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Review

Deep artificial intelligence applications for natural disaster management systems: A methodological review

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ABSTRACT

Deep learning techniques through semantic segmentation networks have been widely used for natural disaster analysis and response. The underlying base of these implementations relies on convolutional neural networks (CNNs) that can accurately and precisely identify and locate the respective areas of interest within satellite imagery or other forms of remote sensing data, thereby assisting in disaster evaluation, rescue planning, and restoration endeavours. Most CNN-based deep-learning models encounter challenges related to the loss of spatial information and insufficient feature representation. This issue can be attributed to their suboptimal design of the layers that capture multiscale-context information and their failure to include optimal semantic information during the pooling procedures. In the early layers of CNNs, the network encodes elementary semantic representations, such as edges and corners, whereas, as the network progresses toward the later layers, it encodes more intricate semantic characteristics, such as complicated geometric shapes. In theory, it is advantageous for a segmentation network to extract features from several levels of semantic representation. This is because segmentation networks generally yield improved results when both simple and intricate feature maps are employed together. This study comprehensively reviews current developments in deep learning methodologies employed to segment remote sensing images associated with natural disasters. Several popular deep learning models, such as SegNet U-Net, FCNs, FCDenseNet, PSPNet, HRNet, and DeepLab, have exhibited notable achievements in various applications, including forest fire delineation, flood mapping, and earthquake damage assessment. These models demonstrate a high level of efficacy in distinguishing between different land cover types, detecting infrastructure that has been compromised or damaged, and identifying regions that are fire-susceptible to further dangers.

1. Introduction

A natural disaster is any calamitous occurrence generated by the effects of natural phenomena rather than human-driven activities that produce significant loss of human life and destruction of the natural environment, private properties, and public infrastructures (Prasad et al., 2017). A natural disaster may be caused by changes in weather and climate events, earthquakes, landslides, and other anomalies on the Earth's surface or within the planet itself. Truthfully, no spot-on Earth is safe from a natural disaster; however, certain types of disasters are often limited to or occur more frequently in specific geographic regions. Natural disasters, such as forest fires, earthquakes, and floods, have devastating and extensive adverse effects on human populations and the natural environment (Wallemacq et al., 2018).

The natural disaster of forest fires, if it is not controlled, can produce blazes over 1.8 m in height that can cause devastating damage to the ecosystems (Kane, 2023). Forest fires are generally triggered by a combination of factors, including wind speed, terrain conditions, and moisture level in the surrounding plants. They have the potential to rapidly intensify, emitting combustible gases and undergoing pyrolysis, burning the plants, and emitting unhealthy smoke, which can have adverse effects on air quality and ecosystems (Dhall et al., 2020).

Abbreviations: CNNs, Convolutional Neural Networks; FCNs, Fully Convolutional Networks; HRNet, High Resolution Network; DL, Deep Learning; NIR, Near Infrared Region; SWIR, Short-wave infrared; OLI, Operational Land Imager; TIR, Thermal Infrared Sensor.

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Managing forest fires requires a comprehensive strategy encompassing prevention, timely identification, and active suppression. Firefighters employ various techniques to put off forest fires, including ground spraying, aerial water drops, and firebreak methods. In addition, recent technological advancements also facilitate the early detection of the fires and efficient deployment of firefighting resources.

Nonetheless, the escalating occurrence and intensity of forest fires underscore the necessity of comprehending interrelated issues such as climate change, land-use patterns, and human behaviors. However, some types of forests are more resilient to fires, increasing their survival rate and boosting the reproduction of plants and animals. Besides, controlled burning can also limit the forest fire side effects and speed up the restoration process to its pre-fire conditions, thus restoring the natural balance (Maxwell et al., 2022).

Apart from forest fires, another type of normally occurring natural disaster is earthquake, which is sudden ground shocks caused by seismic waves passing through rocks in the Earth that occur along geological faults (Bolt, 2023). Earthquakes are the results of tectonic plate movements beneath the Earth's surface, which accumulate tension during their collisions. The stress is released as seismic energy, with the epicenter representing the location directly above the earthquake source. Earthquakes can manifest a range of quake magnitudes, with stronger quakes producing more widespread destruction (Zaccagnino et al., 2022). The impact goes beyond physical damage, affecting communities by disrupting infrastructure, loss of life and prolonged psychological suffering. Dealing with earthquakes requires a combination of preparedness, technological interventions such as deep learning technologies to measure the damage, and to plan the safe and rescue strategies to react to the event so that emergency response personnel can provide immediate assistance and support the emergency medical teams (Mavroulis et al., 2023).

Flooding is also one of the most common natural disasters when overflowing water submerges dry lands. Flood is often caused by one or a combination of the following factors: heavy rains, rapid snowmelt, tropical cyclone storms, or tsunami storms in coastal areas. It can cause widespread destruction, loss of life, and damage to personal properties and public health infrastructures (Rosmadi et al., 2023; Feng et al., 2023). Coastal regions are especially susceptible to flooding caused by storms, but riverine floods typically occur due to extended periods of rainfall or the convergence of many water sources that cause the river to overflow (Mayo et al., 2022). Effective management of flood disasters requires the implementation of preventative measures, the establishment of early warning systems, and the development of efficient response plans. Some infrastructures, such as levees, dams, and flood barriers, can effectively manage the water flow to avoid severe flooding. At the same time, land-use planning and zoning restrictions can also reduce the likelihood of constructing buildings in places that are prone to flooding. Early warning systems, which incorporate weather monitoring, river gauges, and satellite data, offer vital information to local communities that are at risk. Furthermore, global collaboration is essential for effectively managing the danger of floods on time, which is a global concern due to climate change (Kundzewicz et al., 2014*)*.

The management and mitigation of the previously mentioned disasters are crucial in guaranteeing the safety and welfare of the affected communities. In line with this goal, using artificial intelligence technologies has demonstrated immense positive value as a resourceful instrument to effectively address and manage these catastrophe disasters through better relief endeavors and more strategic actions of the long-term recovery process (Chai et al., 2023).

In recent years, extensive studies have been conducted using artificial intelligence to help with disaster management from various perspectives, such as forecasting, projecting natural disasters, and detecting disasters in real-time (Nunavath and Goodwin, 2019). Within this broad spectrum of applications, deep learning techniques, a subset of artificial intelligence, have emerged as powerful tools to help the relevant agencies manage the complexities of natural disasters. Deep learning methodologies, especially multiple layers of convolutional neural networks (CNNs), can learn intricate patterns of specific natural disasters from large datasets, making them useful in natural disaster assessment. They can utilize input from satellite imaging to identify the affected areas and assess the extent of destruction. Deep learning can also aid in real-time disaster detection, like wildfires, by identifying fire outbreaks and tracking the fire progression (Eltehewy et al., 2023). When these techniques are applied to flood prediction systems, their accuracies have improved significantly by leveraging long historical weather and river-level data. The application of this technology to imaging data has yielded significant success, surpassing human-operated systems in various use-case scenarios, particularly in the most demanding computer-vision applications: classification, object detection, and segmentation tasks.

Moreover, deep learning has revolutionized image classification and object recognition. Deep learning relies on CNNs to teach machines unique patterns from large datasets. Computer vision and deep learning have enabled more advanced image analysis and classification automation. Image classification technology is widely used in content organization, image search engines, medical diagnosis, and autonomous vehicle perception. (Teng et al., 2019; Elizar et al., 2022). Apart from the classification task, the object detection task uses advanced deep learning models to identify and locate objects of interest in images or video frames. Some object detection applications are autonomous vehicles, surveillance systems, retail, and manufacturing applications that provide safe, efficient, and automated processes. (Mohamed and Zulkifley, 2019; Song et al., 2020a).

Many previous studies have shown that implementing various deep learning techniques in natural disaster management has produced outstanding outcomes, particularly for applications that require segmentation outputs. In segmentation, a deep model architecture is usually based on CNN architecture, which has stood out as one of the predominant methods for achieving precise and automated delineation of objects within images (Saleh et al., 2023). Some examples of segmentation models based on CNNs architecture include SegNet, U-Net, FCN, FCDenseNet, PSPNet, HRNet, and DeepLab. These segmentation models have demonstrated their efficacy in diverse natural disaster scenarios, showcasing their adaptability and robust performance. Their utilization extends beyond static image analysis, with applications in dynamic situations such as monitoring evolving disaster landscapes in real-time.

Hence, from the following background, the main contributions of this article are as follows:

1. This is the first comprehensive review of semantic segmentation in the natural disaster domain.
2. This review explains, in detail, the main categories of the semantic segmentation deep architectures that include SegNet, U-Net, FCN, FCDenseNet, PSPNet, HRNet, and DeepLab,
3. This is a comprehensive review of the semantic segmentation-deep-learning usage in various main natural disasters, such as forest fires, earthquakes, and flood disasters.

The originality of this article is based on the comprehensive new insight into semantic segmentation deep learning techniques in natural disasters. We have also provided insight related to the practical perspectives of various segmentation deep-learning architectures in the form of how they work and their strengths and weaknesses. The remainder of this article is organized as follows. Section 2 provides a research methodology. Section 3 provides an in-depth description of remote sensing platforms. Section 4 describes the semantic segmentation-deep learning models used in this review paper. Then, Section 5 provides extensive descriptions of segmentation deep learning applications in forest fire, earthquake, and flood disasters. Section 6 discusses the methods used in the previous sections. Finally, Section 7 provides concluding remarks on semantic segmentation deep learning in natural disaster applications.

2. Research methodology

The preparation of this review paper involved a structured four-stage process to ensure the content's comprehensiveness and clarity. In the first stage, the objectives of the review are clearly outlined by identifying research gaps in this reviewed domain. This step assists in establishing a clear focus for this review paper. The second stage involves an exhaustive and unbiased literature search through a wide search of academic sources, including proceedings, books, journals, and official websites, which are gathered using prominent search engines such as Google Scholar, Elsevier, MDPI, Springer, Hindawi and IEEE (search period: 2014 – 2023). The gathered documents are meticulously sorted based on their relevancy to the research questions that were previously formulated. As a result, a total of 260 articles were initially identified.

However, the list is further refined through keyword-based filtration as shown in Fig. 1, targeting terms such as “natural disaster segmentation,” “semantic segmentation,” “deep learning segmentation,” “satellite imagery,” “forest fire deep learning,” “earthquake deep learning,” and “flood disaster deep learning.” This rigorous selection process has resulted in the inclusion of only 124 of the most pertinent articles.

Then, the third stage involves the extraction of crucial information from the filtered articles. Several key parameters are studied and analyzed, such as methods, types of deep architecture, performance accuracy, and detection capability, which are central to the original research questions. To further facilitate the understanding of the readers, this information is organized and presented in table formats for better understanding and clarity, which are also supported by several infographic references. In the final section of this review article, a comprehensive revision of the reviewed methods is also conducted.

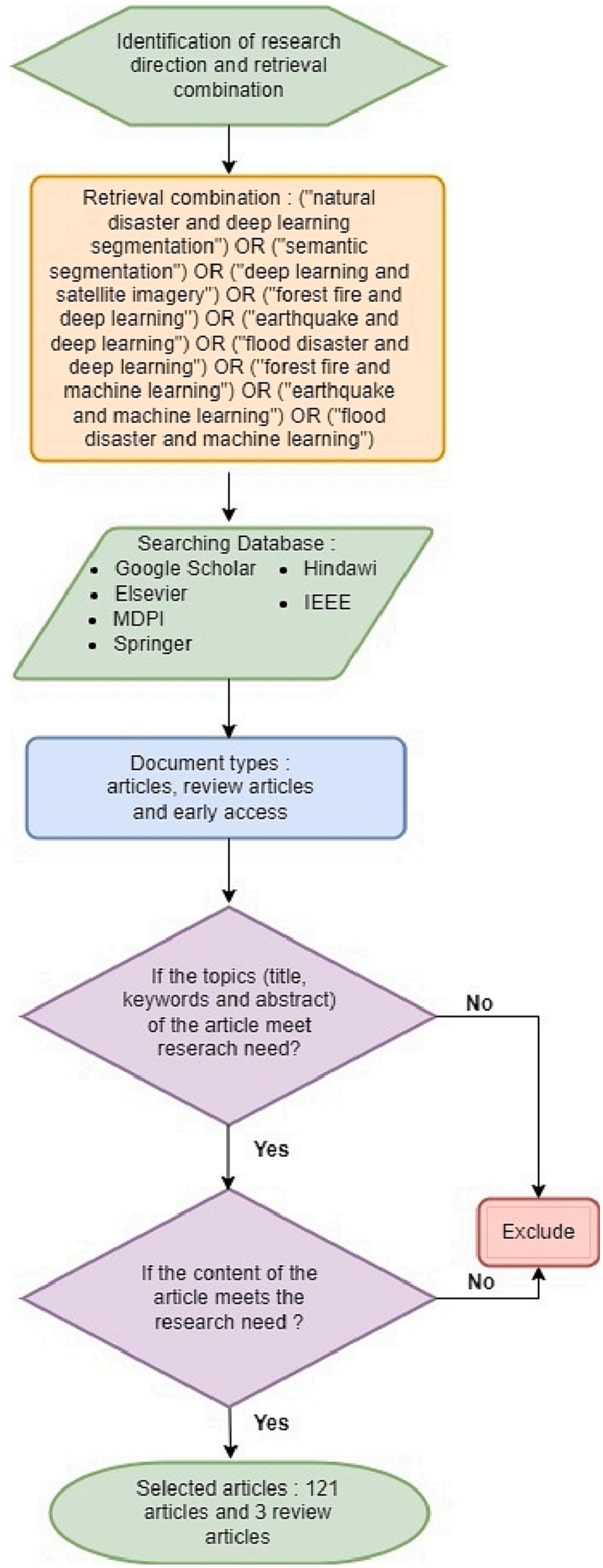

Fig. 1. Articles selection process.

3. Remote sensing platform in natural disaster detection

3.1. Satellite imagery

Satellite imagery helps comprehend and manage natural disasters. It has helped officials monitor and detect hurricanes, floods, and wildfires in early warning systems. High-resolution satellite imagery aids disaster response by assessing damage quickly. Search and rescue teams might utilize it to find survivors and determine access to damaged areas. (Kim et al., 2022; James et al., 2023). Moreover, it can be used in post-disaster monitoring systems, which is crucial to facilitate efficient recovery planning and speedy reconstruction efforts.

The main advantage of satellite imagery is its capability to provide unparalleled coverage, especially in remote or inaccessible regions, making it an essential resource for disaster management and recovery. Integrating satellite imagery with advanced technologies like advanced deep artificial intelligence can further enhance disaster-related analyses, thus improving disaster preparedness and mitigation strategies (Sublime et al., 2019).

One of the most popular satellite imageries is the Landsat series of satellites, spanning from 1972 to 2021, which are equipped with advanced imaging sensors. They capture detailed multispectral data across various spectral bands, providing invaluable insights into the Earth's surface characteristics. Landsat satellites typically carry sensors with multiple bands, each sensitive to specific wavelengths of light. The Landsat sensors operate in the visible, near-infrared, and thermal infrared regions of the electromagnetic spectrum. Originally introduced in 1972, Landsat 1 offered significant observations regarding the history of the land cover of the environment. Then, Landsat 2 and 3 continue this effort, which is further supplemented by Landsat 4 and 5, which expand the program's capabilities. These satellites have become indispensable instruments for resource management, environmental monitoring, and scientific study. Despite its failure to achieve orbit, Landsat 6 continues to provide crucial data for disaster management purposes. Landsat 7, which was introduced in 1999, carried the Enhanced Thematic Mapper Plus, extending the dataset continuity. Landsat 8, which was launched in 2013, brought about the inclusion of the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (Hemati et al., 2021). The most recent one, Landsat 9 is a replica of Landsat 8, providing more radiometric and geometric data than previous Landsat family-satellites. It uses two types of sensors: Operational Land Imager 2 (OLI-2) and Thermal Infrared Sensor 2 (TIRS-2). OLI-2 captures earth motion, while TIRS measures horizontal and vertical frame radius. With superior radiometric resolution, Landsat 9 can accurately identify subtle distinctions, especially in regions with little atmospheric or aquatic presence, and can quantify 16.384 distinct colors within a designated geographic region (Wulder et al., 2022).

OLI-2 is composed of nine spectral bands: band 1 of Visible Coastal Aerosol, band 2 of Visible Blue, band 3 of Visible Green, band 4 of Red, band 5 of Near-Infrared, band 6 of SWIR 1, band 7 of SWIR 2, band 8 of Panchromatic (PAN), and band 9 of Cirrus. Meanwhile, TIRS-2 has two spectral bands: band 10 of TIRS 1 and band 11 of TIRS 2 (Masek et al., 2020).

In the context of semantic segmentation, Landsat imagery becomes invaluable for precisely delineating and categorizing different land cover classes. Leveraging advanced computer vision techniques then enables the disaster management systems to automate the identification and classification of specific features within the Landsat imagery.

3.2. Airborne sensor

Airborne sensors were employed as additional data sources in the field of remote sensing. The initial airborne sensors commonly consisted of push broom systems, which were designed to gather data cubes with high spatial resolutions (ranging from 2 to 5 m depending on the altitude of the flight) and spectral resolutions (ranging from 200 to 300 spectral bands in the VNIR to SWIR range).Airborne Sensor Operators operate on manned platforms, such as fixed-wing and rotary-wing aircraft, for various purposes. Fixed-wing aircraft are typically single or twin-engine general aviation airframes, while military aircraft range from small to large wide-body jet aircraft. manned rotorcraft are light turbine or twin engine helicopters. Unmanned platforms, such as UAVs, are operated off-board by airborne sensor operators. The primary categories of UAVs supported are Mid-Altitude Long Endurance (MALE) and High-Altitude Long Endurance (HALE). A UAV sensor operator manages flight, sensor, and data-link operations. (Van Wesemael and Chabrillat, 2023).

They often incorporate sophisticated imaging systems such as cameras, multispectral and hyperspectral sensors, LiDAR (Light Detection and Ranging), and synthetic aperture radar (SAR). Each sensor type offers unique capabilities. Cameras provide high-resolution images for visual inspection and interpretation. Multispectral and hyperspectral sensors capture data across multiple bands, enabling detailed analysis of vegetation health, mineral composition, and land use. (Cowley., 2018).

Airborne sensors play a crucial role in the surveillance and mitigation of natural disasters such as forest fires, earthquakes, and floods. They offer up-to-the-minute information for prompt identification, evaluation, and intervention endeavors. Thermal imaging sensors deployed on airplanes or drones provide the capability to detect heat signatures and ascertain the size of fires, so facilitating the allocation of resources and the planning of evacuations. Thermal imaging sensors detect and measure infrared radiation using microbolometers. They absorb light and convert it into electrical signals, generating thermal images. These images represent temperature distribution, allowing real-time identification of hotspots and cold areas. They are used in fields like military surveillance, firefighting, medical diagnostics, and industrial inspections, providing crucial insights into thermal dynamics (Pour et al., 2019).

LiDAR sensors have the capability to survey impacted regions in order to evaluate the extent of structural harm, generating intricate 3D maps for the purpose of search and rescue missions. LiDAR uses laser pulses to detect objects and calculate distances. It uses time-of-flight and light speed to calculate distances. LiDAR systems use scanning to cover areas, collecting data on range, angle, and intensity. This data is used in topographic mapping, forestry management, urban planning, and infrastructure monitoring. As technology advances, its capabilities expand, making it crucial for remote sensing and geospatial analysis (Kim G et al., 2021).

Synthetic aperture radar (SAR) has the capability to observe water levels, create maps of areas that have been flooded, and detect possible dangers. Synthetic Aperture Radar (SAR) employs microwave pulses emitted by a mobile platform to detect and analyze the surface of the Earth. The system employs sophisticated algorithms to produce high-resolution images, even under unfavorable weather circumstances or during nighttime operation. Synthetic Aperture Radar (SAR) data is employed for the purposes of topographical mapping, land use monitoring, vegetation change detection, and natural catastrophe assessment. The high adaptability and dependable data of this equipment make it highly helpful for Earth observation and remote sensing applications in various fields. The capacity of the system to deliver data that is both consistent and trustworthy renders it a viable instrument for the purposes of Earth observation and remote sensing. With the progression of technology, it is anticipated that airborne sensors would augment disaster response endeavors, thereby enhancing resilience and adaptive capability in the presence of natural hazards (Chaturvedi., 2019).

3.3. Multispectral resolution

Remote sensing studies electromagnetic radiation from the Earth's surface, encompassing various wavelengths. Spectral wavelength focuses on understanding how materials interact with light at different wavelengths, which helps in identifying and characterizing Earth's surface characteristics. Each substance has a distinct spectral signature, which can be used to distinguish land cover types, identify changes, and track climatic conditions. Multispectral remote sensing uses sensors that collect data across multiple bands or channels within the electromagnetic spectrum, identifying specific light spectrums. This allows for the extraction of useful information about Earth's surface features, such as vegetation indices like the Normalized Difference Vegetation Index (NDVI), which is used in agriculture to evaluate crop vitality and biomass (Janga B et al., 2023).

The multispectral capabilities of Landsat satellites allow for the creation of various band combinations, enhancing the interpretability of satellite imagery, which is useful for natural disaster detection and management. For instance, combining the red, green, and blue bands will result in a true-color image that closely resembles the human eye's perception of the landscape. Additionally, combinations involving the near-infrared band are useful for vegetation analysis, whereby healthy vegetation strongly reflects near-infrared light. The thermal infrared band is also crucial for assessing surface temperatures that can aid in the detection of features like wildfires or variations in water temperatures (Jian et al., 2019; Qi et al., 2022). The commonly used Landsat bands include the blue (Band 1), green (Band 2), red (Band 3), near-infrared (Band 4), shortwave infrared (Band 5), mid-infrared (Band 6), and thermal infrared (Band 10). These bands offer a comprehensive view of land features, vegetation health, and thermal patterns, enabling scientists and researchers to analyze the Earth's surface in detail (Zhao et al., 2016; Potapov et al., 2020; Aghababaei et al., 2021).

Spatial resolution determines the ability to discern fine details and distinguish between objects or features in an image. It refers to the level of detail captured in an image, specifically how small or closely spaced objects or features can be resolved. In satellite imagery, spatial resolution is typically measured in meters per pixel, indicating the size of the ground area represented by each pixel in the image. Factors influencing spatial resolution include the characteristics of the imaging sensor, the altitude and platform from which the sensor operates, and the processing techniques applied to the data. Higher spatial resolution results in smaller pixel sizes and finer detail, but it often comes with trade-offs such as increased data volume, higher costs, and reduced coverage area. Balancing these factors is essential in designing imaging systems for specific applications to ensure accurate mapping, analysis, and interpretation of observed phenomena (Zhang et al., 2023).

Temporal resolution refers to the measurement value assigned to observations or measurements throughout a given period, which serves as an indicator of the speed at which data is gathered or revised. It impacts the system's capacity to observe and analyze changes, patterns, or occurrences over time. Temporal resolution in satellite-based Earth observation systems is commonly measured using revisit time, which denotes the duration between consecutive passes over a given region of the Earth's surface. A high temporal resolution system enables the regular observation of dynamic processes, seasonal variations, or short-term occurrences with a high level of temporal accuracy. In order to attain a high level of temporal resolution, it is necessary to take into account various factors, including the orbital properties of the sensor platform, the strategic planning of data gathering missions, and the capabilities of data processing. Spatial and temporal resolution may give rise to trade-offs, however it holds significant importance in various domains such as environmental monitoring, weather forecasting, and disaster management (Kotawadekar, 2021).

4. Semantic segmentation using deep learning techniques.

In this section, this review introduces several core deep learning models that focus on semantic segmentation tasks. One of the effective types of artificial neural networks used for segmentation tasks is the convolutional neural network (CNN or convnet). CNN is a deep network architecture used explicitly for image recognition and pixel data processing tasks (Taye et al., 2023). Semantic segmentation is a computer vision task that divides an image into meaningful and semantically homogeneous regions, assigning a specific label to each pixel. Unlike object detection, which provides a bounding box that surrounds the objects, semantic segmentation aims to classify and describe the content of each pixel, providing a detailed understanding of the scene. Hence, the main goal of semantic segmentation is to recognize and label each pixel in the image with its corresponding class (Guo et al., 2023). This enables a more detailed understanding of the scene, enabling applications such as scene understanding, image editing, and autonomous navigation, which is very helpful in understanding the affected natural disaster scenes. For semantic segmentation tasks, these various CNN-based architectures, such as SegNet, U-Net, FCN, FCDenseNet, PSPNet, HRNet, and DeepLab, are commonly applied for natural disaster management. Fig. 2 illustrates the deep learning segmentation method based on CNN architecture. SegNet specializes in semantic segmentation with a focus on memory efficiency. Unlike VGG, it employs a two-stage process to assign class labels to each pixel in an image, as shown in Fig. 3. The encoder extracts hierarchical features, storing max-pooling indices for spatial preservation (Daniel et al., 2022). In the decoder part, SegNet uses these indices for precise upsampling, ensuring accurate segmentation. This memory optimization is crucial for real-time applications that balance computational resources and accuracy. SegNet has been used in diverse applications due to its adaptability and efficiency in pixel-wise classification (Badrinarayanan et al., 2017; Oliveira et al., 2018). Meanwhile, U-Net utilizes a U-shaped encoder-decoder topology. Its encoder collects hierarchical features, while its decoder uses upsampling layers to recreate spatial details (Benedetto et al., 2023). Fig. 4. shows skip connections between encoder and decoder layers that preserve tiny details for exact pixel-wise segmentation. Some of the applications that have deployed the U-Net model are satellite imaging analysis, automated industrial inspection, and intelligent disaster monitoring. Furthermore, it is also able to handle little training data while retaining good deployment performance (Marzuraikah et al., 2021a; Asad et al., 2023). Apart from U-Net, FCN, as shown in Fig. 5, modifies basic encoder-decoder architecture by replacing fully connected layers with convolutional layers, allowing variable input sizes (Barin et al., 2022). It also integrates skip connections that link corresponding layers of the same scale to enable multi-scale feature learning. It is found to be good for object detection and image-to-image translation applications, thus enabling direct pixel-wise predictions for comprehensive scene understanding (Gao et al., 2019; Shelhamer et al., 2014; Marzuraikah et al., 2022b). Another semantic segmentation model is FC-DenseNet which integrates DenseNet to the base fully convolutional networks, capturing detailed spatial information while minimizing parameters for effective mapping (Noh et al., 2021; Wu et al., 2019; Brahimi et al., 2018). A specially built model for multi-scale applications is PSPNet, which excellently combines the innovative Pyramid Pooling Module (PPM) with the base ResNet encoder to capture comprehensive contextual information. This module divides input feature maps into grids and performs pooling operations separately as shown in Fig. 6 by analyzing local and global context concurrently (Zhou et al., 2019). The PPM enhances scene understanding of the mapping process by integrating multi-scale features into the encoder's output. PSPNet is found to be good at combating the vanishing gradient problem, and benchmarking results have proven its ability to handle diverse scales and intricate details effectively (Hengshuang et al., 2017; Fang et al., 2019).

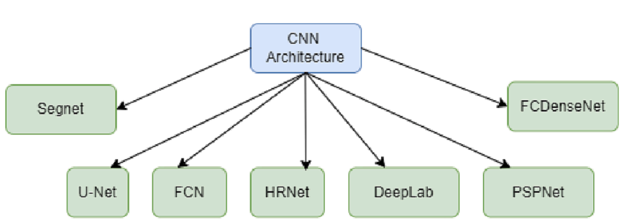

Fig. 2. Deep Learning-based CNN Architecture.

In addition, HRNet is tailored for high-resolution image comprehension, particularly for semantic segmentation tasks. Unlike previously mentioned networks that downsample feature maps gradually, HRNet maintains high-resolution representations throughout the network by integrating multi-resolution streams (Wang et al., 2021a). This design combines high-level and low-level elements, ensuring both context and spatial precision. It possesses extensive interconnectivity among its parallel streams, thus enabling seamless information transmission across resolutions. With four parallel convolutions operating at various scales, HRNet achieves exceptional performance in segmentation benchmarking, proving its effectiveness for tasks requiring accurate localization and comprehensive comprehension. Its adaptability extends to object identification and facial landmark localization, highlighting its versatility (Kim et al., 2023).

Another unique model, DeepLab, also employs multi-scale methodology through atrous convolutions, also known as dilated convolutions, to capture features of various scales efficiently (Zhang et al., 2020). In some versions of DeepLab, a post-processing method is also executed through conditional random fields (CRFs) decision-making for a more refined mapping. By leveraging deep learning and advanced image processing methodologies, it achieves precise pixel-level classification, making it one of the popular base models for applications like object detection, scene understanding, and medical image analysis (Chen et al., 2018; Zhu et al., 2018).

5. Application of semantic segmentation using deep learning.

This section focuses on highlighting semantic segmentation applications based on deep learning methodologies in three natural disaster management, which are forest fire, earthquake, and flood disasters.

5.1. Semantic segmentation for forest fire applications

Forest fire segmentation is a technique employed in image analysis and computer vision to identify forest fire-affected areas. The extent,

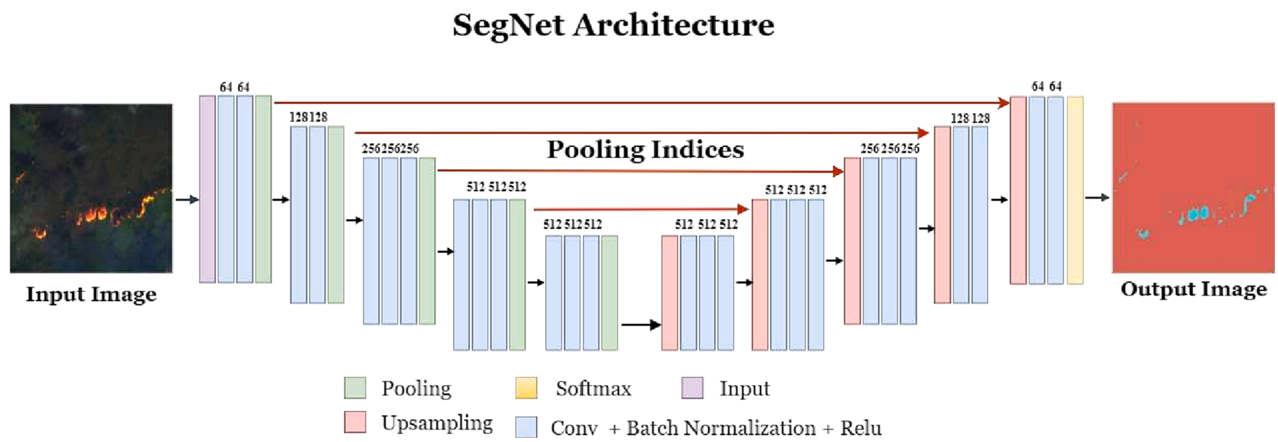

Fig. 3. SegNet for Forest Fire Detection.

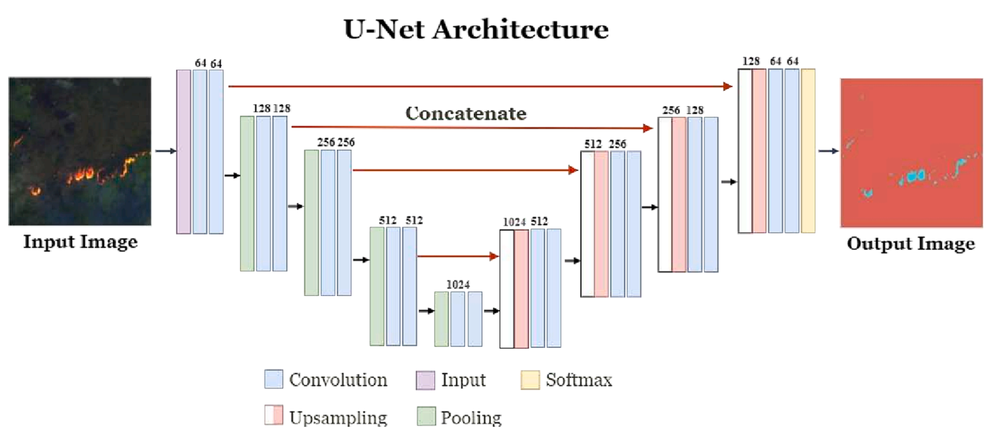

Fig. 4. U-Net for Forest Fire Detection.

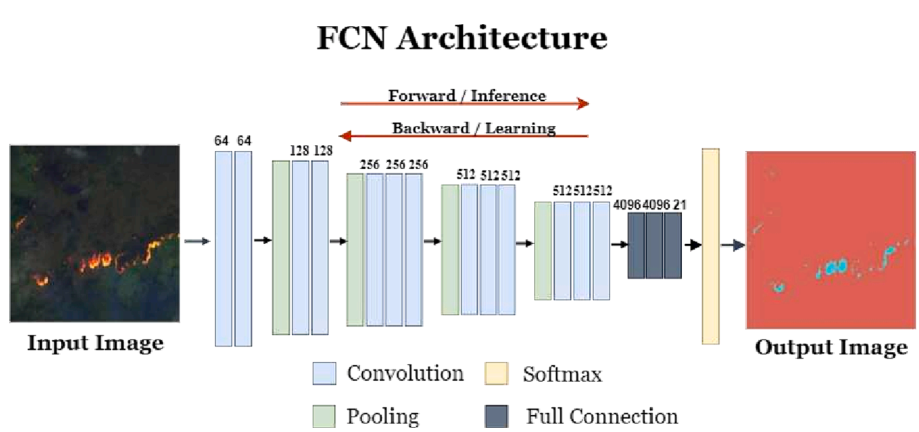

Fig. 5. FCN for Forest Fire Detection.

location, and intensity of the fires must be recognized for appropriate monitoring, evaluation, evacuation, and recovery. It helps construct predictive models for future fire behavior and analyze prospective dangers for early fire spot detection. (Guan et al., 2022).

In recent years, Deep learning segmentation algorithms can recognize and analyse complex patterns and characteristics in satellite or aerial photos, especially for forest fires (Alkhatib et al., 2023). Segmentation-based CNNs are widely used because they can gain hierarchical visual data representations, local pattern recognition, and fire-related spatial element discrimination. This review examines CNN-based deep learning segmentation methods for forest fire detection. Most segmentation applications detect forest fire hotspots. U-Net is the most popular forest fire model reviewed. Some applications use HR-Net, which has high-resolution feature representation capabilities, for forest fire detection. Using these methods comprehensively segments forest fires and improves wildfire management and response.

Some works, such as by de Almeida Pereira et al., 2021 have proposed several variants of the U-Net model. They have introduced three CNN architectures for active fire detection, in which each variant is trained and tested to approximate five different fire situations. Each of the three considered sets of conditions is comprehensively combined to produce 15 test scenarios. The three CNN variants are U-Net (10c), U-

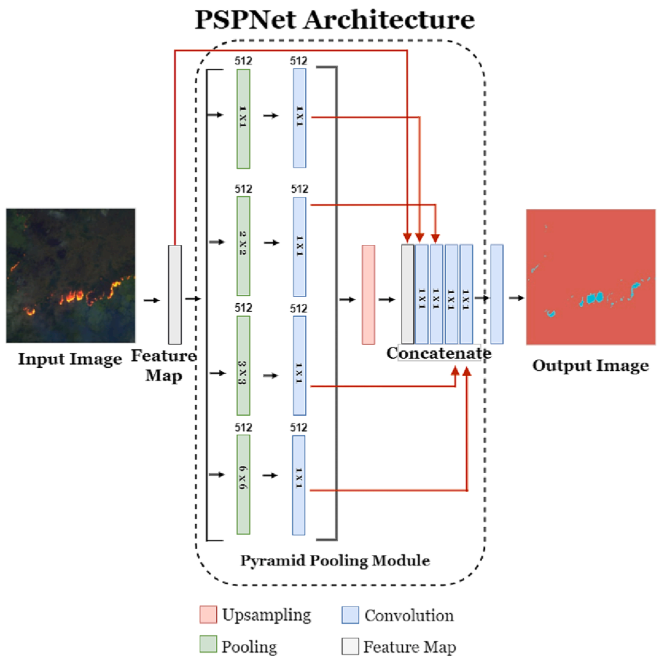

Fig. 6. PSPNet for Forest Fire Detection.

Net (3c), and U-Net-Light (3c), whereby channels c7, c6, and c2 of the satellite image were found to contain most of the information needed for detecting active fire. The CNNs successfully mapped the target masks, considering the presence of fire in a certain small area, with most differences at the pixel level being relatively small. Recently, Hong et al. (2022a) proposed a unique Fire Detection Convolutional Neural Network (FireCNN) model, which is compared with five other methods for performance benchmarking. These methods include a traditional thresholding method, machine learning methods such as Support Vector Machine and Random Forest, and deep learning methods like Back Propagation neural network and simpleCNN. For further analysis, Table 1 summarizes several related works that have used automated mapping through segmentation algorithms for forest fire applications.

5.1.1. Deep learning and Machine learning method in forest fire application

Deep learning and machine learning approaches have been increasingly useful in forest fire application, improving early detection, prediction accuracy, and resource allocation efficiency. Through the utilization of advancements in artificial intelligence and data analytics, these methodologies facilitate a thorough examination of diverse environmental variables. For further analysis, Table 2 summarizes comparison performance deep learning and machine learning algorithms for forest fire applications.

5.2. Segmentation in earthquake

Segmentation application is used in earthquake disaster management to identify and delineate seismically active zones using satellite or aerial imagery. For earthquake analysis, a deep CNN model is trained using annotated satellite pictures to map each pixel to damaged or undamaged areas for disaster severity assessment. The trained deep model identifies visual signs of structural failures, residual fragments, and environmental changes (Bao et al., 2021; Li et al., 2023). After training, the deep CNN model may be used in real time to analyze the latest images, detect and distinguish devastated areas, and create complete maps of the affected regions. The computerized segmentation technique will quickly and accurately assess earthquake-related destruction, helping emergency responders and decision-makers allocate recovery resources (Shafapourtehrany et al., 2023). This subsection summarizes previous studies that use deep segmentation techniques based on CNN architecture to detect earthquake-induced damages. The review also includes the CNN models used to identify cracks that manifested after the earthquake, which is crucial in identifying damaged buildings.

Several previous works that have utilized segmentation techniques for earthquake-related applications are summarized in Table 3.

5.2.1. Deep learning and Machine learning method in earthquake applications

The integration of deep learning and machine learning methods in earthquake applications represents a significant advancement in seismology and disaster management, offering innovative approaches to earthquake detection, prediction, early warning systems, structural damage assessment, and post-event analysis. For further analysis, Table 4 summarizes comparison performance deep learning and machine learning algorithms for earthqauke applications.

5.3. Semantic segmentation for flood applications

Automated segmentation helps flood disaster management locate and map flood-affected areas. Floods are common global natural disasters produced by natural and artificial causes (Chaudhary et al., 2021). Thus, image processing and deep learning, particularly the CNN architecture, must be used to automate flood-affected areas to recognize visual patterns associated with rising water levels and submerged structures. Flood disaster management uses deep learning and semantic segmentation to assess flooding severity. Labeling each pixel in an image helps assess flooding, infrastructure damage, and risk. Deep CNN models automatically assess flood-affected areas quickly and accurately (Muhadi et al., 2021). CNN architecture-based flood catastrophe detection technologies include PSPNet, Deeplab, FCN, SegNet, and U-Net. This computerized mapping of flooded areas will improve flood disaster analysis and response techniques. Several flood disaster management studies have used segmentation, which are summarized in Table 5.

5.3.1. Deep learning and Machine learning method in flood disaster applications

Deep learning and machine learning techniques are revolutionizing flood disaster management by identifying, forecasting, evaluating potential hazards, implementing early warning systems, and analyzing flood occurrences. These advancements address the global impact of floods on infrastructure, human lives, and economic disruptions, highlighting the need for improved methodologies to understand, observe, and address these catastrophic disasters. Table 6 summarizes comparison performance deep learning and machine learning algorithms for flood disaster applications.

6. Discussion

In light of the methods discussed earlier, three standout models have garnered significant interest: basic CNNs, U-Net, and DeepLab. Here, we present a case study that delves into the current status, challenges, and future prospects of these methods. This study serves to offer a comprehensive grasp of the status and potential of these methods in the realm of natural disaster research.

In this review, previous forest fire disaster research has leveraged advanced CNN architectures to detect active fires in satellite imagery with high accuracy. High-resolution imagery aids in identifying smaller fires, facilitating early detection and swift firefighting responses. Temporal analysis tracks fire progression, aiding in predicting its future spread. Multispectral and hyperspectral data distinguish between fire, smoke, and other land cover types, reducing false positives. Beyond basic CNN models, deep learning techniques like U-Net and HRNet have enhanced classification accuracy and served as performance benchmarks. U-Net, particularly, improves the detection and delineation of

Table 1
The Application of Automated Segmentation Techniques in Forest Fire Disaster Management.

Literature	Target Task	Network Structure	Sensor Data	Method	Strength	Weakness
de Almeida Pereira et al. (2021)	Detection Active Fire	U-Net	Landsat-8 Satellite	U-Net base model with three variants are considered: U-Net (10c), U-Net (3c), and U-Net-Light (3c), each with varying approximations for bandwidth, memory usage, and storage space.	CNNs excel in active fire detection due to their ability to accurately approximate handcrafted-based algorithms and encode complex rules with precise weights, coefficients, and thresholds.	Human-readable rules and potential false detections in urban areas, necessitate different approaches like temporal analysis to address persistent errors.
Hong et al. (2022a)	Detection Active Fire	CNN	Himawari Satellite	The active fire detection system uses a novel convolutional neural network (FireCNN) based on Himawari-8 satellite images to extract accurate fire spot characteristics.	The FireCNN model, incorporating multi-scale convolution and residual structure, improving fire detection accuracy by 35.2 %, enables real-time application	Limited dataset, regional focus, and lack of environmental factors may affect the model's generalizability and applicability across different regions and environmental conditions.
Seydi et al. (2022)	Improve the detection of active fires using remote sensing (RS) technologies	Multiscale-CNN	Landsat-8 Satellite	The active forest fire detection task utilizes machine learning classifiers like KNN and SVM, utilizing multiscale-residual convolution layers-based architecture strategies like multiscale kernel convolution, residual blocks, and Depth/Point-wise convolution block.	The comprehensive approach includes initial data screening, partitioning, detection of thermal anomaly pixels, contextual analysis, and confirmation of thermal anomaly pixels for more accurate fire detection.	The detection of small fires and non-fire objects can be problematic, especially when dealing with medium and low-resolution RS datasets like VIRIIS, MODIS, and Sentinel-3
Zhang et al. (2021)	Accuracy of the active fire with a large number of small fire objects	DCPA + HRNetV2	Sentinel-2 Satellite	DCPA + HRNetV2 network, which is trained on the dataset constructed using SWIR, NIR, and red bands in Sentinel-2 Level-2C products	The framework uses a DCPA + HRNetV2 network for active fire detection, achieving high accuracy with an average IoU of over 70 % for a 20 m spatial resolution.	The dataset, which contains numerous small fire regions, may overestimate results due to synergy between the AFD-S2 method and Sentinel-2 band combinations, with some omitted fires and mislabelled pixels.
Rostami et al. (2022)	Develop a new efficient Convolutional Neural Network (CNN) architecture for Active Fire Detection (AFD) in satellite imagery	CNN	Landsat-8 Satellite	This study created a robust MultiScale-Net architecture, utilizing data augmentation techniques to enhance generalization and minimize overfitting, particularly in limited data availability.	The MultiScale-Net architecture, developed using Landsat-8 imagery, has demonstrated robust performance in active fire detection, extracting various-sized fires under various geographical and illumination conditions.	The study utilized Landsat-8 images for active fire detection but did not test its performance on other satellite imagery or address any possibility of cloud interference.
Ghali et al. (2023)	To identify and locate active fires	Convolutional Networks such as VGGNet, DenseNe, ResNet, and SE-Net, FCN	Sentinel-2 and Landsat-8 Satellite	This study explores data augmentation techniques for fire detection, mapping, and damage prediction using satellite imagery, combined mathematical models, artificial intelligence, and hybrid intelligence systems for forest fire danger modeling.	Employs various deep learning models like VGGNet, DenseNet, ResNet, SE-Net, FCN, PSPNet, SegU-Net, Unet++, and U-Net for fire detection, mapping, damage prediction, and satellite remote sensing data processing.	The accuracy of deep learning models heavily relies on the quality of satellite remote sensing data, as any errors or inaccuracies can significantly impact their performance.
Kang et al. (2022)	To reduce the detection latency, or the time it takes to detect a fire after it has started	CNN	Himawari Satellite	The detection algorithm, using data from the Himawari-8 Advanced Himawari Imager, reduced detection latency and false alarms using Random Forest and Convolutional Neural Network techniques, outperforming the RF model in accuracy, precision, recall, and F1-score.	A CNN model outperformed Random Forest in detecting forest fires, achieving accuracy, precision, recall, and F1-score, detecting all fires within 12 min and even earlier than recording time.	The CNN approach's effectiveness is limited by a 40 % missing value ratio within 9 x 9 windows, potentially causing false alarms and inaccurate fire detection results.
Wang et al. (2022b)	A wildfire smoke detection algorithm	U-Net	Landsat-8 Satellite	The study used a deep learning Smoke-Unet in semantic segmentation experiments, utilizing neural network algorithms, SVM classifiers, K-means clustering, and Fisher linear classification.	The study introduced a novel algorithm, Smoke-Unet to enhance remote sensing smoke features and reduce data redundancy, undergoing extensive experiments to evaluate its performance.	The study focuses on selected wildfire-prone regions like the USA, Canada, Brazil, and Australia.

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Table 1 (*continued*)

Literature	Target Task	Network Structure	Sensor Data	Method	Strength	Weakness
Martins et al. (2022)	Classify satellite imagery into burned or unburned classes using a U-Net architecture	U-Net	Landsat-8 Satellite	The U-Net architecture classifies 256x256 pixel patches into burned or unburned classes using green, red, and NIR surface reflectance from PlanetScope and Landsat-8 OLI images.	The study validated a radiometric normalization method for PlanetScope images, demonstrating high classification accuracy, and emphasizing the need for fine-tuning the U-Net model for improved transferability and burn classification.	The study reveals that per-pixel confusion-matrix results struggle to distinguish between omission and commission errors due to misclassification of burned patches and surface changes.
Shamsoshoara et al. (2021)	Accurately localizing and extracting fire regions	U-Net	UAV-Drone	Classifies camera frames as fire or non-fire, using the normal range spectrum of images using U-Net Architecture	high specificity in fire detection, with a reported specificity of 99.96 % (). This indicates that the method is highly effective in correctly identifying non-fire instances, minimizing the likelihood of false positives in fire detection scenarios	Fire detection and segmentation is the reliance on binary classification of video frames based solely on the presence or absence of fire flames, which achieved a classification accuracy of 76 %
Shahid et al. (2023)	Accurate and early detection of forest fires	U-Net	UAV-Drone	The proposed method uses a multi-stage fire detection approach combining CNN and LSTM networks to detect forest fires in UAV videos, aiming to reduce false alarms and achieve lower computational cost and higher accuracy in an IoT application context.	High accuracy and adaptability to natural corruption, as evidenced by an F1-Score ranging from 0.809 to 1 and an accuracy of up to 0.979. the model demonstrates a strong correlation between fire pixels in keyframes and reference frames within a temporal window, indicating its effectiveness in detecting fire pixels accurately	Decreased robustness in certain types of natural corruption, such as motion blur, Gaussian noise, and fog. There is a notable decrease in Intersection over Union (IoU) values when these conditions are present. Specifically, the IoU decreases by 2 %∼4% in foggy weather, 6 %∼8% with Gaussian noise, and 10 % ∼14 % with motion blur

Table 2
Comparison Deep Learning and Machine Learning Method in Forest Fire Applications.

Model	Literature	Target Task	Result	Wavelength Type
Deep Learning				
U-Net	de Almeida Pereira et al. (2021)	Detection Active Fire	Prec: 91.8 %, Rec: 0.972, F1: 0.897, IoU: 0.814	Multispectral
Fire CNN	Hong et al. (2022a)	Detection Active Fire	Prec: 98 %, Rec: 99 %, Acc: 89.7 %, IoU: 0.814	Multispectral
FireNet (CNN Based)	Seydi et al. (2022)	Improve the detection of active fires using remote sensing (RS) technologies	Prec:95.98 %, Rec: 98.04 %, Acc: 97.24 %, IoU: 0.99	Multispectral
HRNet	Zhang et al. (2021)	Accuracy of the active fire with a large number of small fire objects	Australia dataset IoU: 73.4 %, US dataset IoU: 76.2 %	Multispectral
Deep Multiple Kernel Learning (CNN Based)	Rostami et al. (2022)	Develop a new efficient Convolutional Neural Network (CNN) architecture for Active Fire Detection (AFD) in satellite imagery	Precision: 91.56 %, F1: 0.9058, IoU: 0.8279	Multispectral
CNN Based	Ghali et al. (2023)	To identify and locate active fires	FireCNN Acc: 99.50 %, FCN Acc: 99.50 %, CNN: 96.48 %, FU-NetCastV2 = 94.60 %	Multispectral
CNN	Kang et al. (2022)	To reduce the detection latency, or the time it takes to detect a fire after it has started	Precision: 91 %, Rec: 0.63, F1: 0.74, Acc: 98 %	Multispectral
Smoke-UNet	Wang et al. (2022b)	A wildfire smoke detection algorithm	Recall: 83.8 %, F1:0.0775, Acc: 72 %	Multispectral
U-Net	Martin et al. (2022)	Classify satellite imagery into burned or unburned classes using a U-Net architecture	Confident Threshold = 0,9, CE = 2.51 %, OE = 11.25	Multispectral
U-Net	Shamsoshoara et al. (2021)	Accurately localizing and extracting fire regions	Precision: 91.99 %, Recall: 83.88 %, F1 = 87.75 %, IoU = 0.7817	Multispectral
FPS-U-Net	Shahid et al. (2023)	Accurate and early detection of forest fires	Acc = 97.9 %, Precision = 96.3 %, Recall = 0.94, F1 = 0.95, IoU = 0.868	Multispectral
Machine Learning				
RF-FR	Mohajane et al. (2021)	Forest fire mapping	Acc: 90,4%, Prec:0.91 %, Sens: 0.89, Speci: 0.91	Multispectral
BRT	Pourghasemi et al. (2020)	Identify forest fires zones and assess	Acc: 83 %, Prec: 82 %, F1: 0.84, Fallout: 0.17, Speci: 0.86, Sensi:0.81, TSS: 0.67	Multispectral
BN	Pham et al. (2020)	Predicting and mapping fire susceptibility	PPV: 100, NPV: 88,24, SST: 89,47, SPF:100, Acc: 94,12 %, Kappa: 0.88	Multispectral

Table 3
The Application of Automated Segmentation Techniques in Earthquake Disaster Management.

Literature	Target Task	Network Structure	Sensor Data	Method	Strength	Weakness
Chen et al. (2022)	Assessing post-earthquake disasters and requires a model that can accurately and quickly identify cracks	VGG16 as the base	Small multi-rotor UAV	The 16-layer VGG16 network was optimized for deep learning semantic segmentation, enhancing image features and combining multi-scale information for improved segmentation results	The study proposes a workflow using convolutional neural networks to extract cracks from post-earthquake UAV images, enabling efficient surface rupture detection using medium-sized UAVs and a CA103 ortho camera.	The deep learning method effectively identified cracks in high-precision UAV images, but it sometimes failed to accurately identify cracks or falsely identified as non-crack features.
Song et al. (2020b)	To extract earthquake-damaged buildings from post-earthquake images	DeepLab v2	ADS40-Airborne	This study used SAE, CNN, and SLIC methods for super-pixel segmentation, enabling accurate extraction of earthquake-damaged buildings from post-earthquake images, potentially saving time in future rescue measures.	Experimental results confirmed the effectiveness of the DeepLab v2 and SLIC super-pixel segmentation method in accurately identifying damaged buildings after an earthquake event.	The study utilized eight sub-areas from ADS40 digital aerial images, yielding promising results, but its effectiveness in other areas or different types of images remain unknown.
Jia and Ye (2023)	Review the application of Deep Learning (DL) for Earthquake Damage Assessment (EDA) from four dimensions	CNN,AlexNet, VGGNet, ResNet, Inception, Xception, DenseNet, SqueezeNet, and MobileNet	Optical Remote Sensing Satellite, Synthetic Aperture Radar (SAR), Interferometric Synthetic Aperture Radar (InSAR) and UAV	Various deep learning models, such as CNN, MLP, TL, RNN, GAN, and hybrid models, are tested for EDA to automate building characterization and seismic risk assessment.	This research uses various DL models like CNN, MLP, GAN, RNN, TL, and hybrid, analyzing each respective model's advantages, disadvantages, functions, and application stages in EDA.	The tested data quality is relatively low due to insufficient image resolution, limited information conveyed by the images, coupled with noise interference.
Xia et al. (2022)	Quickly assess building damage after earthquakes	BDANet-CNN Base	Very High Resolution (VHR) satellite and synthetic aperture radar (SAR) satellite	This model evaluates the extent of damage to buildings using high-resolution earthquake imagery. It achieves enhanced accuracy in detecting damage by including multi-scale feature fusion and cross-directional attention techniques.	Robust and versatile for rapid building damage assessment in disaster-stricken areas, enhancing detection accuracy, m and prioritizing rescue efforts while reducing training time.	Limitations in identifying buildings with similar coloration and predicting accuracy for atypical buildings, requiring further optimization for diverse environments.
Huang et al. (2019)	Improve the classification accuracy of earthquake damage images	Combined Multiscale Segmentation (CMSCNN)	Very High Resolution (VHR) Satellite	The CMSCNN is used for earthquake damage mapping, improving classification accuracy by considering spatial information in high-resolution VHR images.	Enhances the accuracy of object classification and boundary delineation in very high-resolution images	CNNs' insensitivity to object boundaries and CMSCNN's limitations in dealing with complex spatial information and varied object scales in high-resolution remote sensing images can lead to misclassifications.
Hu et al. (2022)	To detect faults in seismic amplitude images	VGG16 Net-CNN	Seismic Sensor	A CNN model was trained on a small dataset of seismic amplitude images, refined using skeletonization method, and further refined using a postprocessing method.	The proposed method simplifies the VGG16 model to identify faults in seismic data, improving accuracy and mean intersection over conventional CNN and LargeFOV methods.	The study employs a small dataset for training a model, indicating its potential limitations in generalizability to other seismic data, and its performance on a larger, more diverse dataset is untested.
Jena et al. (2020)	Predict earthquake events and develop a probability map for the Indian subcontinent	CNN	Landsat-8 Satellite	Used a deep learning model, specifically a CNN model to predict earthquake events and develop a probability map	The model achieved an accuracy of 92.05 % in earthquake prediction and probability mapping, classifying earthquake (1) and non-earthquake (0) values, providing a comprehensive understanding of potential earthquake events.	The model's generalizability may be limited due to testing samples from India only, which may not cover other geographical regions with varying seismic characteristics.

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Table 3 (*continued*)

Literature	Target Task	Network Structure	Sensor Data	Method	Strength	Weakness
Hong et al. (2022b)	Designed to extract semantic information of different damage levels	CNN	UAV	EBDC-Net is a framework comprising a feature extraction encoder module and a building damage classification module, designed to extract semantic information from post-disaster aerial images.	The study introduces a novel CNN model, EBDC-Net, designed for identifying building damage from aerial images, demonstrating high accuracy in classifying buildings with varying damage levels.	The model's performance is highly dependent on the quality of post-disaster aerial images, with poor quality or high noise levels potentially affecting its performance.
Yang et al. (2021)	Capture the damage information of buildings after an earthquake	CNN	High-resolution satellite	The study employs a hierarchical fuzzy logic model, deep learning, and 3D point cloud features from aerial images for earthquake damage detection, fine-tuned using a Convolutional Neural Network, and traditional machine learning methods for high accuracy.	Hierarchical type-2 fuzzy logic models and deep learning enable rapid evaluation of earthquake hazard safety in buildings, while high-resolution images and 3D point cloud features provide comprehensive data for disaster damage detection.	The models were impacted by an imbalance in the distribution of training samples, a common issue in earthquake disaster preparation, affecting the accuracy of the network model.
Bilal et al. (2022)	Predict seismic events from continuous data collected by seismic stations	CNN	Waveforms (BHN, BHE, and BHZ) seismic sensor	The study uses CNN, GNN, and RNN models for earthquake prediction, aiming to minimize societal impact by predicting seismic events from continuous data and applying it to early warning systems.	A novel deep learning model for earthquake prediction, combining graph convolutional neural network, batch normalization, and attention mechanisms, thus outperforms baseline models in accurately estimating earthquake parameters.	The model's performance in other locations and under different seismic conditions is unknown, as it was tested on datasets from Alaska and Japan only.
Masoud et al. (2022)	Damage assessment and damage recognition after earthquake	U-Net	VHR satellite	Using Unet architecture aims to offer a flexible damage map according to the information available, whether it involves data before and after the earthquake or only post-event data	Offers a faster assessment, achieving a final damage map in less than 7 h, making it crucial for emergency response management and recovery planning.	Additionally, the accuracy of the method is impacted by the labeling of damage, with a pixel-based approach being more accurate but also having its limitations.
Gupta et al. (2021)	Identification of damaged areas and accessible roads in post-disaster scenarios	U-Net, VGG16 ResNet34	Satellite-Synthetic Aperture Radar (SAR) and high-resolution optical images	Utilized UNet and LinkNet architectures to update OpenStreetMap (OSM) data, thereby identifying accessible routes in the aftermath of the disaster.	OpenStreetMap for training, graph theory for precise network updates, and pretraining segmentation models on ImageNet for improved accuracy and convergence speed. This combination makes it a powerful tool for disaster response mapping, accurately identifying impacted areas and accessible roads.	Need for extensive manually annotated data, making it unsuitable for rapid disaster analysis. OpenStreetMap (OSM) data, though used for training, is considered weakly labeled due to issues like mis-registration and outdated labels, potentially limiting the accuracy and reliability of the models.

scorched regions in satellite images. Its architecture incorporates global and local feature extraction, enhancing segmentation performance. By integrating skip connections, U-Net enables precise detection of forest fire spots at high resolutions. Data augmentation and comprehensive evaluation metrics like IoU or F1-score provide valuable insights into U-Net's impact on forest fire research.

The integration of HRNet with other approaches consistently produces excellent results in accurately segmenting burned areas or recognizing fire patterns in satellite images. HRNet's ability to preserve significant spatial information enhances segmentation efficiency, crucial for comprehending and detecting regions impacted by forest fires. It accurately identifies subtle borders between affected and unaffected areas and addresses segmentation challenges with high-resolution data. Some studies integrate satellite and ground sensor data to improve fire detection reliability, enabling real-time processing for timely evacuation and firefighting. Deep learning models require extensive annotated ground truth data for validity, where satellite data proves suitable, facilitating global fire detection even in remote areas. Encouraging open-source tools and deep models can replicate successful fire detection methods, showcasing the potential of remote sensing technologies for forest fire detection, crucial for disaster management and environmental protection.

Conversely, one major weakness identified in forest fire disaster studies is false alarms and inaccuracies stemming from the small 9 x 9 windowing approach, leading to misclassification of burned patches and surface changes. Detecting small fires and non-fire objects proves challenging, particularly with medium or low-resolution satellite imagery like VIRIIS, MODIS, and Sentinel-3. Cloud interference further obscures

Table 4
Comparison Deep Learning and Machine Learning Method in Forest Fire Applications.

Model	Literature	Target Task	Result	Wavelength Type
Deep Learning				
VGG16	Chen et al. (2022)	Assessing post-earthquake disasters and requires a model that can accurately and quickly identify cracks	Acc: 98 %, F1: 0.51, mIoU: 0.50	Spatial
Deeplab V2 with SLIC	Song et al. (2020b)	To extract earthquake-damaged buildings from post-earthquake images	Overall Acc: 98.50 %	Spatial
CNN,AlexNet, VGGNet, ResNet, Inception, Xception, DenseNet, SqueezeNet, and MobileNet	Jia and Ye (2023)	Review the application of Deep Learning (DL) for Earthquake Damage Assessment (EDA) from four dimensions	YOLOv4-based object detection acc = 95.7 % and SVM-based damage classification acc = 97.1 %.	Spatial
BDANet-CNN Base	Xia et al. (2022)	Quickly assess building damage after earthquakes	Prec: 80.43 %, Rec: 84.17 %	Spatial
Combined Multiscale Segmentation (CMSCNN)	Huang et al. (2019)	Improve the classification accuracy of earthquake damage images	OA: 96.88 %. Kappa: 0.96	Spatial
VGG16 –CNN	Hu et al. (2022)	To detect faults in seismic amplitude images	Acc: 93.98 %, mIoU: 0.5289	Seismic wave signals
CNN	Jena et al. (2020)	Predict earthquake events and develop a probability map for the Indian subcontinent	Acc: 92.05 %	Spatial
CNN	Hong et al. (2022b)	Designed to extract semantic information of different damage levels	OA: 95.86 %, Kappa: 0.91, MSE: 0.04	Spatial
DenseNet121	Yang et al. (2021)	Capture the damage information of buildings after an earthquake	Acc: 82.1 %, F1 = 0.80, Kappa = 0.64, Prec. Damage = 86.8 %	Spatial
CNN	Bilal et al. (2022)	Predict seismic events from continuous data collected by seismic stations	Alaska RMSE: Small: 1.62, Medium: 2.57, Large: 2.87 – Japan RMSE: Small: 2.21, Medium: 2.43, Large: 2.66.	Spatial
U-Net	Masoud et al. (2022)	Damage assessment and damage recognition after earthquake	Acc: 69.71 %, Kappa: 37.7 %	Multispectral
U-Net, VGG16 ResNet34	Gupta et al. (2021)	Identification of damaged areas and accessible roads and building in post-disaster scenarios	IoU Road: 41.13, IoU Building: 60.04	Spatial
Machine Learning				
LSTM	Wang et al. (2020c)	Prediction earthquake damage in different location.	Acc without Decomposition: 82.42 %, Acc with Decomposition: 87.59 %	Spatial
ANN	Khan et al. (2020)	Improve earthquake detection using ML	Acc: 94.02 %, Prec: 93.12 %, Rec: 0.9518, F1:0.9414	Spatial
RF	Apriani et al. (2020)	Estimation of earthquake magnitudes from seismogram data	Acc: 80 %, Log Loss: 69 %	P wave
SVM	Chanda et al. (2021)	Estimating Magnitude and Location of an Earthquake	For elevation angle with different level of noises – RMSE: 0.0056, R-Squared: 1.0, MSE:0.00003, MAE: 0.0015 (without noise – RMSE: 0.0127, R-Squared: 1.00, MSE: 0.0001, MAE: 0.011 (1 % Noise) – RMSE: 0.0094, R-Squared: 1.00, MSE: 0.00008, MAE: 0.003 (3 % Noise)	P Wave and S Wave
RFR	Ghimire et al. (2022)	Seismic damage prediction at a regional scale	Acc: 0.49 (Damage Grade), MAE: 0.69, MSE: 0.81	Spatial

the ground view, impacting fire detection accuracy. The dataset quality heavily relies on satellite remote sensing data, where errors can significantly affect deep learning model performance. Good quality datasets may still pose overfitting risks, especially with limited data availability, limiting model generalizability. Limited testing across satellite data types may cause performance degradation on other remote sensing platforms. Addressing these weaknesses necessitates further research and development to enhance the accuracy and reliability of fire detection using remote sensing technologies. The most commonly used remote sensing data in forest fires are satellites with landsat-8 and himawari types. Landsat-8 and Himawari satellites are widely used for monitoring forest fires due to their unique features. Landsat-8 provides detailed images of forested areas, while Himawari offers higher-resolution data for broader coverage. Both satellites offer frequent revisits, with Landsat-8 orbiting Earth every 16 days and Himawari providing near-real-time data updates every 10 min. This temporal resolution allows for continuous monitoring of fire dynamics, enabling timely response efforts. The multispectral sensors onboard capture data across visible, near-infrared, and thermal bands, enabling the detection of fire signatures like smoke, heat, and vegetation health changes. The accessibility of these data and their integration with other data sources enhances fire detection and management capabilities. Thus, Landsat-8 and Himawari satellites are indispensable tools in the fight against forest fires worldwide.

Deep learning methods, such as U-Net, Fire CNN, and HRNet, effectively detect active fires from satellite data with exceptional precision, recall, and accuracy. The models provide strong performance metrics, characterized by precision rates over 90 % and recall rates nearing 99 %. These results confirm their efficacy in properly detecting instances of fire. FireNet and Deep Multiple Kernel Learning models demonstrate significant enhancements in detection accuracy, surpassing precision and recall rates of 95 % and 98 % respectively. Furthermore, FPS-U-Net places significant emphasis on the significance of early detection, attaining elevated levels of accuracy, precision, recall, and IoU scores. These metrics are of utmost relevance in facilitating prompt fire management and mitigation endeavors.

On the other hand, in the field of fire mapping and susceptibility prediction, machine learning methodologies such as RF-FR, BRT, and BN employ conventional techniques such as Random Forest, Boosted Regression Trees, and Bayesian Networks. Although the accuracy values of these methods range from 83 % to 90 %, they frequently display significantly worse precision and recall in comparison to deep learning

Table 5
The Application of Automated Segmentation Techniques in Flood Disaster Applications.

Literature	Target Task	Network Structure	Sensor Data	Method	Strength	Weakness
Pally et al. (2022)	Image recognition and classification, specifically for detecting and identifying objects within images	CNN	US department of Transportation (DOT) 511 traffic cams and USGS River Web Camera	Utilize deep learning models to detect and identify objects within images. Fast R-CNN and Mask R-CNN process the image, extract feature vectors, and produce SoftMax probabilities.	Deep learning techniques like Fast R-CNN and Mask R-CNN enable efficient object detection and identification in images, processing entire images, producing feature maps, and extracting fixed-length vectors.	Deep learning techniques struggle to detect small objects due to image resizing, object appearance variations, pose, illumination conditions, and clutter, which can fool the recognition systems.
Basnyat et al. (2021)	Enhance the vision capability of the Floodbot by implementing semantic image segmentation for flood detection	U-Net, CNN	FloodBot's camera	The Floodbot uses deep learning models to identify flood risk areas by capturing images and performing real-time semantic segmentation using a standard U-Net model.	The research employs a U-Net model for image segmentation, achieving 82 % and 84 % accuracy in standard and modified U-Net with dropout, respectively, for decision support in natural scene parsing.	The U-Net model's performance is influenced by the quality of the training data, weather conditions, and regular landmass shape, affecting its ability to accurately predict segmentation mass.
Daud et al. (2023)	Segmentation in post-disaster high resolution aerial images	Multi-scale CNN	Satellite	Res-inception unit in the encoder and decoder modules and utilizes PSPNET as the bridge module	Res-inception units enhance flood segmentation accuracy by capturing detailed information, while PSPNET enhances scene context understanding.	The proposed framework's performance on other datasets may vary, and fine-tuning may be necessary for optimal results due to the challenging and publicly available dataset.
Safavi and Rahnemoonfar (2023)	Post-disaster aerial imagery datasets	CNN	UAV-Drone	Comparative study methods used in flood segmentation like UNet, UNetFormer, HarDNet, SegFormer, BiSeNetV1, BiSeNetV2, DDRNet, PIDNet.	Lightweight segmentation models, achieving over 60 % intersection over union on FloodNet dataset and qualitative image results, highlight the importance of balancing accuracy and efficiency in real-time aerial-scene segmentation of UAV systems.	Real-time semantic segmentation neural networks rely on human-centric datasets, unsuitable for aerial applications due to a lack of annotated aerial images during catastrophic events.
Maryam et al. (2021)	Image classification, semantic segmentation, and visual question answering (VQA)	VGGNet, ResNet, InceptionNet, Xception, MobileNet, FCN, PSPNet and DeepLab	UAV	Uses various networks for image classification, semantic segmentation, VQA, and feature extraction, including VGGNet and Two-Layer LSTM, for semantic segmentation and feature extraction.	FloodNet, a unique dataset of small UAV imagery for disasters, uses high-resolution images for clarity, semantic segmentation, VQA, and image classification.	This paper's models rely on high-resolution images from low altitudes, but their effectiveness in other natural disasters is not tested or guaranteed.
Binayak et al. (2022)	Improve flood detection	U-Net and Feature Pyramid Network (FPN)	Sentinel-1 Satellite	Two deep learning models, UNet and Feature Pyramid Network, were used, both based on EfficientNet-B7′s backbone.	NASA's Sentinel-1 dataset offers diverse flood events, demonstrating potential for scalable flood detection using deep learning models, allowing for efficient, automatic, and scalable coverage of larger areas.	The authors suggest a more specific classification for floods, including open, flooded vegetation, and urban floods, as the current binary classification models may not accurately represent all flood types.
Wu et al. (2023)	Improve the efficiency of flood detection and mapping	FCN-8, SegNet, UNet, and DeepResUNet	Sentinel-1 Satellite	The study utilizes synthetic Aperture Radar (SAR) images and deep learning models like FCN-8, SegNet, UNet, and DeepResUNet for real-time flood detection and automatic mapping.	The study utilized Sentinel-1 SAR images and 12.5 m DEM for high-quality data, compared four deep learning models for flood detection, and evaluated their effectiveness using metrics like accuracy, precision, recall, and F1-score.	The study uses Sentinel-1 SAR images for flood detection in the Yangtze River Basin only, but its limitations and applicability to other regions are not highlighted.
Hernández et al. (2021)	Create a real-time segmentation system embedded in a UAV.	U-Net	UAV-Drone	The study combined deep learning and semi-supervised learning techniques to segment aerial images of flooded areas using the FloodNet dataset, focusing on image segmentation.	The FloodNet dataset, capturing Hurricane Harvey images, enhances the study's relevance. Its focus on semantic segmentation and low-power GPU-based edge computing devices, thus enhances its novelty and practicality.	The study acknowledges the limitations of deep learning models, including memory size and execution on different edge devices, potentially affecting the solution's scalability.
Thapa et al. (2022)	Automate the process of accurate flood and drought recognition in paddy fields	Deeplabv3 model with ResNet-50 as a feature extractor	Mobile Camera Application	Pixel-based semantic segmentation uses the Deeplabv3 model with ResNet-50 for disaster image segmentation, while object-based scene recognition uses ResNet-18 model for 365-classification.	The object-based method, trained using location-tagged images from a mobile application, offers superior accuracy, data preparation, computational speed, and cost, enhancing the practical relevance of research.	Poor-quality images from farmers and incorrect camera viewing angles make disaster detection challenging. The DeepLabV3 + model misclassifies pixels in the water body training dataset, causing incorrect predictions.
Munoz et al. (2021)	Trained with single, double, and triple dataset	CNN	Landsat Satellite	CNN uses multispectral imagery, radar, and digital elevation models to map flood areas, distinguishing between permanent water bodies and floodwater, and generating comprehensive images.	The model uses two-dimensional convolution, rectified linear units, and average pooling operations to extract feature information from patch images, integrating low, mid, and high levels of feature abstraction.	Uncertainty in input data, model structure, and parameters can lead to misclassification and prediction errors. Acquired dates of SAR data may reduce flood extent and match the coastal watermarks.

Table 6
Comparison Deep Learning and Machine Learning Method in Flood Disaster Applications.

Model	Literature	Target Task	Result	Wavelength Type
Deep Learning				
CNN	Pally et al. (2022)	Image recognition and classification, specifically for detecting and identifying objects within images	IoU = 75 %, Precision = 69.9 %, Recall = 79 %,	Spatial
U-Net, CNN	Basnyat et al. (2021)	Enhance the vision capability of the Floodbot by implementing semantic image segmentation for flood detection	IoU = 0.82, Dice = 0.84	Spatial
Multi-scale CNN	Daud et al. (2023)	Segmentation in post-disaster high resolution aerial images	mIoU = 84.72 %	Spatial
CNN	Safavi and Rahnemoonfar (2023)	Post-disaster aerial imagery datasets	mIoU = 61.6 %	Spatial
VGGNet, ResNet, InceptionNet, Xception, MobileNet, FCN, PSPNet and DeepLab	Maryam et al. (2021)	Image classification, semantic segmentation, and visual question answering (VQA)	mIoU = 80.35 %	Spatial
U-Net and Feature Pyramid Network (FPN)	Binayak et al. (2022)	Improve flood detection	Precision = 97.2 %, Recall = 97.5 %, F1-Score = 97.3 %, mIoU = 75.76 %	Spatial
FCN-8, SegNet, UNet, and DeepResUNet	Wu et al. (2023)	Improve the efficiency of flood detection and mapping	Acc = 0.986, Precision = 0.980, Recall = 0.973, F1 Score = 0.976	Spatial
U-Net	Hernández et al. (2021)	Create a real-time segmentation system embedded in a UAV.	mIoU = 39.4 for Unet GPU	Spatial
Deeplabv3 model with ResNet-50 as a feature extractor	Thapa et al. (2022)	Automate the process of accurate flood and drought recognition in paddy fields	Accuracy = 93.64 %	Spatial
CNN	Munoz et al. (2021)	Trained with single, double, and triple dataset	Accuracy = 92.37 %, F1-Score = 91.82 %	Spatial
Machine Learning				
NBT and NB	Khosravi et al. (2019)	Modeling flood susceptibility in one of China's most flood-prone areas	Acc-NB: 91 %, Kappa-NB: 0.91, RMSE-NB: 0.15, MAE-NB: 0.14 – Acc-NBT: 0.90, Kappa-NBT: 0.89, RMSE-NBT: 0.16, MAE-NBT: 0.17	Spatial
KNN	Shahabi et al. (2020)	Mapping flood susceptibility	Bagging Tree–Coarse KNN (98.6 %), Bagging Tree–Weighted KNN (97.1 %), Bagging Tree–Cosine KNN (96.6 %), and Bagging Tree–Cubic KNN (94.3 %).	Spatial
Bag-ADTree	Mohammadi et al. (2020)	Detected flood locations and mapped areas susceptible to floods	Acc: 86.61 %, RMSE: 0.30, AUC Success Rate: 0.736, AUC Prediction Rate: 0.786	Spatial
LSTM and RNN	Rajab et al. (2023)	Modelling to forecast floodwater levels and velocities	LSTM-Loss: 0.0904, LSTM-RMSE: 0.3007, LSTM-Val_loss: 0.0906, RNN-Val RNN-Mean Absolut Error: 126.54, RNN-Loss: 124.1010	Spatial

models. However, machine learning approaches continue to hold significant value due to their interpretability and capacity to effectively handle a wide range of datasets.

Deep learning approaches have shown improved effectiveness in the field of fire detection, especially in situations involving complex patterns and large datasets. Machine learning methodologies continue to be of utmost importance, particularly in scenarios characterized by limitations in processing capabilities or a prioritization on interpretability. Both techniques significantly contribute to improving fire detection and mapping capabilities, offering unique advantages in addressing the complexity of wildfire monitoring and control.

CNN models in earthquake disaster studies analyze imaging data to identify visual patterns of damages and impacts. They excel in recognizing and locating affected regions, enabling the construction of visual maps of infrastructural damage for evaluating earthquake impact. Deep semantic segmentation algorithms precisely localize affected areas, facilitating better emergency response and disaster recovery planning. Through comprehensive deep learning technologies, efficient strategies can be executed to address earthquake disasters.

One unique deep model has been introduced by Jena et al. (2020) for earthquake prediction, which integrates graph convolutional neural networks, batch normalization, and attention processes. Notably, this model surpasses the performance of baseline models in properly assessing earthquake parameters by obtaining a 92.05 % accuracy in earthquake prediction and probability mapping. While, another notable deep model was presented by Hong et al. (2022b) through their EBDC-Net which is specifically developed for the purpose of detecting building damage from aerial images. Efficient surface rupture damage detection was evaluated utilizing medium-sized UAVs and a CA103 ortho camera by employing the combined DeepLab V2 model and SLIC super-pixel segmentation approach. Their findings also showcased the efficacy of the technique used for segmenting each pixel into distinct categories, achieving a remarkable mean class accuracy of 96.88 % and a mean intersection over union of 93.92 %. Other than that, an old model through VGG16 backbone has been developed by Chen et al. (2022) that consists of 16 layers, which is also specifically designed and fine-tuned segmentation models for earthquake-related mapping by improving the representation of learned features and effectively integrates various information from several scales. The combination of diverse machine learning and deep learning techniques in earthquake prediction seeks to achieve high precision in forecasting seismic occurrences from continuous data, which can be integrated into early warning systems to alarm the respective residents and reduce the social consequences when facing the after consequences of the earthquake.

Apart from the reported strengths, there are also notable weaknesses of the reported models, especially for the cases that occurred far from the sampled locations and seismic conditions that have been used to train the model. It is observed that the deep learning model can sometimes fail to identify gaps in the damaged building and also falsely identify non-crack features. Furthermore, the imaging quality of UAVs can vary a lot from one machine to another, which will decrease the detection performance. Moreover, some studies by Hu et al. (2022) employ a small-sized dataset to train the deep models, indicating their potential limitations in generalizing the inference output to other seismic data, whereby it is more desirable to train each model by using more diverse datasets. On a similar note, some models by Yang et al. (2021) were also impacted by an imbalance dataset distribution of the training samples, which is a common issue in earthquake disaster preparation, and thus, affecting the accuracy of the proposed models. In fact, some models by Bilal et al. (2022) are only applicable to a particular region due to the specific location and varying applicability in real-time applications.

Airborne and Unmanned Aerial Vehicle (UAV) sensors such as those used by Chen at al. (2022) and Song et al. (2020b), widely used in earthquake disasters due to their ability to provide high-resolution imagery, rapid data acquisition, and accessibility to remote or hazardous areas. These sensors, such as LiDAR and SAR, offer precise mapping of earthquake-induced changes to the landscape, including ground deformation, surface rupture, and structural damage. UAVs, also known as drones, are versatile and cost-effective platforms for earthquake disaster reconnaissance, capturing high-resolution imagery from different perspectives, enabling detailed analysis of infrastructure damage, landslide susceptibility, and terrain deformation. The real-time data acquisition capabilities of these sensors enhance the efficiency and effectiveness of emergency response operations, saving lives and minimizing property damage.

Various deep learning models, including VGG16, Deeplab V2 with SLIC, and U-Net, have exhibited notable proficiency in effectively identifying and evaluating the extent of post-earthquake destruction. These models provide a notable level of accuracy, precision, and recall rates, hence facilitating their ability to accurately detect fractures, remove structures that have been damaged, and evaluate the extent of structural damage. It is worth mentioning that the incorporation of spatial data, such as spatial imagery and seismic wave signals, plays a crucial role in improving the effectiveness of these models. As an illustration, the VGG16-CNN model demonstrates a notable level of precision, reaching 93.98 %, in the identification of faults within seismic amplitude images. This outcome underscores the efficacy of deep learning techniques in effectively handling spatial data obtained from seismic signals.

LSTM, ANN, RF, and SVM are machine learning algorithms that are essential in earthquake damage assessment. They are particularly useful in predicting earthquake events and determining earthquake magnitudes. The models demonstrate commendable levels of accuracy and offer significant insights into earthquake activity. In addition, the incorporation of diverse wavelength categories, such as P wave and S wave, within seismic analysis enhances the resilience of machine learning methodologies in capturing seismic attributes and forecasting earthquake-related variables.

For the assessment of earthquake damage, both deep learning and machine learning approaches offer valuable resources, each with their own unique advantages and limitations. Deep learning demonstrates remarkable expertise in handling spatial data, including imaging and seismic signals, resulting in significant levels of precision in detecting and assessing post-earthquake damage. Machine learning approaches make substantial advances to the comprehension of seismic activity and the forecasting of earthquakes, particularly when dealing with temporal data and seismic wave signals. By integrating additional wavelength types, such as spatial and seismic data, the efficacy and robustness of these methodologies are enhanced, leading to a more accurate and comprehensive assessment of seismic damage.

Meanwhile, deep learning segmentation techniques, such as U-Net, DeepLab, PSPNet, FCN, and SegNet have also played a vital role in dealing with flood disasters. CNN-based models have been employed to extract geographic characteristics from flood-related data, whereby U-Net is one of the most used models. A model based on DeepLab by Thapa et al. (2022) is good in detecting flooded areas, while PSPNet by Daud et al. (2023) is good in capturing contextual information at several scales. Likewise, FCN by Wu et al. (2023) is noted to be advantageous for making predictions at the pixel level for flood-related applications, while SegNet by Wu et al. (2023) is noted to be efficient in mapping unique features at the pixel level. This deep learning-based methodology empowers academics and professionals to carry out intricate examinations on various applications such as enhancing the delineation of inundated regions, evaluating infrastructure deterioration, and formulating strategies for responding to flood disasters. This demonstrates the versatility of deep learning in addressing complex calamities. Furthermore, the ability of object detection-based deep learning techniques like Fast R-CNN and Mask R-CNN are also found to be efficient in identifying flood-related features. The most popular deep model, U-Net, has achieved high accuracy for decision support in natural scene parsing, with further enhancement also being reported through the introduction of Res-inception units and PSPNET to capture detailed information better and enhance scene context understanding. Uniquely, the utilization of NASA's Sentinel-1 dataset, even with fewer channels, still offers good detection performance for diverse flood events, demonstrating its potential for scalable flood detection using deep learning models, allowing for efficient, automatic, and scalable coverage of larger areas. Rather than focusing on the deep model, the work by Safavi and Rahnemoonfar, (2023) focused on developing a balanced and comprehensive dataset through the introduction of FloodNet. This dataset captures high-resolution images for clarity purposes, particularly useful for UAV-based systems in developing deep models for flood disaster scenarios. This comparative study validates its findings by using various networks for image classification, semantic segmentation, and feature extraction, including VGGNet and Two-Layer LSTM.

The previously mentioned studies also reveal several weaknesses concerning flood disaster management, whereby the deep learning models need better training data so that prediction errors due to factors like training data quality and task complexity can be avoided. A simple method like the binary classification model by Binayak et al. (2022) for floods may not accurately represent all flood types, and thus, more scenarios should be considered as the respective features are difficult to combine effectively. Furthermore, a popular model like U-Net, even though it is easy to implement, can be influenced easily by training data quality, weather conditions, and landmass shape regularity. Inaccurate images and incorrect camera viewing angles can also make disaster detection more challenging, leading to potential prediction inaccuracies. Finally, we would like to highlight that the usage of the DeepLabV3 + model by Thapa et al. (2022) has produced significant misclassification for water body cases, and led to uncertainty in input data and model structure that affects the model reliability.

The utilization of satellite sensors, Unmanned Aerial Vehicles (UAVs), and flood cameras plays a pivotal role in the management of flood disasters owing to their synergistic capabilities. Satellite sensors provide extensive coverage and regular updates, yielding vital data on the extent of floods, water levels, and changes in land cover. Unmanned Aerial Vehicles (UAVs), which are equipped with optical cameras and thermal imaging systems, provide detailed and high-resolution images of flood-affected areas. This helps in quickly assessing the extent of damage, conducting search and rescue operations, and monitoring infrastructure. Flood cameras offer visual data at ground level, improving the understanding of the situation for local authorities and emergency personnel. Sensor technologies provide a comprehensive strategy for managing flood disasters by integrating space-based observation, aerial reconnaissance, and ground-level monitoring. This method facilitates informed decision-making, disaster response, and community resilience initiatives.

Table 6 provides an extensive examination of flood detection and mapping methodologies, categorized into deep learning and machine learning methodologies, primarily relying on spatial data. Various models, including CNN, U-Net, and Deeplabv3, have been utilized in the field of deep learning for the purpose of flood detection. These models have demonstrated impressive performance in terms of accuracy metrics such as Intersection over Union (IoU) and Dice coefficient. These models utilize sophisticated architectures and methodologies such as semantic segmentation and real-time UAV-based segmentation in order to precisely detect areas that have been inundated. Although certain models, such as U-Net, have shown promising results in real-time UAV segmentation, there are still areas that require additional development.

In contrast, many machine learning techniques such as NBT, NB, KNN, and LSTM have been utilized in the field of flood susceptibility modeling and floodwater level forecasting. These methods have demonstrated strong performance and a high level of accuracy in predicting the occurrence of floods and accurately predicting water levels. Furthermore, the utilization of the wavelength spatial method highlights the importance of incorporating spatial data, including aerial imaging, GIS, and satellite data, in order to improve the precision of flood detection and facilitate well-informed decision-making. Through the utilization of geographical data and sophisticated modeling techniques, these methodologies make a substantial contribution to the development of efficient flood control plans. They enable the establishment of early warning systems, facilitate risk assessment, and support disaster response endeavors.

7. Conclusion

This work comprehensively reviews semantic segmentation applications using deep learning methodologies for various natural disaster management systems. In this review, deep-learning segmentation architectures are first categorized and discussed according to their usages and applications, which cover three main categories: forest fire, earthquake, and flood disasters. After reviewing the strengths and weaknesses of various literature works that have utilized semantic segmentation based on a deep learning approach, it is proven that remote sensing technologies are fundamentally crucial for managing natural disasters effectively. This improvement can specifically be observed in forest fire detection systems, whereby the accuracy and efficiency of the reviewed works have helped the firefighters in executing efficient firefighting. Semantic segmentation allows complex spatial patterns to be identified, as such active fires can be distinguished from the background using advanced CNN architectures, coupled with high-resolution satellite images. Nevertheless, several shortcomings are also observed, especially in the cases of small-sized fires and cloud interferences.

For earthquake-related applications, semantic segmentation has been applied for earthquake prediction, damage assessment, and risk evaluation. The development of these innovative models with optimized deep architectures has demonstrated the versatility and potential of this technology in advancing seismic research. However, several major weaknesses have been identified, including limited generalizability, potential inaccuracies, and dataset-related challenges that require further refinement of these deep models. Addressing these limitations through extensive testing on diverse datasets by considering regional variations is critical in improving the reliability and real-world applicability of automatic earthquake-related systems. These improvements are needed to ensure the effectiveness of the model in various settings and to produce better disaster preparedness and response strategies.

Meanwhile, semantic segmentation has also shown potential for flood disaster management. However, several weaknesses have been identified, including misclassification, limited representation of all flood types, and difficulties in detecting small flooded regions that highlight the need for continuous refinement and adaptation of the deep learning models. Furthermore, it is also observed that a more accurate semantic segmentation model has also improved the subsequent processing steps, such as object detection and classification tasks for flood-related systems.

8. Future work

In the realm of natural disaster management, future research endeavors can significantly benefit from the integration of multi-sensor and deep learning techniques (Min et al., 2022). Additionally, researchers may employ deep learning methodologies to integrate information from various sensor modalities at different levels of abstraction. Such architectures can offer a comprehensive understanding of the disaster scenario by amalgamating data from disparate sources. Additionally, extending multi-sensor fusion to incorporate data from heterogeneous sources, such as social media and IoT devices, could offer valuable insights into the broader impact of disasters on affected communities.

Credit authorship contribution statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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