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Identifying abandoned buildings in shrinking cities with mobile sensing images

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Abstract

The number of abandoned buildings in shrinking cities is increasing sharply, posing environment risks, threatening the safety and health of residents, affecting the real estate market, and burdening government finance. Abandoned building detection provides fundamental information for refined urban management, real estate transactions and government decision-making. However, emerging sources of data, such as satellite imagery and commercial street views, are insufficient to timely collect this fine-scale data, lacking large-scale and fine-grained detection method. Therefore, in this research, we aim to define the connotation and identification criteria of abandoned buildings, develop an effective deep learning method based on image segmentation, and detect individual abandoned buildings from large-scale mobile sensing images (MSIs) with high accuracy. The study conducted a mobile sensing campaign in a shrinking city in Northeast China, collecting 11,359 street-level images of 126.2 km of urban roads. The accuracy of the deep learning detection method was 83.8%. The study compared with the detection of commercial street view images (latest in 2015) and analyzed the dynamic changes of abandoned buildings. From 2015 to 2021, the number of abandoned buildings in the case city decreased from 102 to 50 and became more concentrated in the old city area. Our study demonstrates the feasibility of MSIs in detecting abandoned buildings and shows the enormous potential to timely detect abandoned buildings in large spatial ranges.

Keywords Street view, Deep learning, Image segmentation, Urban renewal

1 Introduction

As the global process of deindustrialization in cities gradually accelerates, urban shrinkage phenomena are becoming increasingly common, which refers primarily to a reduction in the size and concentration of populations within urban areas, and the decrease in population projected onto the built environment results in the redundancy of physical space (Lang et al., 2020; Long & Gao, 2019; Long & Zhang, 2021). Many countries around the world are facing the issue of abandoned buildings (Molloy, 2016; Zavadskas & Antucheviciene, 2006). The definition of abandoned buildings usually refers to buildings that cannot be used normally and need to be demolished or extensively renovated. This definition covers many types of buildings, such as demolished blocks, abandoned industrial complexes, or closed cultural and leisure facilities, etc. Abandoned buildings can reduce community vitality, induce crime, and decrease commercial attractiveness (Accordino & Johnson, 2000; Spelman, 1993; Williams et al., 2019), leading to negative impacts on urban management, landscapes, and safety (Han, 2014). Overall, abandoned buildings are generally regarded as failed, stalled projects, degenerative processes, or the decay of the built environment, and are considered “pathological”, which has sparked discussions and reflections on how to treat and utilize these resources. In 2000, abandoned buildings became a major focus of the global academic community and a key issue to be addressed in the development of shrinking cities.

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So far, research on abandoned buildings around the world has mainly focused on several topics: the definition of abandoned buildings (Ariffin et al., 2018; Mallach, 2006; Lami, 2020; Villa et al., 2019), the causes of and countermeasures to prevent building abandonment (Mallach, 2006; Han, 2014; Ariffin et al., 2018; Jeon & Kim, 2020); countermeasures to address social problems caused by abandoned buildings (Tavakoli, 2019; Mallach, 2006), and strategies for renovating and reusing abandoned buildings (Pavlovskis et al., 2017; García & Ayuga, 2007; Simons et al., 2016; Banachowska, 2019; Lami, 2020).

Although some studies have defined abandoned buildings from the dimensions of property management and community impact (Mallach, 2006; Lami, 2020), a clear definition and characterization of the spatial dimensions of abandoned buildings is still lacking, which poses a challenge to identifying and analyzing them from a physical space standpoint. In terms of research scope, current studies have focused on relatively microscopic objects such as individual buildings (Pavlovskis et al., 2017; Banachowska, 2019) or rural dwellings (Xu et al., 2019), with a lack of large-scale measurement of abandoned buildings. Furthermore, existing research mostly targets specific types of buildings such as industrial (Pavlovskis et al., 2017), religious and school buildings (Simons et al., 2016), which limit the understanding and exploration of the urban environment and hinder the excavation and summarization of regular features.

In terms of research methods, established studies have used traditional field surveys, geographic analysis based on utility data, remote sensing interpretation and automatic detection based on commercial street views (Zou & Wang, 2021). In summary, the physical features detected through remote sensing are limited, and only vegetation conditions or damaged roofs can be used to infer abandoned buildings. Therefore, the combination of the extensive coverage of commercial street view images (SVIs) and the human-scale perspective of field data facilitates the detection of derelict buildings in terms of both validity and universality. Moreover, commercial companies, such as Google and Baidu, provide millions of panoramic street-view images worldwide, with a wide coverage that provides a better visual characterization of abandoned buildings than traditional remote sensing images from the top.

However, a key challenge arises when using commercial SVIs to detect abandoned buildings. In shrinking cities, mostly underdeveloped areas, there is a lack of street view data and therefore no access to up-to-date information on buildings; or the commercial SVIs have not been updated for years and cannot keep up with the rapid urban renewal, where abandoned buildings or changed facts occur. A new data source is required to obtain timely information on abandoned buildings. Mobile sensing images (MSIs) has great potential for sensing abandoned building research. With the widespread use of smartphones and their embedded cameras, researchers can take pictures and collect visual information on urban environments quickly and at low cost. This information, in combination with machine learning algorithms, can be used to detect and classify abandoned buildings, providing a valuable tool for urban planning and policy-making. Additionally, MSIs can capture up-to-date information on changing urban landscapes, making it a more flexible and adaptable source of data than traditional methods such as remote sensing or field surveys.

Therefore, the aim of this study is to establish a quasi-real-time abandoned building identification system by utilizing sensors and image capture functions on mobile devices, to more accurately detect and locate abandoned buildings. The study aims to improve the efficiency and accuracy of abandoned building detection and provide more accurate data support for urban planning and management. The main research questions of this study include: How to effectively utilize the sensors and image capture functions on mobile devices for data collection of abandoned buildings? How to design appropriate algorithms and models to process and analyze large amounts of perceptual image data and better identify abandoned buildings?

2 Materials and methods

2.1 Study area

The project partner city of Heihe, Heilongjiang Province, a typical shrinking city in Northeast China, is the study area (Fig. 1). The Northeast region of China has been experiencing a decline in population and economic growth since the 1990s, leading to the emergence of "shrinking cities" characterized by abandoned buildings, empty streets, and a deteriorating infrastructure. This phenomenon arises from a combination of various factors, which may include the decline of state-owned enterprises, the relocation of young people to more prosperous regions, and the aging of the population. According to the data released by the National Bureau of Statistics from the seventh national population census, the total population of the case city in 2020 was 1,286,401. This represents a decrease of 23.15%, or 387,498 individuals, compared to the sixth national population census conducted in 2010. The average annual growth rate during this period was -2.60%. Additionally, Hegang covers an area of 14,665 square kilometers, according to data from the Ministry of Civil Affairs of the People's Republic of China.

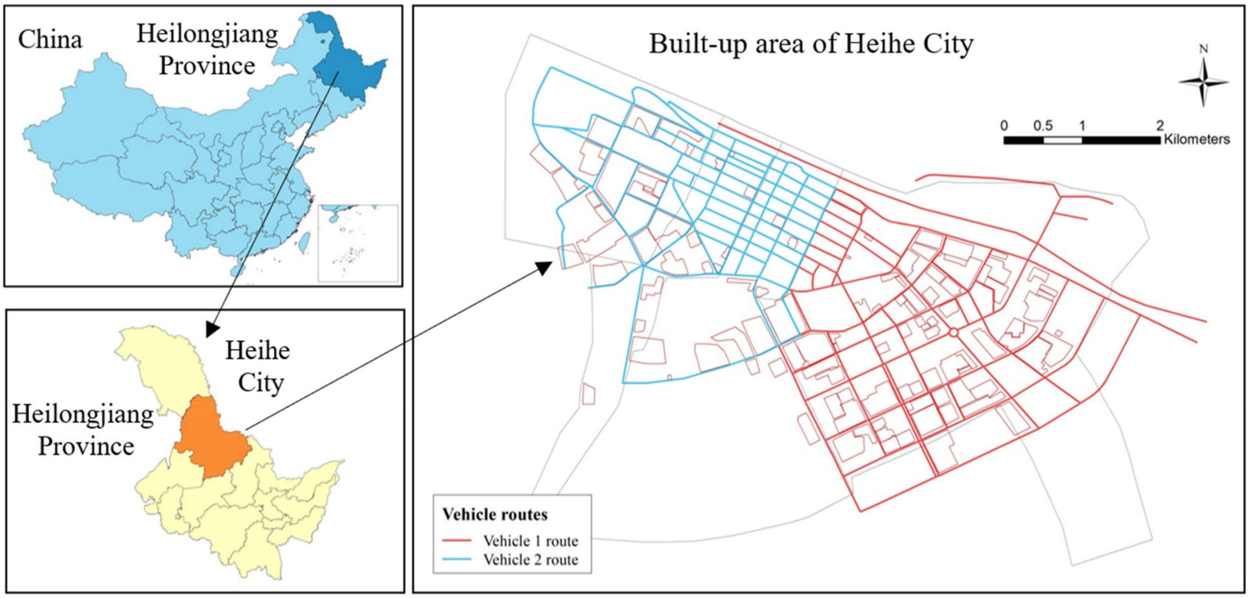

Fig. 1 Central Heihe City is the study area

2.2 Identification criteria for abandoned building

A crucial prerequisite for developing an abandoned building recognition model is to clarify the meaning and standards of abandoned buildings, and to develop detailed recognition guidelines based on the requirements of deep learning model. Existing research and practice have defined abandoned buildings from the perspectives of owner responsibility, social impact, and building function. The New Jersey Abandoned Property Rehabilitation Act stipulates that public officials can consider any property as abandoned if it has not been legally utilized for six months and satisfies any of the subsequent conditions, including lack of proper maintenance, unfinished construction, and deemed as a hazardous factor (Mallach, 2006); Stefano Moroni and his colleagues believe that abandoned buildings are buildings that do not have all functions or possible uses that are not being used, and their owners have not fully complied with their responsibilities to maintain ownership (Lami, 2020); Allan Mallach contends that a property should be deemed as an abandoned building if the owner fails to fulfill one or more crucial property ownership responsibilities, resulting in the property being vacant or expected to be vacant soon, and the unoccupied property becomes a disturbance to its neighbors (Mallach, 2006). Research on abandoned areas in the Lombardy region of Italy believes that "abandoned areas" are areas that no longer perform their intended functions and are in a state of disuse and abandonment (Zou & Wang, 2021).

It can be seen that the existing definitions revolve around two aspects: "the state of the building itself" and "the way people use and maintain the building". Therefore, based on these two points, this study defines abandoned buildings from a spatial perspective as "buildings that do not have normal usage conditions and clear usage traces". "Normal" refers to being generally consistent with the expected function and spatial quality of the building, and "obvious" means that it can be identified through appearance characterization.

Based on this, and in combination with fine-scale street view pre-identification, the abandoned building recognition guidelines (Table 1) are refined and developed. The guidelines are divided into two sections: sufficient and special situations. Sufficient conditions provide an explanation for the definition and are divided into six dimensions: overall building structure, doors and windows, walls, roof, signage, and demolition signs, totaling nine standards. Meeting one of them is sufficient to be recognized as an abandoned building. The special situation section is gradually supplemented and revised during the application process of the guidelines, mainly for the identification of easily confused objects. The abandoned building recognition guidelines provide a structured reference for manual annotation training sets and post-validation, and are an important tool for ensuring the stability and accuracy of abandoned building recognition.

2.3 MSI collection

The mobile sensing data collection campaign was conducted on September 23, 2021. Dedicated vehicles traveled along the outermost road closest to the street edge to capture the buildings on both sides of the street, avoiding

Table 1 Abandoned building identification guideline

Component	Appearance	Image sample	Source
Sufficient situations			
Structure	The building envelope is clearly identifiable, with only the building frame remaining An intact building adhered to an abandoned frame is not considered abandoned		Mallach, 2006; Lami, 2020
	Unfinished construction, e.g., obvious window or door openings Buildings with signs of construction (machinery, material stockpiles, scaffolding, hoardings, etc.) are not considered abandoned		Mallach, 2006
Doors and windows	Broken or missing doors/windows		Mallach, 2006; Lami, 2020
	Window blocked by masonry/iron/wood panel Plastic film and curtain coverings are not considered abandoned buildings		Mallach, 2006
	No access conditions, e.g. weeds blocking the entrance, debris piles blocking the entrance, etc		Zou & Wang, 2021
Wall	Cracked, partially demolished or collapsed building facade		Mallach, 2006; Lami, 2020
Roof	Roof collapsed or demolished		Mallach, 2006
Demolition Signs	The building wall has the words "demolished" / "letters + numbers" (e.g. A1,X13 for the demolition serial number) "dangerous wall end building", "relocated"		Audin, 2018

Table 1 (continued)

Component	Appearance	Image sample	Source
Signage	Commercial, factory, office and other building logos, door signs and other signage have been defaced, broken, or removed Buildings with clear signs of use are not considered abandoned		Audin, 2018
Special situations			
Environment Shabby	Environmental dilapidation is not decisive; a building is not abandoned unless the building itself is abandoned		Mallach, 2006; Lami, 2020
Dilapidated Building	Note the distinction between dilapidated and derelict buildings: buildings that can be used without renovation are not considered derelict		Mallach, 2006; Lami, 2020
Temporary Construction	Temporary buildings such as blue and white boarding houses and tin houses are not considered abandoned buildings		New
Podium	Abandoned podiums count as abandoned buildings		New

occlusion by passing vehicles. The vehicles traveled at a speed of 20–30 km/h to capture clear images. GoPro 9 cameras were mounted on the vehicle windows with clips (Fig. 2(a)) and adjusted to an angle of approximately 10 degrees and a field of view of 170 degree, to capture complete buildings and the environment in front of them (Fig. 2(b)). At the same time, the GPS coordinates were recorded at 1-s intervals using a mobile phone application called GPS Status. To cover the entire study area, route planning algorithms, also known as the Mixed Chinese Postman Problem (MCPP) were applied to calculate the optimal route path (Helbich et al., 2019). In this study, the agents had to serve on both sides separately. First, we obtained the dual-sided road network data for the city center from Amap, one of the main navigation service providers in mainland China. For the 126.2 km of roads in the city center, two dedicated vehicles were hired to collect data in two areas simultaneously, with route lengths of 61.2 km and 65.0 km, respectively (Fig. 1). The routes were planned based on the MCPP algorithm to ensure that the entire area was covered within half a day. Finally, the two vehicles spent 2.19 and 3.09 h, respectively, to complete their respective collection areas.

To obtain an image database with coordinates, image frames were extracted from the videos at one-second intervals to obtain images with timestamps. The images with timestamps were then matched with GPS coordinates with timestamps to obtain an image database with

(a) (b)

Fig. 2 GoPro 9 cameras mounted on the window of motor vehicles for data collection (**a**) and collected videos (**b**)

GPS coordinates and timestamps. Based on GPS coordinates and driving speed, the spatial resolution was approximately 11.11 m (40 km/h multiplied by 1 s). In total, 11,359 image frames were extracted from the video data.

2.4 Abandoned building identification

The research explores the use of a deep learning method for segmentation known as Mask R-CNN (He et al., 2017), for identifying abandoned buildings. Mask R-CNN is a region-based deep learning model that can simultaneously perform object detection and instance segmentation tasks. This model is a continuation of the Faster R-CNN architecture, using ResNet or ResNeXt as the feature extraction network and adding a segmentation branch outside of the detection branch. Unlike traditional object detection and classification algorithms, Mask R-CNN can accurately segment the contours of each detected object in the image, meaning that it can detect and segment multiple overlapping objects separately, contributing to an improved comprehension of the abandoned building scene depicted in the image.

To train the segmentation-based deep learning method, we used LabelMe segmentation annotation software to annotate the instance of each building in each image according to the determined recognition criteria for abandoned buildings, labeling the contours of each building and its use status. A total of 2,321 buildings (9,284 images in total) were collected as raw data, including 207 abandoned buildings and 2,114 normal buildings. The annotated dataset was partitioned randomly, with 50% allocated for training, 10% for validation, and 40% for testing. To reduce the training time, a transfer learning approach was used to fine-tune a pre-trained CNN model instead of training it from scratch. The pre-training was conducted using the Common Objects in Context (COCO) dataset, which is a popular benchmark dataset for object detection, segmentation, and captioning tasks, to improve the Mask R-CNN model. Before learning, the images were rescaled to 1024×1024 pixels to conform to the input requirements of the model. Keras was used to implement the learning process (https://github.com/matterport/Mask_RCNN, accessed on March 5, 2023). The operating environment is Windows 10, equipped with an NVIDIA GTX 1080 Ti GPU accelerated by cuDNN5. The model uses hyperparameters such as a learning rate of 0.001, a training iteration of 1000, and a batch size of 32, with cross-entropy loss used as the loss function.

As machine learning model may lead to misidentification, the co-authors confirmed the images of the abandoned buildings identified by the machine learning model and deleted the wrongly labeled abandoned buildings, in order to obtain correct distribution of abandoned buildings.

Based on the results of manual correction, abandoned buildings were classified into four categories according to their common types: industrial heritage, commercial heritage, residential heritage, and construction sites. Industrial heritage usually has a grand scale and industrial appearance, such as large factory buildings, mines, and warehouses. These buildings are usually made of brick or concrete structures and sometimes have iconic chimneys or water towers. The appearance of the building is usually rough, with many obvious industrial features such as pipes, machinery, and equipment. Commercial heritage, such as shops, restaurants, and entertainment venues, usually have a smaller scale and a decorative appearance. These buildings are usually made of brick, stone, or wood structures, and sometimes have iconic decorative facades, windows, and doors. They often have many commercial features, such as signs, advertisements, and signage. Residential heritage, such as apartments, villas, and houses, has a residential appearance. They are usually made of brick, stone, or wood structures and sometimes have iconic roofs and porches, containing residential features such as windows, balconies, and gardens. Construction sites usually has an unfinished appearance, such as abandoned construction sites and unfinished building projects. These buildings are usually made of reinforced concrete or wood structures, with many unfinished building features such as unpainted walls, uninstalled windows and doors, and unfinished structures and decorations.

3 Results and discussions

3.1 Accuracy of abandoned building identification model

To assess the abandoned building recognition model's precision, the study employed the accuracy metric, which calculates the percentage of accurately identified images out of the total number of images, typically expressed as a percentage. There are 2,321 buildings in the study area that have MSIs available for detection. Out of the 173 buildings in the testing dataset, 145 were correctly identified, resulting in an overall detection accuracy of 83.8%

Table 2 Confusion matrix of abandoned building detection

		Ground-truth Abandoned	Normal	Total	Accuracy
Predicted	Abandoned	65	10	75	86.7%
	Normal	18	80	98	81.8%
	Total	83	90	173	
	Accuracy	78.3%	88.9%		Overall: 83.8%

(Table 2). Out of the total abandoned buildings, 65 were correctly detected, while 10 normal buildings were falsely identified as abandoned and 18 abandoned buildings were not detected.

3.2 Changing dynamics of abandoned buildings

In 2021, there were a total of 50 abandoned buildings within the jurisdiction of Heihe City, mainly located in the north and also in the old urban area of Heihe (Fig. 3). There are four main types of abandoned buildings (Fig. 4): (1) Industrial heritage, such as abandoned factories, mines, and warehouses. (2) Commercial heritage, such as abandoned shops, restaurants, and entertainment venues. (3) Residential heritage, such as abandoned apartments, villas, and houses. (4) Construction site heritage, such as abandoned construction sites and unfinished building projects. The proportion of industrial heritage and residential heritage is relatively high, with 18 and 16 locations respectively, while the proportion of commercial heritage and construction site heritage is relatively low, with 9 and 7 locations respectively.

As Commercial Street View (Baidu) was updated to 2015, the segmentation method was applied here to Baidu Street View to capture the change in abandoned buildings from 2015 to 2021. We retrieved and downloaded open-access Baidu SVIs as input images. Along with the navigation road network data consistent with mobile sensing, coordinate points were generated every 10 m and potential images of abandoned and

Fig. 3 The spatial distribution of abandoned buildings in 2015 and 2021

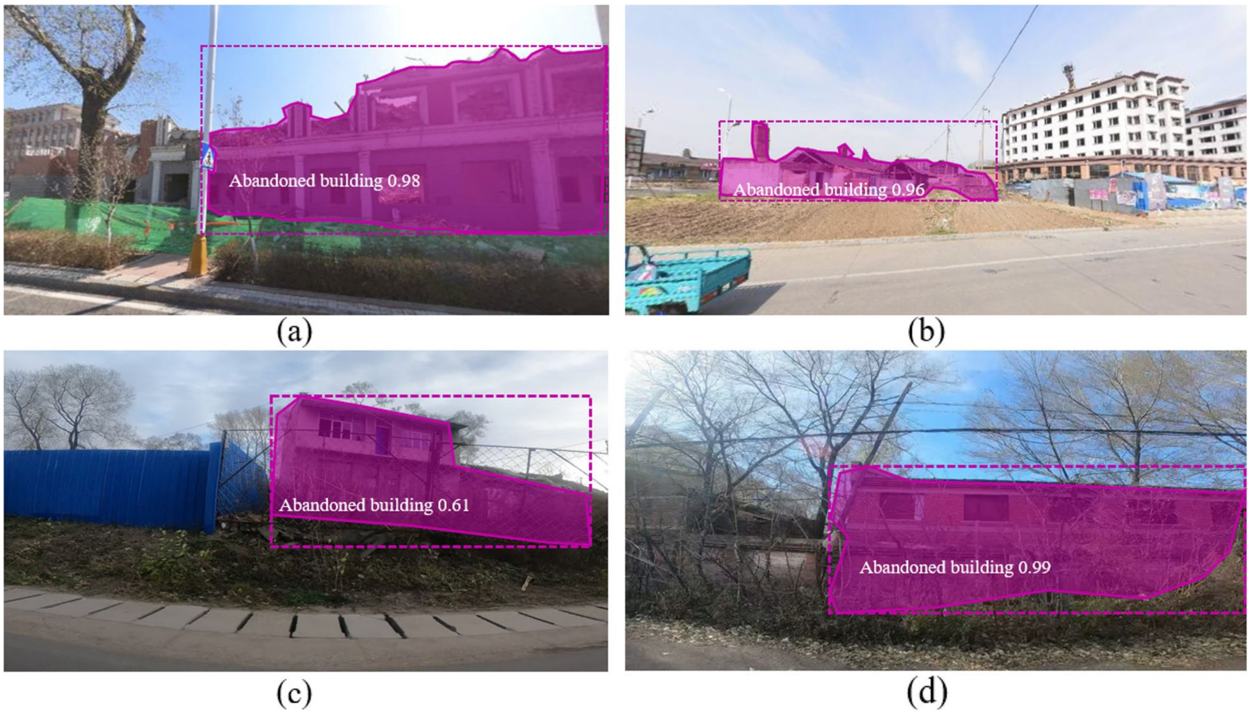

Fig. 4 Four main types of abandoned buildings in 2021: commercial heritage (**a**), Residential heritage (**b**), Construction sites (**c**), and Industrial heritage (**d**)

normal buildings were collected using these coordinate points as inputs. For each coordinate point, the Baidu Application Programming Interface (API) returned the nearest SVI of the address facing the street edge. Other input parameters included a field of view for the image set to 120 degrees, the camera's vertical angle adjusted to 0, and the output image size given as 800×400.

In 2015, a total of 102 abandoned buildings were identified from Baidu street views, mainly consisting of abandoned residential and industrial buildings. These buildings were scattered throughout the entire city and did not show a clustering pattern. Compared to 2021, the number of abandoned buildings has decreased by 52, almost half. The distribution has shifted from across the entire city to mainly concentrated in the old town area, indicating an improvement in the peripheral new city environment. From 2015 to 2021, four buildings remained abandoned, all of which were industrial abandoned buildings.

3.3 Comparison with commercial street view and remote sensing

Although commercial street views such as Google and Baidu have the advantages of wide coverage and easy accessibility, in the context of shrinking cities in China, most of these cities are underdeveloped and the street views are outdated. The latest street view is from 2015, which is eight years ago, just like the case city. Figure 3 shows the rapid changes of abandoned buildings from 2015 to 2021, which were identified by commercial street views and our MSIs, respectively. The results of commercial street views are no longer sufficient to support the rapid development of our cities and related urban planning and renewal projects, which are widely present in the 193 shrinking cities in China and are the main motivation for our mobile sensing campaign. Regarding data quality, commercial street views are collected by commercial companies using standard procedures. In our experiments, mobile sensing activities were conducted according to the handbook we designed, to ensure that our experiments in different shrinking cities were conducted under the same criteria. In terms of spatial resolution, both commercial street views and our MSIs capture continuous street views and therefore have the same spatial resolution. However, in terms of coverage, commercial street views only cover the urban boundaries in 2015, while our mobile sensing routes are flexible and can be adjusted according to the urban boundaries in

2021 or other requirements. The main advantage of our MSIs is their temporal resolution. As mentioned above, commercial street views in shrinking cities have become outdated and cannot keep up with the rapid development of the cities, which hinders the decision-making of urban renewal projects.

Remote sensing images are widely used in studies of built environments, as they can provide broad coverage and high spatial resolution, allowing for the capture of building structural information from a top-view perspective. In contrast, MSIs serve as a self-collected data source, providing good flexibility, coverage, and accessibility for capturing appearance information from a human perspective. Pedestrians or vehicles typically collect these images, acting as carriers for the imaging devices. This approach better reflects the true condition of abandoned buildings, as it offers a more detailed and realistic view of the environment. Consequently, it holds great potential as a tool for detecting and monitoring abandoned buildings. In terms of timeliness, mobile sensing can collect street view information at any time period required for the project, while remote sensing images have longer time intervals. For this study, as there was no Google remote sensing image available on September 23, 2021, the day of mobile sensing data collection, only images from June 25 and October 24, 2021, were available. Therefore, the remote sensing image from October 24 was selected for comparison with abandoned buildings. The study compared the identification results with remote sensing images of the buildings and found that only 58% of the abandoned buildings in 2021 (29 out of 50) could be identified from the remote sensing images. The size, location, resolution of the remote sensing image, and the time of collection all had an impact on the identification. Some buildings were more obvious in SVIs but were obscured by clouds, fog, or inadequate resolution in the remote sensing images, making them unidentifiable (Fig. 5).

3.4 Comparison of segmentation-based and identification-based approach

This study compared with the identification-based deep learning method, Faster R-CNN (Girshick, 2015). Faster R-CNN is an efficient and accurate object detection algorithm that uses Region Proposal Network (RPN) to automatically learn candidate object boxes, resulting in significant improvements in both detection speed and accuracy. In addition, it uses a shared convolutional network, which allows feature extraction and region extraction to be performed simultaneously, further improving detection speed. Therefore, Faster R-CNN has shown outstanding performance in various object detection tasks, particularly in complex scenes. In the experimental results, the identification-based Faster R-CNN method achieved an overall accuracy of 80.4%. The segmentation-based deep learning method outperformed the recognition-based method, increasing the accuracy from 80.4% to 83.8% (Fig. 6). Specifically, the image segmentation method Mask R-CNN divides the pixels in the image into different classes, providing more detailed contour information of abandoned buildings. The recognition method Faster R-CNN aims to classify the input image and mark the position with a rectangular box. Although the recognition method has the advantage of being computationally fast, the downside is that it does not provide contour information at the pixel level. In our experiments, it was found that the segmentation method had lower training and testing speed than the recognition method. The training time for Faster R-CNN was approximately 8.5 h, while the training time for Mask R-CNN was around 12.1 h. The test time per image was 0.47 s and 2.51 s, respectively.

It should be noted that we chose the Mask R-CNN model based on our comparison of models, which showed that it has a relatively high reported accuracy compared to other models, such as Faster R-CNN. Additionally, we implemented a transfer learning approach, where we fine-tuned pre-trained models on our specific dataset to further improve the accuracy of our results. Furthermore, the core of our approach is separate from the models, as we focused on analyzing abandoned buildings from the latest mobile sensing images. Thus, if necessary, new models can be used in the identification part of our methodology, as our approach is model-agnostic.

3.5 Implications for urban planning

Abandoned building data can be collected by various organizations and individuals. During urban planning and renewal processes, urban planning institutions may collect relevant data on abandoned buildings to aid in decision-making. Local governments can collect data on abandoned buildings through city management and maintenance work to ensure the safety and cleanliness of the city. Community organizations can use crowdsourcing to collect relevant data on abandoned buildings during community patrols and maintenance activities, alerting local governments or urban planning institutions to promptly deal with these buildings. Collection frequency for abandoned buildings can be counted on an annual basis since changes in them do not occur frequently. Therefore, organized mobile sensing data collection initiated by urban planning institutions or governments can be carried out annually to observe changes in abandoned buildings. Community-initiated crowdsourcing is not limited by collection

Fig. 5 The cluttered surroundings of abandoned buildings as seen in remote sensing images (**a**), abandoned buildings that cannot be judged from remote sensing images due to obscuration (**b**) and the buildings that can only be observed from remote sensing images (**c**)

time and can report abandoned building data at any time.

Abandoned buildings are a representation of spatial disorder and a manifestation of urban environmental degradation, often occurring alongside other elements of spatial disorder such as garbage accumulation and disordered greenery (Chen et al., 2023). The characteristics of spatial disorder include the interruption and irregularity of spatial elements, which are associated with negative economic, public health, and social stability outcomes, such as property devaluation, psychological stress, fear, and crime. Based on collected mobile sensing images, the spatial disorder around abandoned buildings can be identified. Identifying and monitoring these abandoned buildings and their surrounding environment can help urban planning institutions better manage the urban environment and promote sustainable development.

4 Conclusions

This study represented one of the early attempts to illustrate the potential of utilizing MSIs for the identification of individual abandoned buildings. To effectively and accurately locate abandoned buildings, we developed a segmentation-based deep learning method and conducted experiments. Based on the investigation, the main conclusions can be summarized as follows: (1) MSIs as a new data source, has good flexibility, coverage, and accessibility. It can better compensate for the lack of timeliness of existing commercial SVIs and better characterize the appearance information of abandoned buildings from a human scale perspective, i.e., from the human eye angle, compared to the aerial perspective of remote sensing images; (2) By comparing with the identification results based on commercial SVIs (the latest being 2015), it was found that the number of abandoned buildings in the study area has

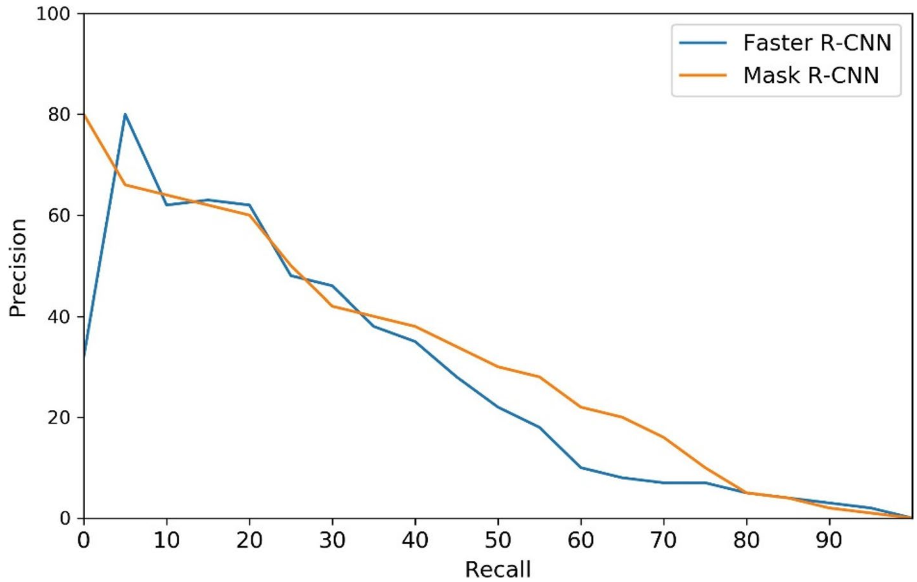

Fig. 6 A comparison of the identification-based Faster R-CNN method and segmentation-based Mask R-CNN method

gradually decreased with urban renewal from 2015 to 2021, but the types of abandoned buildings have become more diverse. (3) By comparing with the identification results based on remote sensing images, it was found that abandoned buildings are more likely to be obstructed by clouds and high-rise buildings in remote sensing images. Only 29 out of 50 can be identified from remote sensing images, and most of them are buildings with messy surrounding greenery and dilapidated roofs; (4) Whether to use a segmentation-based or classification-based deep learning method needs to be determined according to the research objectives. Both methods have comparable accuracy, but segmentation can obtain more accurate building information, while classification is more efficient from annotation to detection model.

The existence of abandoned buildings poses many challenges to urban renewal and reconstruction, including condition assessment, and planning decision-making. This study defined the connotation of abandoned buildings and used novel mobile sensing and deep learning techniques to quickly and accurately identify abandoned buildings and provide relevant information and data. This study enriched the theory and methods of abandoned building research, while improving the efficiency and quality of urban renewal and reconstruction, helping urban planners and managers to timely identify and deal with abandoned buildings, and promoting sustainable urban development.

At the same time, the method proposed in this study has certain limitations and challenges. For example, the data collection may encounter many challenges, such as narrow roads or crowded areas with heavy pedestrian traffic, difficulties in vehicle access or inability to collect data. Therefore, future research needs to further explore multi-carrier mobile sensing methods, such as using (electric) bicycles or human carriers for local data collection. Moreover, the performance of segmentation-based methods depends on the accuracy of the annotated shapes, and we need to balance the number of shape nodes and the expression of features. More accurate shapes require more nodes and more manual annotation work. However, if the shape nodes are too few, the predicted shape may be inaccurate. In addition, although this study combined the surrounding environment for manual classification, future research can further explore the automated classification of types to improve the adaptability and scalability of the model to meet more refined needs.

Abbreviations

MSI	Mobile sensing image
SVI	Street view image
MCPP	Mixed Chinese postman problem
API	Application programming interface

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Authors' contributions
Conceptualization: Yan Li, Ying Long; Methodology: Yan Li, Ying Long; Formal analysis and investigation: Yan Li, Xiangfeng Meng, Wenyue Li; Writing—original draft preparation: Yan Li; Writing—review and editing: Yan Li, Xiangfeng Meng, Huimin Zhao, Ying Long; Funding acquisition: Ying Long; Resources: Ying Long; Supervision: Ying Long.

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Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
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Competing interests
The authors declare no conflict of interest.

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