

Techniques of deep learning neural network-based building feature extraction from remote sensing images: a survey

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ABSTRACT

Recently, due to earthquake disaster, many people have lost their lives and homes, and not able to settle to new locations immediately. Therefore, a framework or a plan should be ready to immediately relocate the people to different locations or do resettlement. Much research has been done in this field but still there are problems of identifying clear building boundaries, rectangular houses, due to the problem of different shapes of the buildings. These techniques were explored for identification of clear building boundaries, rectangular houses, buildings which are more highlighted and smaller size buildings for pre-disaster and post-disaster building extraction scenarios. In this survey of building extraction techniques, most of the approach is training the network, second approach is refining the trained output features, running the trained samples on the predefined models of neural network. Several issues and their assessment are studied in these techniques. These are beneficial to the various researchers for different building extractions.

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1. INTRODUCTION

Automated building feature extraction from satellite imagery is crucial for urban planning [1] and population density estimation [2]. It is also crucial for the creation, maintenance, and fabrication of physiographical maps. Automatic detection is therefore essential. Even though automatic feature extraction is a difficult undertaking, in recent years it has become increasingly important. The difficulties came from shadows, noise, and uncertainty in the satellite data's background pictures [3]. Making effective and efficient use of the data from remote sensing (RS) has become a laborious task. It is simple to obtain these aerial data from a number of sources [4]. This surplus of high-resolution satellite data has become a dilemma for the scientific community. Neural networks with deep learning (DL) have gained prominence in satellite RS during the last couple of decades [5].

Natural catastrophes can have an impact on building structures. This makes a post-disaster automatic measurement based on satellite data crucial. A vast amount of training data is needed to train the training data set for the need of automatization in order to train a deep neural network. It is quite challenging to gather such large amounts of training data in a real-time context. Satellite pictures are a type of remotely sensed image that may cover wide areas and have high resolution, revisit time, and capability. Large mounds of debris were found by concentrating on partially and completely collapsed building structures, and this

resulted in significant contributions. Perhaps not the best for the cracks, spalling, and façade. However, a few top researchers concentrated on façade from photos taken after disasters [6].

The automatic vectorization of the building's shape is used in urban management and geodatabase updating. Recently, deep convolutional neural network (DCNN) has been applied to extract architectural features; the output is raster output rather than vector images. It frequently falls short of the need for locating the buildings. Many techniques exist for converting raster images to vector formats; however, the result is often an excessive number of vector points and asymmetrical shapes. DL algorithms are primarily applied to image classification these days. It has also been extensively utilized for picture recognition and image segmentation in a variety of applications. These algorithms outperformed typical or conventional algorithms thanks to the contextual features in their neighbours; yet, they have certain local issues of local feature optimisation and global feature optimisation from the neighbourhood objects [7].

The task of building separation from satellite data is distinct because diverse building shapes exist. Furthermore, finer details of elements like shadows, spaces between buildings, and floors, are provided by high resolution images. Thus, it is still difficult to extract better accuracy from high spatial resolution images. Building footprint extraction with baseline network-based semantic segmentation utilizing DL techniques is successful. Therefore, the amount of space available between building zones is limited [8].

In military and map implementation, feature extraction plays a vital role. Spectral signature is used to identify a feature from high resolution image. There are sixteen million colors available in any given image. It is difficult to identify an image based on its colors. Similar colors are grouped together for better analyzation of the image. For this purpose, machine learning (ML), DL, clustering approaches are being used by many of the researchers. From the segmented image, spectral information of buildings, road, green spaces features are extracted. Spectral information alone is insufficient as soils and features have a similar spectral signature. Researchers have developed the concept of mathematical morphology, which is applied to separate features from non-similar objects with different spectral signature [9].

2. TECHNIQUES OF BUILDING FEATURE EXTRACTION

2.1. Overview

There are various techniques of building feature extraction which are explored by the researchers in the last few years. In this paper, few major techniques have been reviewed. The details and limitations are identified from the techniques. Various techniques involve the differentiation of buildings by image segmentation with Unet with different encoders architecture, which was experimented on high-resolution satellite images. In these techniques there are various problems, of concrete base floor being unclassified, neighbouring buildings poorly recognised, wrongly classification of shadows as buildings in some parts, building hidden below vegetation also poorly classified. In the next section all the techniques are identified and explained in detail from point no 2 to 17.

2.2. Unet

Unet is the backbone of the neural network. The location data of the underlying information and the semantic data of the abstract characteristics were only mixed in the original Unet. This method combines class features, pixel features, and abstracted characteristics with location information to increase the accuracy of the network and its semantic representation [10]. Overlapping tile strategy had been used to segment seamlessly of large arbitrary biomedical images. The contracting and expanding path are used for capture context and precise localization. It is possible to train this network with few photos [11]. To extract multiscale properties of the target, the multi-Unet approach creates an effective network residual module under a multisensory field (RMMF). Optimizing feature information involves the employment of an attention mechanism. The residual module approach learns network properties at various scales by employing parallel convolutional layers. Builds leftover blocks by adding shortcut connections between stacked layers, fusing high-level semantic information with low-level granular information. By substituting the residual module for the convolutional layer in the Unet structure, the network structure is strengthened. For testing, the Gaofen-2 and Potsdam data sets were utilized [12].

2.3. Res2-Unet

The DL algorithms such as Unet, ResUnet, ResNet50, ResUnet dilated, use encoder, and decoders in the Unet structure. High spatial resolution image-based multi-scale learning at the granular level is employed in the ResUnet technology for building detection. In dilated ResUnet, which explored coarse resolution images use dilation convolution instead of max pooling layer. A broad field of reception or worldview is provided in dilated convolution without dropping the resolution of the images. Contextual information is more visible about the objects. Small size objects overlapped with other features in coarse resolution images. It is difficult to find small objects. A residual unit, skip connections along with dilated convolution operation

are used in the model [13]. In this technique, resolved the issues of misclassification. Furthermore, there exists a potential avenue for enhancement concerning the precision of the training and validation datasets. This may not have been as concerned with increasing the DABE-Net method's speed and using it to handle increasingly difficult RS picture segmentation jobs. The technique of oversampling and augmentation on the small objects in building detection may be used in the Res2-Unet framework. Building differentiation via image segmentation on high-resolution satellite pictures with Unet architecture is carried out in Res2-Unet. This investigates the possibility of autonomous building extraction in high-density residential regions with artificial intelligence assistance [14].

2.4. Dense-attention networks

This method involves moving the “Resampler” in an attention gate so that it is in line with the Sigmoid function for the purpose of extracting buildings. These networks are capable of efficiently extracting building contours by autonomously learning various kinds of building structures from high-resolution RS photos [15]. The use of Lidar data in conjunction with RS RGB photos is limited in its ability to enhance building shape detection and simultaneously yield building height estimates. raise the regularity and accuracy of building extraction. In the convolutional neural-deep belief neural networks (CNDBNN) approach, data augmentation and weight regularization are applied to prevent overfitting. The generalization model was raised by it. There is a smaller sample size, and the ideal size is not known. Getting more accurate building footprints has its limitations [16].

2.5. Multilevel, multi-granularity DL and deep belief networks

Using an ensemble of convolutional neural network (CNNs), this technique uses automatic building extraction in high-density residential neighbourhoods to classify the EAC dataset [17]. Regarding the estimating issues, there is limited identification of the building's corners with additional configuration, which are primarily rectangular in shape. There was a restricted number of high-confidence samples with more useful information chosen to take part in the model's training and increase the accuracy of semantic segmentation. A regularized building boundaries extraction from RS data based on augment feature pyramid network (AFPN) and morphological constraint (MC) is utilized in the AFPN and MC approach. In order to prevent feature information loss, this AFPN is constructed to give more precise and dense global features for semantic segmentation tasks. In this, the morphological aspects are analysed, and the building shape is manually classified as linear or curved. To obtain the finer depiction of contour in accordance with various building shapes, the extraction results are regularized. Finally, tests were done on the benchmark dataset to see if the regularized building boundary extraction was available [18].

2.6. Intensity-based selection

Many applications of the ML in RS imagery are successful in post disaster scenarios, for extracting buildings which are damaged. Traditional methods cannot evaluate the complexity of training of the input datasets. In this technique, numerical simulation and modeling intensity is introduced for the automatic extraction of the detecting damaged buildings. Considered low and high intensity areas and depending upon intensity of the area, buildings are categorized. Moderate to severe areas of intensity contain strongly damaged buildings. Support vector machines (SVM) classifier is trained with the use of two parameters of regularization using these training samples for learning calibrating. In this framework, manual interpretation of selection of training samples is avoided [19]. In CF Net: eigenvalue preserved technique, class feature module is used in decoder part of attention network for separation of the building features and the background areas and objective feature output is considered for final output. With the channel attention module (CAM) and the global relational attention module (GAM), this attention module is dual attentive in nature. The long-range dependence of pixel space and pixel location is resolved by the dual-attention mechanism, which can effectively enable the backbone network to gather remote contextual information for scene understanding [20]. This is because some earlier research by academics produced local features that could cause the network to interpret the content incorrectly due to its limited perceptual field. A four-layer coding layer that uses down sampling to extract features makes up the entire backbone network. It allows the network to be trained without difficulty owing to gradient disappearance and explosion by going too deep, all the while guaranteeing feature extraction.

2.7. Autoencoders

In order to reinforce the features, a spatial attention fusion module was employed in conjunction with an encoder and a decoder component made of lightweight DenseNets. propagation and the introduction of higher-level feature data to muffle noise and low-level features [5]. Change vector analysis (CVA) of optical satellite images was used to reduce errors and omissions by combining more optimized deep neural networks with pre- or post-processing methods. This helped to overcome the issue of effective extraction

accuracy and efficiency, which was affected by complex backgrounds, special buildings, and unremarkable buildings [21]. Rather than handling the network and pre- and post-processing techniques independently, both are not taken into account at the same time for increased accuracy and efficiency [22]. To pinpoint exact changes in land-use and land-cover (or cropping pattern) using this technique. Appropriate categorization techniques are not extended to differentiate between various sorts of changes. The effectiveness of the autoencoder-enhanced distance measurements within a deep metric learning framework (such as the siamese network or triplet network) may not have been investigated in this technique. This method uses a multi-task [23] encoder-decoder network to search for various autoencoder architectures in the reconstruction of spectral data, such as convolutional autoencoders [24].

2.8. Multi scale feature transformer

Building extraction from high spatial resolution, satellite images is a complex task due to the difference in shape of buildings and colors. There are complex background objects which deter the building features from selection. These methods are based on DL techniques with encoder and decoder structure. In these details of the small buildings is not captured. The building with blurred boundaries is captured. For this, proposed frequency-spatial learning transformer for extracting features of buildings. In this technique, different frequency features and multi-scale features are captured and synthesized. In this, spiking convolution is used to enhance frequency. It distinguishes the multiscale features from the background features. Masked attention transformer refines the boundary features. By training and assessing photos with varying spatial resolutions from various research areas and datasets, the practical transferability of this method was assessed in this way. The boundary loss function technique was employed to optimize and improve the multiclass semantic segmentation of urban regions by extracting buildings in border areas using a derivative boundary loss function. The suggested boundary loss function that originated from the segmentation network is computed using the distance transform image (DTI), which is formed from predicted and ground-truth pictures [25].

2.9. Multitarget domain adaptation

With this method, RS addresses vast differences in location, time of year for acquisition, and abundance of sensors. Due to the challenge of obtaining labeled data that accurately captures every event, data-hungry DL models are frequently trained using labeled data from a source domain that is constrained in the aforementioned ways. This strategy allows domain adaptation (DA) techniques to modify these models for use on target domains that have distributions that differ from the source domain. It is necessary to train a different target classifier for every target domain because the majority of RS DL techniques are meant for single targets. This is lessened by multitarget DA, where several unlabeled target domains are learnt using a single classifier. This method builds a multitarget classifier to efficiently collect characteristics from various unlabeled target domains and the labeled source. This method makes use of coteaching, a graph neural network-based methodology that may be used to unlabeled data. If the network finds it easier to adapt to the closest target domain, it will initially adapt on the easier target domains using the sequential adaptation technique that was introduced [26].

2.10. Improved pseudo masks generation

This method combines gated convolution (GC) and adversarial climbing (AC) in a poorly supervised building extraction framework. In order to enhance pseudo mask generation and reliably extract buildings from high resolution (HR) RS pictures, the ACGC framework treats image-level labels as weak supervision. There are three main parts to the entire pipeline. Building class activation maps (CAMs) are created and optimized with AC in the first component. Next, in the second component, a gated convolution module (GCM) is used to obtain the class boundary maps (CBMs) of the buildings, and in the third component, CAMs and pairwise affinities from the CBMs are used to expand the pseudo masks of the buildings. The generated pseudo masks are the three components of this technique. The ground truth (GT) of training samples for a conventional supervised segmentation model is obtained from the pseudo masks. The program was taught to recognize buildings using the semantic information found in HR pictures. To be more precise, HR RS photos were fed into the trained supervised segmentation model, which produced building masks that showed the extracted buildings [27].

2.11. Multitask learning

This method involved classifying disaster images from social media image streams and using a multi-level feature enhancement network (MFENet) for learning from images based on CNN-like CNN modules. Using nine distinct pre-trained models, classification results are provided that do not require exploration and can be used as a standard for further research. This method, which has not been investigated before, combines transfer learning or poorly supervised learning with the existing global data set of landslide

RS to create LM networks with improved generalization performance. Similar to this, to obtain timeliness and accuracy in building damage, perturbed dual mean teachers uses multitask-based semi-supervised semantic segmentation [28], framework technique, consistency regularization-based semi-supervised framework with multitask semantic segmentation. To confirm the efficacy of this approach, it might not be investigated on further datasets with various disaster scenarios (such as earthquakes and landslides) and data sources (such as aerial and UAV data) [29]. Additionally, when dealing with a high number of unlabeled samples to meet emergency needs in crisis circumstances, it might not increase computer efficiency. Could offer a landslide dataset that is more accurate, enhance the algorithm's ability to predict landslides, and prevent the dataset from growing. Worked with both large and small picture sizes, analysing potential trade-offs between memory consumption and model performance with varying support image sizes [30].

2.12. Multi-scale feature map aggregation and supervised domain adaptation convolutional network

Image segmentation was done using the K-means clustering algorithm, and three distinct methods-VGG-16, VGG-19, and NAS Net-were utilized to identify damaged structures following an earthquake. It may not have been investigated to improve algorithm performance, particularly when classifying less damaged and normal buildings to prevent misclassification [31]. This technique, for the multiclass classification job of demolished structures following an unanticipated tragedy, focuses on an efficient feature extraction and selection process in conjunction with a CNN model [32]. This method uses road damage to quickly redirect the shortest route between the help team and the urgent care facility that is needed. Unsupervised learning is not investigated in this technique to improve extraction performance in unlabeled datasets. Unsupervised learning is not investigated in this technique to improve extraction performance in unlabeled datasets. This method concentrated on increasing the diversity of training samples and developing more efficient network topologies to synthesize textural attributes in order to improve the extraction performance of small building instances [33]. In order to produce significantly better results, the DRRNN approach is not investigated in this methodology for easily confused classifications including industrial land, urban residential areas, and rural residential areas. Building regions from high-resolution RS images (multi-scale and multi-resolution features, enhance the information interaction between different scale features, decrease the difference between the extracted results and the ground truths) accurately using CNNs is possible with the multi-scale recurrent conditional generative adversarial network technique. This method was only applicable to learning that was unsupervised in the extraction of labelled dataset [34].

2.13. Cassification network D-Net and tandem stitching

Disaster types are identified in the above utilizing D-conv, D-linear, D-model, and D-layer modules. Using this method, different disaster types can be identified using Google Earth satellite photos or other online databases. Natural disasters in this approach, known as cassification net, have a significant influence on people's lives and property, thus prompt and efficient handling of disaster categories is imperative. This method uses the D-conv, D-linear, D-model, and D-layer modules to create a new disaster cassification network, or disaster cassification net (D-Net), by tandem stitching. It is discovered that the disaster cassification net performs better than CNN in this methodology when the suggested method is compared to "CNN" and "Transformer" throughout the experiment. When MobileNet_v2, which performs best on the classification dataset, and CCT network are compared with disaster cassification net on the fashion_mnist and CIFAR_100 public datasets, respectively, the results demonstrate that disaster cassification net can still achieve the state-of-the-art classification effect. It was also found that this technique achieves the effect of state-of-the-art (SOTA) on the disaster dataset [35].

2.14. Generative adversarial networks and Web-Net

Using the ultra-hierarchical sampling (UHS) block, this technique extracts more precisely and sharply recognized buildings from the prediction maps, including building areas that are obscured by shadows. High-resolution aerial imagery shows structures with incredibly intricate morphological features, including curves, straight lines, and orientations [36]. The FCN-based networks are unable to directly extract the characteristics, and it is a critical issue to figure out how to incorporate morphological characteristics into CNN structure. high limitations on morphological traits in the various architectural morphologies of the structures in the accident sites [37].

2.15. DCNNs-based edge detection and PCA

This method's automatic vectorization of building shapes from very high resolution (VHR) RS imagery is crucial for a variety of applications, including geodatabase updates and urban management. Although creating edge detection using DCNNs has been effective recently, the results are not vectorized maps but rather raster images, which do not suit the needs of many applications. Raster pictures can be transformed into vector maps using certain methods; these vector maps frequently include an excessive

number of vector points and asymmetrical shapes. A principal component analysis (PCA)-based corner extraction method and DCNNs-based building edge detection were combined to create a building form vectorization hierarchy that allowed for the quick extraction of building corners from building edges. Tests conducted on the Jiang Bei new area buildings and massachusetts buildings datasets demonstrated that our suggested algorithm extracted building vector corners with fewer breakpoints and isolated points and more complete and regular building vector boundaries than the state-of-the-art corner detectors. In order to quickly extract building corners from the building edges, this study suggested a building shape vectorization hierarchy that integrated DCNNs-based building edge detection with a PCA-based corner extraction approach [38].

2.16. Active learning and federated learning

Using federated learning (FL), this method eliminates the need for manual inspection of every training sample by automatically selecting and labeling the data from which it learns. It seems a more difficult task for various reasons that a framework is not extended to an online active learning (AL) by investigating how unlabeled data may be used in training local models during different communication rounds of FL. The decoder portion of an attention-based CNN network is utilized in the code network model (CFNet), which is based on class feature optimization and the class feature (CF) modules technique, to discriminate between building and non-building (background) areas. It distinguished between several ground textures that were mistakenly seen as structures [39].

2.17. Domain adaptation methods using GNN graph neural networks

For the purpose of classifying RS images, target domains were used with distributions that differed from the source domain. Created a technique for identifying and eliminating source samples that aren't relevant but could help with the adaptation process. Mixed target domain settings and multisource multitarget adaptation were investigated. The segmentation of urban buildings from aerial photographs and enhanced learning capacities of the supervised learning model in differentiating buildings in dense areas [40] and extracting buildings covered by shadows were explored in the parallel cross-learning-based pixel transferred deconvolutional network (PCL-PTD net) technique. Its ability to distinguish specific borders and building shapes is limited. The YOLOv3 object detection architecture is utilized in the feature reweighting methodology to accomplish few-shot learning of damage assessment [41] models on the xBD dataset. When compared to the baseline, m AP improved with the few labeled samples. The class-specific reweighting vector produced by the reweighting module was analyzed in this case using t-SNE. This was employed to assess similarities both within and between classes [42].

3. SEVERAL ISSUES IDENTIFIED

Many researchers have found that using the aforementioned methodologies, high-resolution antenna images may be obtained with excellent accuracy for building mapping. We must identify these high-resolution antenna photos. Regarding the estimating issues, it is also evident that identifying the building's corners requires a lot of labour and is often calculated inaccurately. Though the outcome for a building extraction may be better, more configuration is needed in order for the model to understand these structures, most of which are rectangular in shape. Based on buildings, it appears that this was the most difficult aspect of image segmentation because it was difficult to estimate the corners of rectangular buildings. Future research indicates that creating corners in rectangular structures is necessary [43].

Building footprint extraction in complicated metropolitan environments was not accurate even with the use of strong post-processing techniques and the creation of more robust datasets. A post-processing module or an automatic cleaning solution for the training data must be found in order to automatically eliminate tiles that have a mismatch between the ground truth mask and the RS pictures, hence improving the pipeline and producing more accurate building footprints. DL models that are more resistant to noise must be created in order to reduce noise. Normal data is insufficient to improve the detection of building shapes; so, it is necessary to determine how to use LIDAR data in conjunction with RS RGB photos. Additionally, estimations of construction heights at the same time. Needs to increase precision and pinpoint the regularization of building extraction [44].

It is challenging to distinguish between the misclassification of building pixels in spatial resolution photos and the segregation of building boundaries in the case of small buildings that are located closely together. As a result, it is necessary to determine the quantity of sample data that will be used to quantify differences. In order to contribute to the model's training and enhance the accuracy of semantic segmentation, samples must be able to distinguish high-confidence samples with more useful information while maintaining the accuracy of the unlabeled data. The dataset needed to enhance the algorithm's detection performance and provide a more accurate landslide dataset for network training is not present [45].

It is necessary to investigate large and small picture sizes when analysing any trade-offs between model performance and memory utilization with varying support image sizes. In order to prevent issues like incorrectly classifying concrete floors, misidentifying nearby buildings, mistaking shadows for buildings, and failing to recognize buildings covered in vegetation, it is necessary to incorporate more and higher-resolution RS imagery, investigate post-processing techniques to clarify building relationships, and increase the precision of extracting sparsely populated buildings. Furthermore, there exists an opportunity to enhance accuracy about the training and validation datasets [46].

It is necessary to speed up the DABE-Net approach and tackle more difficult RS image segmentation jobs in order to perform multiclass semantic segmentation of metropolitan environments. In order to guarantee precise building extraction and building classification, height data and VHR orthophoto pictures can be utilized [47]. Using these methods, high-resolution 3-D data, such as digital surface models or aerial 3-D point clouds, must be obtained in order to strengthen the connections between the classes that are found. However, with these methodologies, distinctive buildings, ordinary buildings, and complicated backgrounds all had an impact on the extraction accuracy [48]. More optimized deep neural networks and pre- or post-processing techniques are required to eliminate errors and omissions. Rather than considering the network and pre/post-processing techniques separately, both are not taken into consideration concurrently for greater accuracy and efficiency [49]. In cloud various neural network process can be executed for getting more performance and can monitor disaster on various computations and recover various tasks in case of disaster [50].

In order to pinpoint exact changes in land-use and land-cover (or cropping pattern), it is necessary to investigate suitable classification and algorithms that differentiate between various sorts of changes. The autoencoder-enhanced distance measurements performed less well when used in a deep metric learning framework (such as the triplet network or siamese network). There is still room to explore various autoencoder architectures, such as convolutional autoencoders, for the reconstruction of spectral data. These strategies have the potential to improve algorithm performance as more data is gathered, particularly in the categorization of less damaged structures, destroyed buildings, and correctly categorized normal buildings. These methods should concentrate on using a CNN model for the multiclass classification problem in conjunction with an efficient feature extraction and selection procedure. It is necessary to identify various problems, such as road damage, in order to immediately redirect the quickest course between an emergency care facility and an aid team [51].

4. ASSESSING BUILDING FEATURE EXTRACTION TECHNIQUES

In the aforementioned methods, satellite data acquisition is used to create object-based maps that are either non-existent or in need of updating; ground surveying or RS surveying is the preferred primary data acquisition method for obtaining new data. As a result, the primary source of data has to be high-quality satellite photography with a resolution of 0.6 meters. Additional data for the project came from fieldwork and the city's current street guide [52].

Pre-processing of the high-resolution satellite data in the aforementioned techniques: at this point, the image underwent pre-processing, and all geometric and radiometric corrections were applied, enhancing the image's ability to be seen extremely clearly on the ground. Gathering data: it referred to the process of digitization, which converts fresh data needed to create a map into a digital format for archiving, comparing with data attributes, and other processing that is required for research preparation. The dataset, which is the result of ML and DL techniques used to extract features from high-resolution satellite images, is not vectorized through the on-screen digitizing process in order to extract characteristics from the image that should be included based on the interpretation key and automatic extraction procedure using object-based approach that is limited for identification of features information themes, layers created [53].

The main goal of the research project is to use object-based classification to classify all of the pixels in a high-resolution image into groups or themes. The spatial object-based approach is not used in the aforementioned strategies. Its foundation is the classification of picture pixels depending on how those pixels relate to the pixels around them. Not only are aspects like picture texture, proximity, feature size, shape orientation, repetition, and context ignored, but they are also not employed in the process of visual interpretation. For the purpose of producing an interpretation key for every informative class, the categories are not characterized throughout the image [54].

Unsupervised learning must be studied in order to improve extraction results in unlabeled datasets using a variety of approaches. By increasing the diversity of training samples and developing more efficient network topologies to synthesize textural properties, you can enhance the extraction performance of small building instances. Takenouchi and Choh [55] needs to use the DRRNN approach to identify industrial land, urban residential areas, and rural residential regions that are targeted for disaster resilience or vulnerability due to high levels of regional risk. While creating apps for the development of maps used in disaster

prevention, some manual operations must be automated (e.g., computations of Int.V and display of road network conditions on the online map) [56].

In certain methods, it is necessary to create LM networks with better generalization capabilities, which can be done by fusing transfer learning or poorly supervised learning with the current global shortage of landslide RS data [57]. To confirm the efficacy of this approach, further datasets featuring various disaster situations (such as earthquakes and tsunamis) and data sources (such as aerial and UAV data) must be found [58]. Increased computational efficiency is required when dealing with big volumes of unlabeled samples in order to meet emergency requirements during calamities. Map of catastrophe intensity must be located using SVM. Needs to improve the purposeful islanding algorithm based on ML to operate more quickly and make reliable decisions. Needs to locate disaster-related satellite imagery [59].

The ideal size for support images has not been established in the methodologies under study, nor has it been possible to analyse any trade-offs between memory use and model performance with varying support image sizes. Differentiating between support picture sizes is necessary. In addition to providing valuable insights into whether larger or smaller support images lead to better class separation, class imbalance in the training set query images, and improved model performance, t-SNE analysis of the resulting reweighting vectors may also extend the framework to an online AL by investigating how unlabelled data can be incorporated in training local models during different communication rounds of FL, which appears to be a more difficult task for a number of reasons [60].

There are restrictions on the building's exact border and shape segmentation in the aforementioned procedures. In order to prevent incorrect recognition mistakes when some ground textures resemble buildings, a DSM and some postprocessing techniques need to be integrated [61]. Work on the texturing elements of iconic structures is required to find a solution to this issue. Identification and removal of unnecessary source samples that can aid in the adaption process is necessary [62]. Identification of requirements for mixed target domain settings and multisource, multitarget adaptability. Unsupervised learning must be identified in order to improve extraction performance in unlabeled datasets must use the oversampling and augmentation technique to identify small items in building detection [63].

5. CONCLUSION

Now a days, in disaster scenarios, which is a big hazard, when it occurs, it creates loss of buildings, human beings, animals, and natural resources. To overcome this problem, techniques should be developed having a systematic plan in existence for immediate help for identification of correct building structures in case of disaster. Might not know, what the structure of the buildings existed before disaster, how much are the damages and what are the categories of resources were damaged were damaged. How can we identify them? Now a days many disasters are occurring, therefore immediate plan is not ready to identify what were the buildings available before disasters and what remained after the disaster happened. This is an extremely critical problem. To overcome the above problem a systematic framework should be developed for the post-disaster resettlement process. In this survey of building extraction techniques, a technique needs to be identified for identifying structures categories before disaster for proposing and developing a framework for post-disaster resettlement using satellite imagery. Unet is an end-to-end fully convolutional network; therefore, it has not thoroughly examined all the data at its disposal, and it can still be improved.

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C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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