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Identification Method of High Consequence Area of Pipeline based on Deep Learning and GIS Technology

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Abstract

High Consequence Areas (HCAs) represent geographical zones where pipeline leaks pose a significant threat to public safety and could result in severe environmental harm. The boundaries and locations of these HCAs are not static; they evolve as population dynamics and resource environments undergo changes. To address the intricate challenges of identifying and managing HCAs, a sophisticated method was devised that integrates deep learning and Geographic Information System (GIS) technology. This method harnessed a cutting-edge deep learning framework to recognize and analyze satellite imagery maps, coupled with advanced GIS buffer zone analysis techniques. The process encompassed a meticulous sequence of steps: data collection and processing, building extraction, regional classification, and HCA analysis specifically tailored for HCA identification. By resolving issues such as the burden of extensive manual data collection, inaccuracies in identification, and lengthy update cycles, this method achieved automated HCA identification, thereby significantly enhancing accuracy and consistency. The insights garnered from this study promise substantial alleviation of the manual data collection workload during the HCA identification process, while also bolstering the precision and uniformity of identification. This study offers invaluable insights and guidance for engineering practices pertaining to pipeline management.

Keywords: Gas transmission pipeline, High consequence area, Deep learning, Geographic information system, Identification method

1. Introduction

The management of high consequence areas (HCAs) for gas transmission pipelines stands as a cornerstone of oil and gas pipeline safety management, both domestically and internationally. HCAs are defined as regions where potential leaks or failures in pipelines could result in significant casualties, environmental degradation, or both. Such areas typically feature high population densities, concentrated urban development, or the presence of sensitive facilities such as schools, hospitals, and critical infrastructure. The risk associated with these areas is heightened due to the potential for catastrophic impacts in the event of an incident, making them a critical focus in pipeline safety strategies [1].

In China, the importance of HCA management has been recognized through the implementation of various standards and regulations, notably the China Specification for Integrity Management of Oil and Gas Pipelines (GB32167-2015). This regulatory framework provides clear guidelines for the identification and management of HCAs, categorizing them into grades I to III based on the severity of potential consequences. The grades and boundaries of HCAs are dynamically adjusted in response to changes in population demographics, urban development, and environmental conditions. Despite these advancements, the current methods for identifying HCAs largely rely on manual processes, which present a range of challenges. The collection of data required for HCA identification is often vast and complex, leading to potential inaccuracies and inefficiencies. The manual process can be time-consuming and costly, with delays in updating HCA boundaries and classifications posing a risk to public safety and environmental health [2-4]. Moreover, the subjective interpretation of identification rules by personnel can lead to inconsistencies and variability in HCA identification, undermining the reliability and effectiveness of the management process [5, 6]

To address these challenges, this study proposes a novel approach that leverages advanced deep learning frameworks and GIS (Geographic Information System) buffer zone analysis technology. This approach aims to automate the collection and analysis of pipeline-surrounding building information, enabling the precise identification of HCAs with a consistent and unified scale. By integrating deep learning with GIS, the study seeks to overcome the limitations of manual processes, improving the accuracy, efficiency, and timeliness of HCA identification [7]. The ultimate goal of this research is to provide scientific and efficient technical support for the management of HCAs in oil and gas pipelines, enhancing public safety and environmental protection while reducing the costs and complexities associated with manual identification processes.

2. State of the art

As China undergoes rapid urbanization and experiences a surge in demand for oil and gas, the gas transmission pipeline network has expanded extensively, reaching a total length of 124,000 km by 2023. This critical infrastructure has been instrumental in fulfilling the country's energy requirements and driving economic growth. However, the

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dynamic nature of urbanization has introduced new challenges for pipeline operators. Many previously low-risk areas have been reclassified as HCAs due to increased population densities and upgraded regional classifications, thereby heightening the potential safety hazards associated with pipelines in these regions.

To address the evolving issue of HCAs, the pipeline operators must continuously monitor and update their HCA assessments to reflect the latest demographic and environmental changes. This requires the collection and analysis of extensive data, including population statistics, urban development plans, and environmental conditions. However, the manual process is time-consuming, labor-intensive, and prone to errors, hindering operators' ability to swiftly respond to risk level changes. To overcome these challenges, researchers and industry experts are exploring advanced technologies and methodologies. By leveraging data analytics and machine learning algorithms, operators can automate the collection and analysis of pipeline-surrounding building information, enabling real-time identification and updating of HCAs. This will ensure operators remain aware of the latest risk levels and can take timely mitigation measures to safeguard public safety and the environment.

To enhance the safe operation of pipelines in HCAs, various studies have been conducted. Sun and Loughnan [8] conducted a consequence analysis of vapour cloud explosions resulting from the release of high-pressure hydrogen storage. Wang et al. [9] proposed a new type of high-strength flexible cover plate to prevent engineering failures in oil and gas pipeline engineering. Ahmad et al. [10] conducted a case study on high-pressure methanol synthesis using consequence analysis methods for safety and environmental impact assessments. Iqbal et al. [11] introduced how British Columbia oil and gas pipeline companies use a risk-based approach to integrate integrity management programs and safety cultures. Woldesellasse and Tesfamariam [12] applied a method based on integrated Bayesian belief networks and GIS models to evaluate the consequences of external pitting corrosion in natural gas pipelines in Alberta. Additionally, Iqbal et al. [13] mapped safety culture attributes through integrity management programs to achieve oil and gas pipeline evaluation objectives.

Some developed countries, such as the United States and Canada, have accumulated rich experience in oil and gas pipeline safety management. Through legislation, technological innovation, and other means, they have continuously improved the safety management level in HCAs. The United States, which has the longest oil and gas pipeline mileage, has established a comprehensive set of regulations and standards for integrity management to address the severe challenges posed by pipeline accidents. These regulations have promoted the implementation of integrity management, inspection and evaluation, and repair technology development by pipeline operators in HCAs. In 2015 and 2016, the U.S. federal regulations 49 CFR 192 Pipeline Safety: Gas Transmission and Distribution Pipelines and 49 CFR 195 Pipeline Safety: Hazardous Liquid Pipelines were revised to improve data collection, HCA identification, risk assessment, integrity evaluation, pressure testing, risk reduction, and maintenance [14]. Similarly, British Columbia oil and gas pipeline companies in Canada have used a risk-based approach to integrate integrity management programs and safety cultures to enhance pipeline safety management levels [15].

Chinese scholars and experts have proposed innovative methods and technologies that significantly enhance the efficiency and accuracy of pipeline safety management. Yang et al. [16] introduced a HCA identification method for oil and gas pipelines based on GIS. This method leverages the spatial analysis capabilities of GIS to accurately locate and identify potential high-risk areas along the pipeline route. Liu et al. [17] proposed a GIS-assisted HCA identification model for oil and gas pipelines, which not only strengthens the automation of data processing but also improves the reliability of identification results. Ma et al. [18] focused on practical applications and successfully developed software for identifying HCAs in long-distance pipelines, achieving full automation from data input to output. Tang et al. [19] put forward a method for identifying and classifying HCAs in gas pipelines using multi-source data fusion, which integrates data resources from different sources to provide a more comprehensive and in-depth assessment of HCAs. Liu et al. [20] proposed an HCA identification method for pipelines based on high-resolution remote sensing imagery, utilizing the advantages of remote sensing technology to conduct long-distance, large-scale monitoring of the pipeline environment, providing a new perspective and means for pipeline safety management.

The identification of HCAs has also employed various technological innovations to enhance recognition accuracy and efficiency, such as advanced remote sensing technology, geographic information technology, and artificial intelligence methods. For instance, Dai et al. [21] proposed a method for identifying multiple types of HCAs in pipelines using a Mask R-CNN with a fusion attention mechanism. Huo et al. [22] introduced a remote sensing image segmentation method for HCAs along pipelines based on a fuzzy Markov Random Field (MRF) algorithm with a bee algorithm strategy. Xu et al. [23], taking the China-Myanmar natural gas pipeline substation as an example, proposed a risk assessment method for the safe operation of long-distance pipeline stations in HCAs based on fault tree analysis. Díaz-Parra et al. [24] conducted research on HCAs for natural gas pipelines through modeling. These innovative methods and technologies not only improve the accuracy and efficiency of HCA identification but also provide valuable insights and tools for pipeline safety management, enabling more precise and targeted risk management strategies to be implemented.

The rest of this study is organized as follows. Section 3 presents the research framework. Section 4 describes the data collection, identification algorithm and identification effectiveness of HCAs, and finally, the conclusions are summarized in Section 5.

3. Methodology

This comprehensive study delves into the research of HCA identification for gas transmission pipelines, employing advanced deep learning and GIS technologies. The primary objective is to enhance the precision and efficiency of HCA assessments, thereby mitigating potential safety hazards associated with pipelines in densely populated and environmentally sensitive regions.

The research begins with the collection of essential data, including digital orthophoto images and population statistics. These data sources provide crucial geospatial information and insights into the number of households within buildings, which are essential for assessing risk levels.

Next, a sophisticated deep learning-based image recognition algorithm is deployed to process the digital orthophoto images. This algorithm automatically identifies and extracts spatial information of buildings from the images, such as their precise locations, shapes, and sizes. This automated process significantly reduces the time and labor required for manual data collection and analysis, while also minimizing the risk of errors and inconsistencies.

Once the spatial information of buildings is obtained, GIS buffer zone analysis is utilized to further analyze and classify the regions. The spatial information of buildings is seamlessly integrated with the GIS, allowing for the identification of different regional grades based on population density, building density, and other relevant factors.

Finally, the research leverages GIS technology once more, this time incorporating POI (Point of Interest) data to achieve HCA identification. POI data typically include various geographical features such as shops, restaurants, schools, and other points of interest that can impact risk levels. By integrating POI data with the GIS, the research is able to determine the starting and ending ranges and grades of the HCAs, providing a comprehensive and accurate assessment of pipeline risk levels. The research framework, which encompasses all these steps, is illustrated in Fig. 1. This framework serves as a roadmap for researchers and pipeline operators to follow in their efforts to improve HCA assessments and enhance public safety.

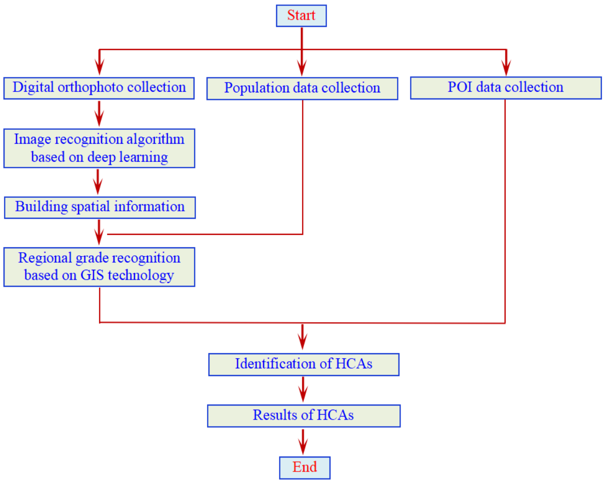

Fig. 1. Schematic diagram of research technology route

In summary, this study integrates deep learning and GIS technology to enhance the accuracy and efficiency of HCA identification for gas transmission pipelines. By leveraging the strengths of both technologies, a comprehensive and automated approach is developed to identify and classify HCAs, providing valuable insights for pipeline safety management and risk mitigation.

4. Data collection, identification algorithm and identification effectiveness of HCAs

4.1 Data collection for HCAs

4.1.1 Collection and processing of remote sensing data

After obtaining satellite imagery with a resolution of 0.6 m, the first step is to screen each image for quality, selecting those with minimal cloud cover and clear imagery. Next, the brightness and color of the images are adjusted to optimize their quality, ensuring uniform brightness and true-color representation to facilitate subsequent tasks.

Following these processes, complete remote sensing images that meet the requirements are obtained. However, these images require significant storage space. To facilitate integration into a visualization system, a buffer zone of 0.5 km on both sides of all pipeline routes is established. By clipping the processed remote sensing images within this buffer zone, pipeline-surrounding remote sensing images that meet project requirements and occupy reasonable storage space are obtained.

4.1.2 Collection and processing of POI data

POI are obtained using coordinate picking services from public internet map software, which are downloaded based on the development API (Application Programming Interface) provided by map vendors. The collected POI data cover a wide range of categories, including commercial and residential areas, companies and enterprises, life services, science, education, and cultural services, sports and leisure services, medical and healthcare services, government agencies and social organizations, transportation facilities, road ancillary facilities, public facilities, scenic spots, shopping services, and more. Each major category is further subdivided into several intermediate and sub-categories. The data labels include ID, name, type, address, latitude and longitude coordinates, telephone number, and administrative district. After obtaining the POI data, it is cleaned, coordinate-converted, and the necessary POI data is extracted based on the subsequently identified HCA.

The POI data is preprocessed by projecting all types of POI data according to latitude and longitude, unifying the coordinate system with the remote sensing images and correcting the images. This data is then merged with the vector files of buildings extracted through image recognition. After extracting all buildings and POI data within the HCA, the attributes of the buildings within the area will be classified. Building attribute classification will be conducted for the following three scenarios [25]:

(1) In cases where a building in the target area contains only a single POI data point, the POI data type can be used as the building's type attribute.

(2) For buildings in the target area that do not contain POI data, a priority is predefined for POI data types. POI data types common in high-consequence areas with contiguous building distributions, such as schools, hospitals, and shopping malls, are assigned higher priorities. By traversing the building data in the high-consequence area, the center points of all buildings are obtained. Using these points as radii, a search is conducted within a 50-meter radius for high-priority POI facilities. Once a relevant POI type is matched, the building without POI data is assigned the corresponding type, and other buildings are classified as residential.

(3) When determining the attributes of buildings in a high-consequence area that contain multiple POI points, a method based on Item2Vec and edge extraction from image buildings is employed, mapping the results into the classification label space for specific locations in the high-consequence area [26, 27].

Finally, all extracted buildings are classified and stored according to three categories: Specific Location I, Specific Location II, and Explosive and Flammable Location III.

4.1.3 Population data collection

Due to the mobility of the population around pipelines, manual surveys are still used for data collection at this stage. In the future, the integration of travel, municipal utilities, household registration, and other data for analysis and acquisition could be explored. Population data can be directly collected by households, or the population count can be converted into households based on the average number of people per household in the current area.

4.2 Building extraction based on deep learning

Convolutional Neural Networks (CNNs) excel in image feature extraction. Therefore, a deep learning algorithm based on CNNs is adopted for building extraction. As shown in Fig. 2, during the building extraction process, building vectors are drawn based on the buildings in high-resolution remote sensing images. Then, building images and the drawn vector files are used to generate building label images of the same size. Sample clipping is performed on the building images and their corresponding building label images to construct a building sample dataset. Combined with the established deep learning algorithm framework, building extraction model training is conducted. Finally, building extraction from remote sensing images is completed.

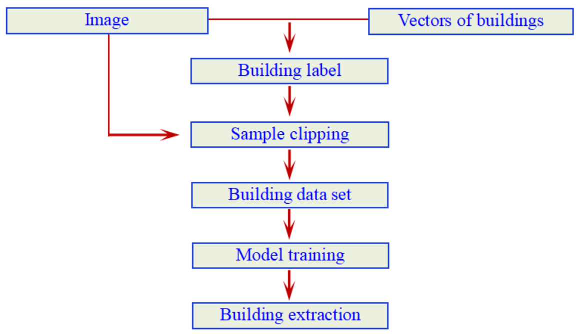

Fig. 2. Building extraction algorithm flow

4.2.1 Annotation of training materials

In the implementation process of the building recognition algorithm model, the annotation of training image materials is a crucial step to ensure that the model can accurately identify the characteristics of high-consequence areas. The annotation work involves careful analysis and processing of the collected image materials to extract valuable information for model training. During the annotation process, according to the identification standards for high-consequence areas of oil and gas pipelines, the features in each image are annotated one by one, and their contours, geographical coordinates, names, and other attribute data are recorded.

The self-constructed building sample dataset consists of 57,251 images, including 47,774 images in the training set, 4,712 images in the validation set, and a note here that there seems to be a discrepancy as the text mentions a validation set of 4,765 images as well, which should be corrected to ensure consistency (for this translation, let's assume the correct number for the second validation set mentioned is a typo and use 4,712 images for both validation sets combined if intended as a total, or clarify if different).

4.2.2 Model training and tuning

As shown in Fig. 3, the OCRHead module, which includes a Bottleneck structure, is utilized. The features extracted by the backbone are further processed through a 3×3 convolutional layer for feature extraction. Subsequently, the Spatial Gather Module aggregates contextual features based on the output (Soft object regions) of the FCNHead to obtain category-specific regional features. Then, the Object Attention Block calculates the relationship between each pixel and each target region and uses these relationships to enhance the representation of each pixel. Finally, the enhanced feature representations are fed into the classification layer (cls_seg) to output the final semantic segmentation results.

The Spatial Gather Module is responsible for weighted aggregation of the predicted probability distribution (Soft object regions) with the feature map to obtain category-specific regional features, which can effectively improve the accuracy of the overall building contour. The Object Attention Block is a module with a self-attention mechanism that calculates the similarity between pixel features and various category features and generates enhanced feature representations. It obtains the probability of each pixel belonging to various categories by calculating the correlation between the feature map (feats) and category-specific regional features (context), thereby enhancing the pixel's feature representation. The benefits of utilizing contextual information include:

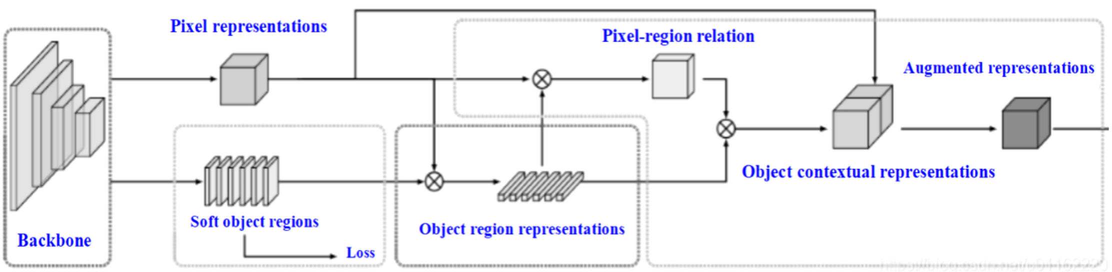

Fig. 3. Building extraction algorithm framework

(1) Integrating global semantic information of contours, allowing the model to understand building contours holistically rather than from local pixels.

(2) More accurately segmenting the boundary areas of building contours and being adept at extracting a large number of densely packed buildings.

(3) Multi-scale fusion, enabling accurate identification of building contours captured at different heights (resolutions).

During the training phase, the operating system used was Ubuntu 22.04, with the compiler being VS Code + Python 3.10. Additionally, four NVIDIA V100-32GB GPUs were utilized to accelerate the training process. The training batch size was set to 24, and the training was conducted for 300 epochs. To increase the diversity of the building data and improve the segmentation accuracy of buildings, various data augmentation techniques were applied during the training process, such as random scaling, random cropping, random adjustments to brightness, contrast, and saturation, as well as random horizontal and vertical flipping. The mean Intersection over Union (mIOU) achieved on the aforementioned validation set was 88.64%.

During the prediction phase, the entire image was used as input, and the output was the extracted results for the entire building. Based on the extracted building results, a building shapefile (SHP) vector was generated, as shown in Fig. 4. This demonstrates the model's ability to accurately identify and delineate building contours, providing valuable information for further analysis and application in fields such as urban planning, disaster assessment, and oil and gas pipeline safety monitoring.

Fig. 4. Extraction results of buildings

4.3 Region classification and HCA analysis based on GIS technology

Buffer analysis, a component of GIS technology, involves creating a polygon area around selected map features (points, lines, or polygons) based on predefined distance conditions, either inward or outward. This method allows for the analysis of geographical data where geographical features extend outward in a plane. In addition to buffer analysis, which relies on spatial relationships, overlay analysis of geographic layers is also one of the primary methods used in GIS to extract spatial feature attributes. Overlay analysis can generate new layers containing information from the original layers and can be used to obtain partially or fully satisfying layer features with different geometric relationships between elements by setting different parameters.

The establishment of buffers varies depending on the analysis object. For point features, there are circular, rectangular, and annular buffers; for linear features, there are bilateral symmetric, bilateral asymmetric, and unilateral buffers; and for polygon features, there are inner and outer buffers. In the analysis of high-consequence areas for oil and gas pipelines, which primarily involves linear features, the bilateral symmetric buffer analysis method is mainly adopted, as shown in Fig. 5. This analysis helps in identifying areas where the potential consequences of a pipeline incident would be severe, enabling better risk management and mitigation strategies to be implemented. By leveraging GIS technology, decision-makers can gain a comprehensive understanding of the spatial distribution and characteristics of high-consequence areas, thereby enhancing the safety and reliability of oil and gas pipelines.

4.3.1 Region classification analysis

A 200-m buffer is created along the pipeline centerline, and the number of households within any 2-km radius from the pipeline's starting point is queried, along with the presence of relatively dense areas. Based on the criteria for region classification, the regions within the 2-km radius are classified from highest to lowest level as follows:

(1) If there is a relatively dense area, it is defined as a Grade IV region.

(2) If the conditions for a Grade IV region are not met, the number of households within the 2-km radius is considered. If there are 100 or more households, it is defined as a Grade III region.

(3) If the number of households is less than 100 but 15 or more, it is defined as a Grade II region.

(4) If the number of households is 1 or more but less than 15, it is defined as a Grade I-B region.

(5) If there are 0 households, it is defined as a Grade I-A region.

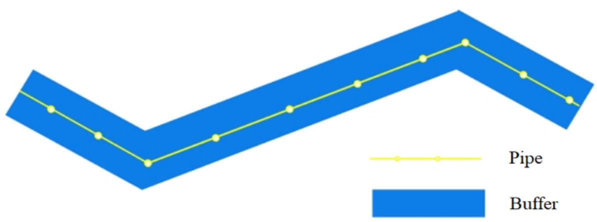

Fig. 5. GIS buffer analysis

As shown in Fig. 6, the region classification within the current 2-km radius and the starting mileage of the pipeline are recorded. Then, the region classification within the next 2-km radius is determined in increments of 10 m. If the region classification for the current segment is the same as the previous segment, the determination continues with 5-m increments for the subsequent 2-km radius. If the region classification for the current segment differs from the previous segment, it indicates the presence of a region classification boundary at that location. This method allows for a detailed and accurate assessment of the regional classifications along the pipeline route, enabling better decision-making in terms of safety, risk management, and resource allocation.

Fig. 6. Results of regional classification recognition

4.3.2 Identification of HCAs

As shown in Fig. 7, buffer analysis is employed to locate sensitive areas within the potential impact radius of gas pipelines. This method involves searching the surrounding area point by point along the pipeline. The information of all risk areas rated as Grade III and IV along the pipeline is traversed. Pipelines passing through Grade IV areas are identified as Grade III high-consequence areas, and those passing through Grade III areas are identified as Grade II high-consequence areas. Additionally, all specific sites and flammable and explosive sites outside Grade III and IV areas along the pipeline are traversed. Areas where flammable and explosive sites exist within a 200-m radius of the pipeline are identified as Grade II high-consequence areas (or, for pipelines with a diameter greater than 762 mm and a maximum allowable operating pressure greater than 6.9 MPa, areas where specific sites exist within the potential impact area of the pipeline are identified as Grade II high-consequence areas). Regions where specific sites exist within the potential impact area of natural gas pipelines and within 200 m on both sides of other pipelines are identified as Grade I high-consequence areas.

The boundary of a HCA is set as a 200-m distance from the outermost edge of the nearest building. When identified HCA segments overlap or are separated by no more than 50 m, they are managed as a single high-consequence area segment. This comprehensive approach ensures that all potential high-risk areas along the pipeline are accurately identified and managed, reducing the risk of accidents and ensuring the safety of both people and the environment.

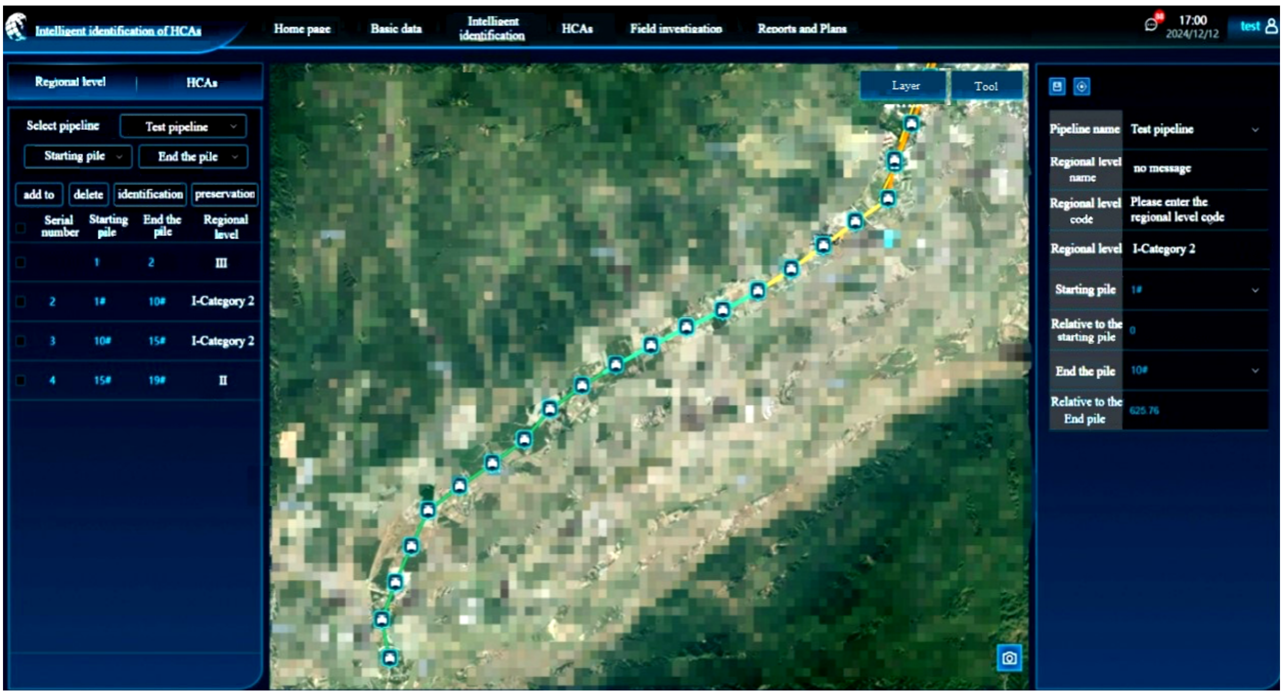

Fig. 7. Identification results of HCA

5. Conclusions

This study explores the method of using deep learning techniques to extract building information from digital orthophoto images, combined with GIS buffer analysis techniques, for the identification of regional grades and HCAs. It addresses the challenges of extensive data collection for buildings around pipelines, the difficulty in accurately collecting spatial locations of elements such as buildings, inconsistent understanding of high-consequence area identification rules, and judgment standards. Through analysis and research in areas such as image recognition, POI data acquisition, attribute mapping, and regional grade and HCA rule algorithms, this study summarizes and proposes a method for high-consequence area identification based on deep learning and GIS buffer analysis techniques. The main conclusions are obtained as follows:

(1) In terms of data collection, an algorithm is used to map POI data to the spatial locations of buildings, automatically obtaining building categories, thereby reducing the workload of building data collection and improving the efficiency of HCA data collection.

(2) Convolutional neural networks (CNNs) are employed to automatically extract building features from remote sensing images. The network structure is adjusted to integrate the relationship between image context information and categorical areas. A self-attention mechanism module is introduced to generate enhanced feature representations, improving the accuracy of building recognition results.

(3) GIS buffer analysis techniques are used to analyze the spatial location relationship between elements around pipelines and pipeline routes. Combined with regional grade and HCA identification rule algorithms, quantitative identification of HCAs is achieved.

The application of this method can greatly reduce the workload of manual data collection, increase the accuracy and consistency of HCA identification, and ensure standardized management of HCAs. In the future, population big data analysis methods can be integrated to further reduce the difficulty of the HCA identification process and increase the frequency of HCA updates.

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