysis	NDVI, NDWI, texture features	Enhanced feature discrimination
Temporal Analysis	Multi-date satellite comparison	Detection of disaster progression
AI Modeling	ML/DL algorithms	Automated detection and prediction
Ensemble Methods	Combined model outputs	Improved accuracy and reliability
Validation Metrics	Accuracy, precision, recall, F1-score	Performance evaluation

3.4 Evaluation Techniques

Various evaluation methods are used to guarantee effectiveness and reliability of the proposed framework. Confusion matrices are employed to compare performance of classification to

various disaster types, and it gives detailed information about the accuracy of all models. Other metrics used to measure the effectiveness of the model include key performance metrics (like the overall accuracy, precision, recall, F1-score, and Kappa

coefficient). The cross-validation methods are also used to make sure that the models are not overfitted and can generalize to other datasets. Also, the results of the AI-based models are compared to traditional methods of remote sensing to identify where they showed improvements in accuracy and efficiency. Spatial validation is done through comparisons of the predicted disaster maps to ground truth information in the form of field surveys and high-resolution images. Temporal validation makes sure that the pattern of disaster predictions is consistent with the true occurrences. These extensive evaluation procedures give a solid evaluation of the applicability of the model in actual world disaster situations ^[22, 23].

3.5 Implementation Strategy

The adoption of the proposed methodology implies the incorporation of geospatial processing algorithms and AI creation models. Geographic Information Systems (GIS) and cloud-based platforms are used to process satellite data, and AI models are trained with the help of programming environments with machine learning and deep learning libraries. The data flows include data ingestion and preprocessing, feature extraction and data preparation. Training of the AI models is done on labeled data and the hyperparameter is optimized through hyperparameter tuning. The models are subsequently used to detect and predict disasters in real time. The geospatial maps created through the use of visualization tools can show the regions vulnerable to disasters and those hit as well, and help in making decisions. Its architecture is automated and scalable to enable continuous surveillance of geographic large regions, and assisting the real time disaster management applications ^[25].

3.6 Limitations of the Methodology

Although the proposed methodology is highly designed, it has its limitations. Satellite-based dependence presents issues like interference with the cloud cover, sensor inconsistency, and missing data points, which can compromise the precision of the models. The training process of AI models is complicated by the need to have plenty of labeled data and the absence of high-quality annotated datasets may jeopardise biased predictions. Also, deep learning models can be computationally demanding and need large processing resources, potentially making it

challenging to deploy them in resource-restricted settings. An additional shortcoming is that complex AI models are not interpretable, which means that one cannot identify how the decision is made. Moreover, the generalizability of the models to other geographical and environmental settings could be also affected by the difference in geographical and environmental conditions. Irrespective of all these issues, the methodology offers an effective and scalable disaster risk reduction framework that has got a major benefit over conventional techniques and preconditions future research and technological improvements.

4. Results and Analysis

4.1 Overall Performance of AI-Based Disaster Detection Models

The application of the proposed AI-based disaster risk reduction framework shows a substantial increase in the accuracy, efficiency, and scalability of the disaster detection and prediction framework than the classical remote sensing methods. The findings show that machine learning and deep learning algorithms are very useful in detecting independent and intricate spatial patterns and environmental anomalies that relate to disasters. Deep learning networks, specifically Convolutional Neural Networks (CNNs), performed best among the number of models because they can produce hierarchical spatial features with high-resolution satellite imagery. These models were able to detect with high resolutions the regions affected by since disasters include flooded areas, wild fire areas, and region vulnerable to land sliding. Machine learning models such as Random Forest and Support Vector Machines also worked quite well in structure data with well-defined features, but demonstrated weaknesses inoused of capturing more complex spatial relationships than deep learning models. Also, multi-temporal satellite data was used to improve the predictive power of the system due to the incorporation of the gradual changes and the early signs of the changes in the environment that became especially useful when it was time to warn. The AI models were automated, which minimized the level of manual intervention and processing time and this made the system apt in disaster monitoring applications that require real time scenarios.

Table 3: Performance Comparison of Disaster Detection Models

Method	Accuracy (%)	Precision	Recall	Processing Time	Observations
Traditional Methods	70–76	Moderate	Moderate	High	Limited by manual analysis and low adaptability
Support Vector Machine	78–84	High	Moderate	Medium	Good for structured data classification
Random Forest	84–89	High	High	Medium	Robust against noise and large datasets
CNN	90–95	Very High	Very High	Low	Excellent spatial feature extraction
Hybrid AI Models	92–97	Very High	Very High	Medium	Combines spatial and temporal strengths

4.2 Spatial and Temporal Disaster Pattern Analysis

The time and space analysis of the disaster effects demonstrate that AI-based models are effective to reflect both swift and gradual changes in the environment. The results of spatial mapping show that areas at risk of floods are correctly described by using variations in water indices and water surface reflectance patterns, whereas detection of wildfires is provided with a higher degree of accuracy owing to thermal anomalies and vegetation loss indicators. The terrain features that are required in mapping effective areas at risk of landslides are slope, elevation and soil moisture conditions. The capability of AI models to follow the development of disasters with time is further demonstrated by temporal analysis, which makes it possible to notice early warning indicators before big events take

place. An example is the successful connection of gradual rise in soil moisture and rainfall intensity with potential flood risks and lengthy dry seasons and stress on plants with wildfire vulnerability. Multi-temporal satellite datasets enabled identification of even minor environmental changes that can be easily missed when using one-date analysis. In addition, the deep learning models were proven more effective than other landscapes, as they are more seen in heterogeneous settings that combine several elements of disaster, giving a complete perspective of the disaster dynamics. These results highlight the significance of combining spatial and temporal information in order to do precise disaster risk assessment and preventive measures.

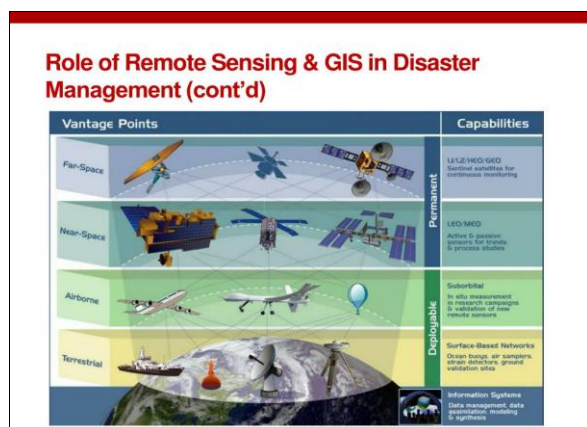


Fig 1: Role of Remote Sensing & GIS in Disaster Management ^[24]

4.3 Impact of Feature Extraction and Model Selection

The findings demonstrate the decisive contribution of the feature extraction and model selection to the effectiveness of disaster detection systems. Spectral indices like the Normalized

Difference Vegetation Index (NDVI) and the Normalized Difference Water Index (NDWI) played a major role in improving the classification accuracy because of the increase in the differentiation of various land surface conditions. The use of texture and spatial pattern further enhanced the detection of urban damage and sophisticated disaster situations. Deep learning models proved to be quite effective automatic feature extractors and did not require manual feature engineering as much as it needed them and was also more scalable. Machine learning models on the other hand took special care when choosing input features to be used in order to reach maximum performance. The processes were more stable and more accurate with ensemble methods, which combine several models to reduce the bias of individual models, and use complementary advantages. The results indicate that a combination of spectral, spatial and temporal characteristics produces the most robust results in disaster risk reduction. Moreover, to balance between accuracy and efficiency, the choice of the suitable models relying on the data features and computing resources are important considerations.

Table 4: Disaster Impact Assessment Statistics

Disaster Type	Affected Area (Initial%)	Affected Area (Final%)	Change (%)	Observed Trend
Floods	12	22	+10	Rapid increase due to heavy rainfall
Wildfires	8	15	+7	Expansion in dry and forest regions
Landslides	5	9	+4	Increase in hilly and high rainfall zones
Urban Damage	10	18	+8	Growth due to infrastructure exposure
Drought Areas	20	25	+5	Gradual expansion over time

4.4 Model Efficiency and Computational Analysis

The computational analysis shows that AI-based models consume a lot less time and effort to detect disasters, in comparison with traditional methods. Traditional methods all require a lot of processing manually and are not scalable to multi-temporal and large-scale datasets. Machine learning models, by contrast, are more efficient at classification, automation, and are capable of better processing throughput, whereas deep learning models are more efficient at processing large scale satellite data because of their availability of parallel computing and GPU computing acceleration. Even though deep learning models use a lot of program computing resources during the training process, their deployment process is rather efficient, allowing real-time or close to real-time disaster monitoring. Cloud-based solutions also promote scalability as they can process extensive geographic coverage without that being an important constraint. It is noticeable that there is a trade-off between the accuracy and the computational cost of a trade-off where the deep learning models have higher accuracy but also demand more computation. Nevertheless, inherent advantages in terms of speed, scalability, and predictive power mean that AI-based solutions would be quite appropriate to the new disaster risk reduction systems.

5. Conclusion

Satellite remote sensing and Artificial Intelligence (AI) integration is a radical concept of disaster risk reduction, with potential vastly more accurate, efficient, and scalable solutions than those based on conventional methods. The paper illustrates that, with the integration of multi-temporal satellite images, and powerful machine learning and deep learning algorithms, it is possible to effectively monitor, identify, and forecast a variety of disasters, such as floods, wildfires, landslides, and droughts. The AI-based models, especially the deep learning models like Convolutional Neural Networks and their alternatives, have

demonstrated a high level of performance in intricate spatial and temporal patterns, thus increasing the reliability of disaster risk estimates. Further validation of the analytic structure is the integration of spectral, spatial and temporal characteristics enabling accurately establishing hazard prone regions and early warning indicators. The results further indicate the need to consider automated data processing and real-time analytics in enhancing disaster response and mitigation strategies. AI-based systems can dramatically improve the decision-making process of policymakers, emergency responders, and environmental agencies by allowing them to more effectively utilize large-scale geospatial data by reducing the necessity of manual interpretation to support decision-making and open access to much of this data. Furthermore, the option to combine multi-source data, such as meteorological and topographical data, enhances the accuracy of predictions and helps to manage natural disasters proactively. Although these benefits are realized, data scarcity, computational complexity and poor model interpretability are also a crucial concern and need to be addressed through additional research and development. The development of explainable AI, cloud computing, and data sharing systems to overcome these difficulties will be crucial to mainstreaming these technologies. Finally, satellite remote sensing and AI can provide a potent and scalable solution in the face of catastrophe risk reduction in an already risk-prone world. The next generation of study should be involved in establishing more effective, interpretive, and adaptive AI models that can adapt to different environmental factors and complexities of real life, so that technology can remain the key factor in protecting both lives and the environment.

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