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Original Paper

Deep Learning Techniques using Remote Sensing Data for Enhanced Disaster Management: A Review

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ABSTRACT

Multimodal remote sensing data plays a crucial role in disaster management by providing comprehensive information for effective response and recovery. However, current disaster detection and prediction mainly rely on satellite images and sensors. This study investigates the use of data fusion techniques and deep learning models to process diverse remote sensing data sources from different modalities to enhance disaster response strategies and decision-making. By synthesizing the existing literature and research findings, this study examines the current state- of-the-art approaches, challenges, and opportunities in leveraging diverse remote sensing data types, such as satellite imagery, LiDAR data, GPS, and GNSS data. This study provides a comprehensive overview of the utilization of multimodal remote sensing data in disaster management for various phases of disasters, such as the pre-disaster, during-disaster, and post-disaster phases. Natural disasters with catastrophic consequences, such as earthquakes, landslides, and floods, are the focus of this study. By critically evaluating the strengths and limitations of existing methodologies, this study aims to identify gaps in research and propose future directions for advancing the use of deep learning in multimodal data.

KEYWORDS

Disaster Management, Remote Sensing, Deep Learning, Multimodal data, GPS, GNSS, SAR, LiDAR, Satellite Imagery

1. Introduction

The term ”Remote sensing” is a geospatial technology concept in which information is acquired from a distance and sensors are utilized to collect data from satellites [1]. Remote sensing is crucial for disaster management. ”Remote sensing plays a vital role in disaster management by providing timely and useful information for emergency responses and recovery” [2]. The data captured from these satellites can have various forms, depending on the sensors used. These data can include images, time-series data, and electromagnetic radiation. [3].Satellites use two types of sensors: active and passive sensors (Figure 1)Both sensors use different data collection methods [4]. The difference between these sensors lies in the way in which they collect data. Active sensors are independent of external resources. The active sensors independently obtained light energy illumination. The target was first illuminated by the emitted light. The information was obtained by recording the reflected light. ”An active sensor sends radar waves that bounce from the Earth's surface” [5]. The time required for the waves to hit the earth's surface and the time taken by the sensor to record the data were utilized to create an image. Light detection and ranging (LiDAR) sensors are an example of such active sensors. It can capture images with high dimensions and provide valu- able information about affected areas [6]. Passive sensors rely on external illumination such as sunlight to provide light. They capture the light emitted by the sun on the Earth's surface. When sunlight illuminates an object on Earth, it is reflected. The passive sensor uses these reflected waves to capture information. Active sensors are believed to be more energy efficient than passive sensors because they do not require external sources to emit light.

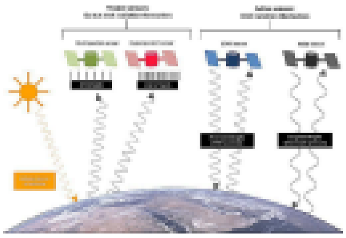


Figure 1. Active and Passive Sensors [7]

Disaster management can be categorized into three phases: pre-disaster, disaster, and post-disaster [8]. In the pre-disaster phase, remote sensing data can contribute to early warning systems. Pre-disaster phase is the period preceding real disasters. Remotely sensed data is highly valuable during the pre-disaster phase for preparedness, planning, and risk assessment [9]. It is used to identify potential natural hazards such as floods, landslides, and earthquakes. By analyzing historical data and patterns, experts can assess the likelihood and magnitude of these hazards in specific areas. A system designed for early warning can provide alerts by analyzing meteorological data. This early warning of disasters can aid in timely decision making [10]. During the Disaster phase, remote sensing is used to provide real-time and near-real-time information to guide emergency response. Remote sensing aids in evaluating damage to critical infrastructure such as roads, bridges, power lines, and communication net- works. Navigational support can be provided for evacuation during disasters. This can include optimized routes, which can easily identify alternative methods, real- time monitoring, and systems that can track public transportation facilities. Drones equipped with remote sensing technology can rapidly capture high resolution imagery of disaster affected areas, particularly in scenarios where access is limited or dangerous for humans. Post-disaster phase provides information about the severity and damage of a disaster can be obtained by analyzing the information from different views of satellite images. DL algorithms can fuse various types of remotely sensed data, such as satellite imagery [11], drone imagery, and social media data, to provide a comprehensive understanding of the real-time impact of a disaster. Images taken before and after an earthquake are compared pixel-by-pixel by change detection algorithms.It can be used to identify significant changes that may indicate a structural damage or collapse particularly image segmentation and object detection models can automatically identify and delineate landslide affected areas, damaged infrastructure, and potential hazards [12].

This study is structured into five sections that comprehensively address the role of remote sensing in disaster management. The first section introduces the various remote sensing techniques used in this field. The second section discusses different types of remotely sensed data and their integration with deep-learning models. The third section focuses on data fusion and explores various techniques for integrating multiple modalities of remotely sensed information. The fourth section evaluates and compares the data fusion methods employed by researchers, providing a critical analysis to identify optimal solutions to the challenges faced in disaster management. Finally, the fifth section summarizes the research findings and outlines the future directions for this important area.

2.Types of Remotely Sensed Data for Disaster Management

2.1.Global positioning system (GPS)

A global positioning system (GPS) can be used for real-time tracking and monitor- ing. GPS is a valuable tool for detecting landslides and earthquakes by monitoring the changes in ground movements. GPS provides precise location information, allowing the detection of even small movements on the Earth's surface, which may indicate the onset of a landslide or earthquake. Hence, they can be used to obtain ground motion maps during earthquakes [13]. Conventionally, earthquake prediction has been performed using various seismological changes that have been used to provide information about the shaking of earth plates[14]. From this, we can determine the magnitude of the earthquake as it relates to the energy released during the event. This can be deter- mined by continuous monitoring of ground movements.

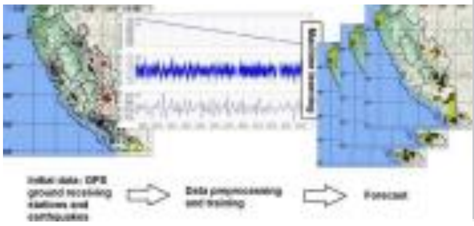
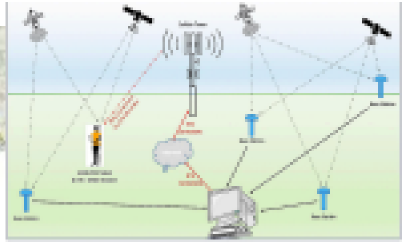



Figure 2. GPS Working Figure 3. GNSS Working [17]

Researchers have found that the energy released during an earthquake is directly proportional to ground displace- ment after an event occurs. Displacement is a measurement of the extent to which a surface moves during an earthquake. The displacement information can be used to predict the magnitude of an earthquake [15]. A station is maintained to monitor this information. The final displacement, which compares the positions of the stations before and after the event, was calculated to determine the magnitude of the earth quake. Because the data were collected at intervals, GPS cannot be utilized to measure genuine ground shaking. The receiver logs data provided by the satellites at regu- lar intervals throughout the day. Therefore, GPS is not used to directly measure the ground shaking during an earthquake. GPS can measure the speed at which ground movement occurs and can be an early indicator of landslide or earthquake activity. They can also measure changes in acceleration, which can help to detect sudden movements associated with earthquakes or landslides [16]. By integrating GPS data with deep learning algorithms, the system can enhance the accuracy of geolocation appli- cations, thereby enabling earthquake prediction (Figure 2). This allows the GPS to provide valuable insights into seismic events and improve early warning systems for earthquakes and landslides.

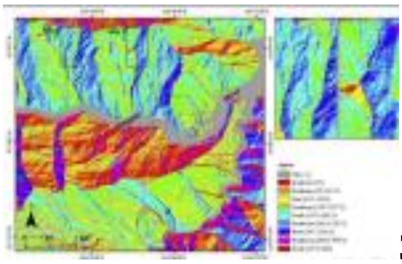
2.2.Global Navigation Satellite System (GNSS)

Global Navigation Satellite System (GNSS) data is a comprehensive system that inte- grates various satellites, such as GLONASS, GPS, and Galileo, to enhance accuracy and reliability. By receiving multiple signals from different satellite transmitters, a single receiver can improve the precision. More signals are equivalent to an increased accuracy and reliability [18]. The system consists of a control segment that monitors and communicates with satellites and a user segment where receivers capture and decode satellite signals. After receiving the signals, the receiver measures the distance by calculating the time delay from which the signal was broadcasted and received. This helps in finding out the location information by comparing the initial satellite locations. The signals are received continuously and can be extracted in time series form. These time-series data can be used to train the DL model to predict locations easily and for route optimization purposes. This method can be used to obtain more accurate results. This may be helpful in the post-disaster phase for rescue teams. The Researchers have found that various GNSS-based techniques can be used to obtain more accurate findings. One of them is GNSS Total Electron Count (TEC). The concept of total electron count (TEC), in which the total number of electrons traveling between the path of the satellite and the receiver is counted, is used to learn more about ionospheric disturbances.Earthquakes cause subtle stress on Earth's crust, and plate tectonic movements occur [19].

Another technique is the GNSS radio occultation (RO) that uses signals from GNSS to study the Earth's atmosphere and ionosphere. Although RO is primarily used for atmospheric studies, it can also provide valuable data for detecting earth- quakes through the following mechanisms: Earthquakes cause disturbances in the ionosphere and upper part of the Earth's atmosphere. These disturbances can be detected using GNSS RO by observing changes in the propagation of radio signals through the ionosphere [20]. Earthquake-induced disturbances in the ionosphere can be detected through GNSS RO by monitoring changes in radio signal propagation, phase, and amplitude. Some studies have suggested that GNSS RO data can capture pre-seismic signals in the ionosphere before an earthquake occurs. These signals are hypothesized to be related to the build-up of stress in the Earth's crust before a seismic event, and can potentially provide an early warning of an impending earthquake.

2.3.Satellite Imagery Data

Synthetic Aperture Radar (SAR) is an active sensor that records data from signals reflected from Earth's surface. SAR satellites provide continuous monitoring capabilities, offering detailed images of affected areas day and night, independent of weather conditions. This provides the advantage of obtaining information regardless of weather conditions. This makes SAR particularly valuable for monitoring disasters in areas prone to natural disasters. High dimensional images can be created using SAR data, through which the smallest amount of information on the Earth's surface can be analyzed, allowing for detailed mapping of affected areas[21]. SAR data can be used to detect changes in Earth's surface before and after a disaster. This includes identifying areas of land subsidence, uplift, or lateral movement that can indicate the potential for landslides or earthquakes. SAR images are analyzed using Deep Learning algorithms to automatically identify and recognize damage, providing a precise assessment of the impacted regions [22]. SAR can offer data on the extent of floods, inundation visualization, landslide detection, and deformation of surface earthquakes.



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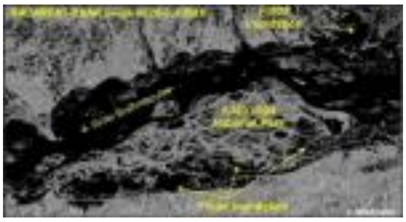

Figure 3. LiDAR [23] Figure 4. SAR

Light Detection and Ranging (LiDAR) is a remote sensing technology that utilizes laser light to measure distances and create high-resolution digital elevation models (DEMs) of Earth's surface [23]. LiDAR works by emitting rapid pulses of laser light towards the Earth's surface and measuring the time it takes for light to reflect back [24]. By analyzing the reflected light, LiDAR can create highly detailed 3D maps of Earth's surface. It can detect subtle changes on the Earth's surface, such as fault lines or ground deformation, which may indicate potential seismic activity. These changes can be identified by comparing LiDAR scans taken at different times. It can identify areas where the ground has shifted or vegetation has been disturbed, which are signs of potential landslide activity. The ability of LiDAR to provide highly detailed and accurate topographic data makes it a valuable tool for assessing earthquake and landslide risks and monitoring changes in the landscape over time [25].

3. Multimodality Data Fusion Techniques

To obtain more precise findings, the concept of data fusion has been implemented in this field of work, in which fusion refers to the process of combining information from multiple sources and modalities. Data fusion techniques are applied at different levels, including raw data-level fusion, feature level fusion, and decision level fusion [26]. There are a few methods for achieving data fusion, including early fusion, late fusion. In the early fusion technique, different modalities were combined at the input level. This means that the data were merged before being fed to the Deep Learning model. Input data from different sources or modalities were combined at the beginning of the network before any significant processing occurred [27]. It allows the model to learn the joint representations of input modalities from the beginning. It can be applied to raw or preprocessed data obtained from remote sensors. At this stage, we can extract the features from the preprocessed data and then combine multiple types of data into a single feature space. Hence, early fusion is also known as feature-level fusion. Hence, early fusion works with the raw data level, as well as the feature level of data fusion. It can be effective in disaster management scenarios involving satellite imagery, sensor data, and social media posts during a disaster and can be used to combine these different types of data into a single input representation for a model to predict the extent of damage or the areas most affected by the disaster. Early fusion combines GPS and GNSS data with satellite imagery at the input level, creating a unified representation that includes spatial information from GPS and GNSS, along with the visual context from satellite images. Fused data can be fed into a deep learning model, such as a convolutional neural network (CNN), for feature extraction. The model can learn to extract features that capture both spatial information (from GPS and GNSS) and visual information (from satellite images) relevant to the disaster management task. The fused data can be used to create detailed maps of the affected areas, showing the extent of the disaster, locations of critical infrastructure, and distribution of affected populations [28]. These maps can help in planning disaster response efforts and effectively allocating resources. The fused data can also be used for damage assessment, helping identify areas that have been most severely affected by the disaster. This information can guide the prioritization of response efforts and allocation of emergency services. Deep learning techniques for multimodal data fusion include early fusion, where input data from different modalities are combined at the input layer, typically through concatenation, summation/averaging, or weighted fusion.

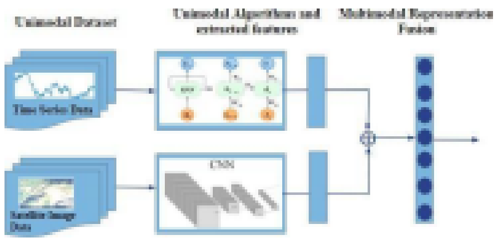

Figure 5. Data Fusion with Deep Learning [29]

In late fusion, every modality is handled independently by a different Deep Learning model (Figure 5). The final decision was made at a later stage by combining the outputs from each model. As a result, decision level fusion is another term for late fusion [30]. Late fusion in deep learning involves combining information from different sources or modalities at a later stage in the network, after they have been processed separately through parallel pathways. Each modality is processed independently and the representations learned from each modality are combined at the fusion stage. The outputs of these networks are then combined, often through concatenation or another operation, and fed into the final classification or regression layer. Because the fused layer receives the output of previously trained Deep Learning models, the late fusion technique provides more accurate results. Consequently, inaccuracies resulting from various models have been addressed. Based on the outcomes of each trained model individually, decision-level fusion was employed to reach the ultimate judgements.

4. Results of Related Works

Several studies on disaster management have been conducted using machine-learning methods that utilize remotely sensed data. A comparative analysis was conducted to identify the research opportunities in this field.

Table 1. Literature Survey

Paper	**Conspectus**	**Technologies and Algorithms Used**	**Research Possibilities**
Valeri Gitis et al. [31], Grapenthin et al.[32], Hodgkinson et al. [33], Lyros et al. [34], Parameswaran et al.[35]	This study presents a new technology that integrates geoinformation of earth remote sensing data utilizing the displacement trajectories of ground stations that receive GPS signals for prediction.	Seismological Data and Conventional tools that record the shaking of the Earth's surface is caused by seismic waves.	Investigating the integration of various data sources, such as satellite imagery, ground sensors, and geological data, to develop a comprehensive approach to earthquake forecasting.
Pan Xiong et al. [36], Li Xuechuan et al. [37], Sivakrishna et al. [38], Reddybattula et al. [39], Aarpac et al. [40], Nayak et al. [41], Costantino et al. [42], Xuechuan et al. [37]	The utilization of GNSS TEC data for earthquake precursor detection, coupled with a cutting edge deep learning framework, contributes to the advancement of early warning systems and seismic activity forecasting methods.	Encoder–decoder Long short-term memory (LSTM) for handling the time series data.	Investigating the integration of diverse datasets, such as seismic data, satellite imagery, and geological information, to improve the performance and reliability of earthquake prediction models.
Stefania Bonafoni et al. [43], Vardaan et al. [44], Chin et al.[45], Cai et al. [46], Wang et al. [47], Mukesh et al. [48]	The utilization of GNSS TEC data for earthquake precursor detection, coupled with a cutting-edge DL framework, contributes to the advancement of early warning systems and seismic activity forecasting methods.	LSTM Model for TEC time series data, Comparison with DNN, Random Forest (RF), Support Vector Machine (SVM), Decision Tree (DT).	Research possibilities need to explore the spatial coverage of GNSS ground-based stations, which may not be uniform across regions, leading to potential gaps in the data collection and analysis.
Amina Khan et al. [49], Hamidi et al. [50], Montello et al. [51],[52], Bai et al. [53], Rao et al. [54], Montello et al. [51], Vincent et al. [53]	A deep learning model is trained on a labeled dataset that includes SAR images before and after earthquakes, with corresponding ground truth labels indicating areas of damage or change.	Convolutional Neural Network (CNN), You only Look Once (YOLO), Deep Neural Network (DNN) models	Research possibilities need to explore SAR images, as the resolution may not always be sufficient to capture small-scale earthquake-induced changes, impacting the precision of detection and prediction.

Gupta et al. [55], Algiriyage et al. [5], Costantino et al. [42], Alizadeh et al. [56], Tanu et al. [55], Algiriyage, Nilani, and Prasanna et al. [5]	This technique combines the outputs from individual models trained on different modalities to create a comprehensive prediction.	Ensemble Deep Learning, CNNs, Encoder-Decoder, Recurrent Networks	The data fusion of GPS, GNSS and Satellite images such as SAR images can be explored

5. Conclusion

In conclusion, the use of deep learning techniques for multimodal data fusion in disaster management has shown great potential for improving the effectiveness of disaster- response strategies. However, there are challenges that must be addressed to improve the effectiveness of these approaches. One of the main challenges is the need for high- quality and diverse data, which are crucial for training DL models and making accurate predictions. The analysis of articles highlighted the successes, current challenges, and future opportunities in using deep learning for disaster management tasks, emphasizing the need for further research to address the existing limitations. This study under- scores the importance of developing robust frameworks that can efficiently extract, analyze, and interpret multimodal data from various sources in real time to sup- port emergency responders in making informed decisions during crises. By addressing these challenges, deep-learning-based multimodal data fusion can significantly enhance disaster response and management efforts.

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