Accurate identification of underground cavities in ground penetrating radar based on deep learning

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Abstract

Aiming at the problem of strong concealment of urban underground cavities and insufficient accuracy of traditional detection methods, this study proposes an intelligent recognition technology of ground penetrating radar based on improved MobileNet convolutional neural network. The high-frequency electromagnetic wave (50MHz-2.5GHz) emitted by ground penetrating radar (GPR) is used to capture the reflected signal of the dielectric constant mutation interface. Combined with three instantaneous attribute analysis (instantaneous amplitude, phase, frequency) and deep learning algorithm, the whole chain prevention and control system of ' data acquisition-intelligent analysis-dynamic early warning ' is constructed. The core innovation is to use a lightweight and high-precision deep learning model, improve the MobileNet architecture, and embed the channel-space dual attention mechanism (SE-CBAM module) and multi-level dilated convolution, which greatly improves the accurate recognition rate of underground cavities. At the same time, based on the identification and positioning images, the dynamic database and risk heat map of underground diseases are constructed to realize the transformation from passive emergency to active prevention and control, which provides an efficient solution for the safe operation and maintenance of underground space in smart cities, and has significant social and economic benefits and engineering promotion value.

Keywords

Underground cavity ; ground penetrating radar ; mobilenet ; precise identification.

1. Introduction

In the process of long-term service of roads, the formation of underground cavities is a common and serious geological disaster problem[1]. Due to the problems of ground precipitation and underground aquifer infiltration, coupled with economic activities and human factors, the development of voids is often hidden and unpredictable. The existence of underground voids is like an invisible bomb under the city, which not only greatly weakens the bearing capacity of the soil, but also may cause disastrous accidents such as ground collapse at any time, directly threatening the safety of people's lives and property and normal traffic production activities[2]. Repairing underground cavities by grouting is a key measure to ensure road traffic safety, and the successful implementation of grouting treatment depends on the location detection and characteristics of the spatial distribution of cavities[3]. Therefore, underground cavity detection and data interpretation are the core links of efficient road management. Its importance lies in : by accurately obtaining the location and connectivity of the cavity, the ground stability of the road can be scientifically evaluated and geological disasters can be prevented ; at the same time, it provides a key basis for grouting parameter optimization and grouting hole layout, avoids waste of resources and treatment of blind areas, reduces construction costs, and finally achieves the dual goals of resource development and ecological protection[4]. The detection accuracy directly determines the effectiveness of governance, which is an important prerequisite for mine safety and economic benefits. From the perspective of geophysics, the necessity of accurate detection of underground cavities can be demonstrated from the following aspects.

Firstly, the accurate detection of the spatial distribution of voids determines the complexity and effect of grouting treatment. From the perspective of geophysical characteristics, the cavity is manifested as a low-density geological anomaly, and its spatial distribution is highly complex, which is mainly reflected in : ① various forms, such as isolated holes, honeycomb networks or fissure-like channels ; ②uneven space, controlled by lithology, groundwater, tectonic stress and other factors, the distribution is very irregular ; ③ Dynamic evolution, which may continue to expand or migrate under the influence of groundwater activities[5]. The complexity of the cavity requires that grouting treatment must rely on accurate positioning data support, otherwise it may lead to : ① treatment failure, grouting holes do not cover key areas, resulting in missed treatment ; ② Parameters are inaccurate, grouting pressure or quantity is insufficient, and filling effect is poor ; ③ cost waste, excessive grouting or repeated construction, raising the cost of governance[6]. Therefore, accurate detection of the three-dimensional spatial location and evolution law of the cavity is the premise of scientifically designing the grouting scheme to avoid waste of resources and improve the efficiency of governance.

Secondly, due to its low density, complex morphology and dynamic evolution, the underground cavity puts forward high standards and high requirements for the detection technology and equipment. Traditional geophysical methods (such as seismic exploration and resistivity method) have limitations in the resolution, efficiency and adaptability of cavity detection. Ground penetrating radar technology has non-destructive and high-resolution characteristics, and is highly compatible with the requirements of underground cavity detection in terms of principle, performance and application scenarios. It is an inevitable and feasible technical means to achieve accurate detection and scientific management[7,8]. In terms of inevitability, based on the significant dielectric constant difference between the cavity and the surrounding rock, the ground penetrating radar realizes three-dimensional imaging with centimeter-level resolution through high-frequency electromagnetic waves (50MHz-2.5GHz), and accurately identifies the spatial location distribution of complex cavities. In terms of feasibility, ground penetrating radar has the advantages of light and flexible, anti-jamming algorithm optimization and low cost, which can dynamically monitor the evolution of voids and efficiently adapt to the needs of underground engineering management[9]. The schematic diagram of ground penetrating radar detection is shown in Figure 1.

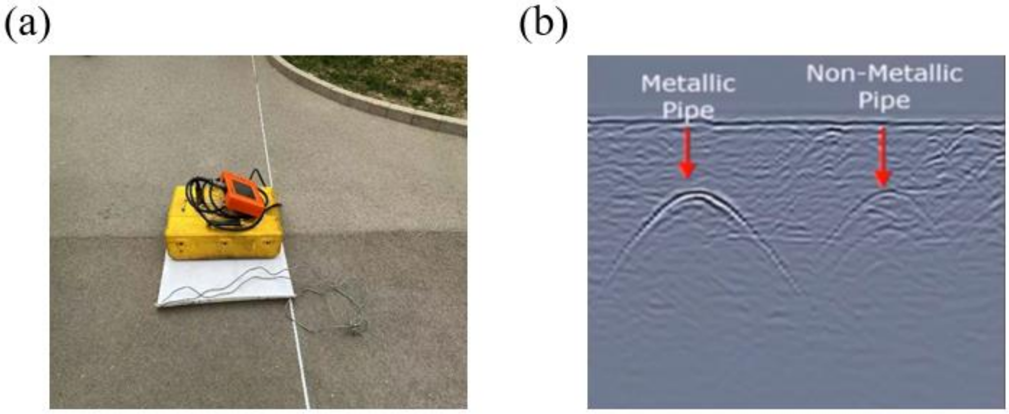

Figure 1. Ground penetrating radar detection schematic diagram: (a) Ground penetrating radar measured process diagram; (b) Detection effect diagram.

Finally, we need to process and interpret the data after obtaining the electromagnetic wave diagram of the measured data of the ground penetrating radar, and accurately identify the spatial location distribution of the cavity. The deep learning model can realize the automatic conversion from electromagnetic wave signal to physical structure by learning the complex mapping relationship between hyperbolic diagram and underground target geometry[10]. Convolutional neural network related models (such as MobileNet architecture) have significant research prospects in image classification and target detection applications. With its powerful feature automatic extraction ability and nonlinear mapping ability, it can efficiently characterize the spatial shape distribution of the target image and accurately explain the geometric position distribution of the detected target object[11,12].

2. Ground penetrating radar cavity detection technology

2.1. Determination of detection target of ground penetrating radar

Ground penetrating radar relies on broadband, short-pulse electromagnetic waves for underground detection. When the system works, the transmitting antenna radiates electromagnetic pulses with a frequency range of 50MHz-2.5GHz (typical pulse width of 0.5-2ns) to the underground. These electromagnetic waves propagate in the underground medium at $1/\varepsilon_r^{0.5}$ times the speed of light (ε_r is the relative dielectric constant of the medium). When encountering an interface with a dielectric constant difference of more than 5% (such as soil and void, concrete and void layer), part of the electromagnetic wave energy will be reflected according to the Fresnel reflection law, and the remaining energy will continue to propagate downward until it is attenuated to the noise level. The receiving antenna captures the reflected wave signal by high-speed sampling (160GS/s), and records the key parameters such as two-way travel time, amplitude and phase[13]. By moving the radar host, it can continuously collect data and then generate a B-Scan radar waveform. Through in-depth analysis of the waveform, the depth and spatial distribution of underground objects can be inferred according to the waveform characteristics, strength changes and geometric shapes. When the dielectric constant of the medium changes, the behavior of electromagnetic waves is similar to the reflection and refraction of light in different media. The intensity change of the electromagnetic wave depends on the electrical properties of the medium, which provides a key basis for the subsequent detection to identify different underground structures and objects[14]. The travel time of electromagnetic wave from emission to reception is calculated by the following formula :

$$t = \frac{\sqrt{4h^2 + x^2}}{v}$$

In the formula, the travel time of t-electromagnetic wave from emission to acceptance, ns ; h-the actual depth of the reflection interface, m ; x-the distance from the transmitting antenna to the receiving antenna, m ; v-radar pulse speed, m/s.

The calculation of velocity usually depends on the known dielectric properties, such as dielectric constant, which can be obtained by pre-test or data query. Once the velocity data of the radar pulse is available, combined with the previously mentioned formulas and calculation methods, the actual depth of the reflection interface in the underground can be accurately calculated. This depth value actually represents the specific location of the detection target in the underground[15].

$$v = \frac{c}{\sqrt{\varepsilon}}$$

In the formula, the propagation speed of c-electromagnetic wave in the air, m/s ; relative dielectric constant of ?-dielectric. The working principle is shown in Figure 2.

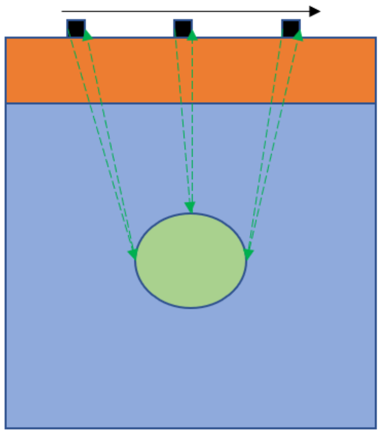

Figure 2. Schematic diagram of ground penetrating radar detection principle.

Ground penetrating radar attributes can enhance the effect of anomalies on the profile, which is helpful to explain the results and further infer the characteristics or properties of the detection target. Therefore, in addition to the basic target anomaly detection, it is often necessary to perform three-instantaneous attribute analysis. The 'three instantaneous' attributes refer to instantaneous amplitude, instantaneous phase and instantaneous frequency, which are the most commonly used attributes in attribute analysis methods. The acquisition of the 'three instantaneous' attribute of ground penetrating radar is obtained by separating the complex signal constructed by Hilbert change of the real signal. The instantaneous amplitude attribute reflects the energy and attenuation of the reflected signal at the specified time. When the electromagnetic wave passes through different media, the instantaneous amplitude will change strongly. The instantaneous phase attribute reflects the continuity of the events on the radar profile, which is not affected by the amplitude, and has a good reflection effect on the signal with weak deep energy. The instantaneous frequency attribute reflects the change of the reflected wave frequency at the specified time. It is the time change rate of the phase, which is susceptible to noise and has a good reflection on the physical properties of the medium[16]. Below is a B-Scan and three-moment property profile.

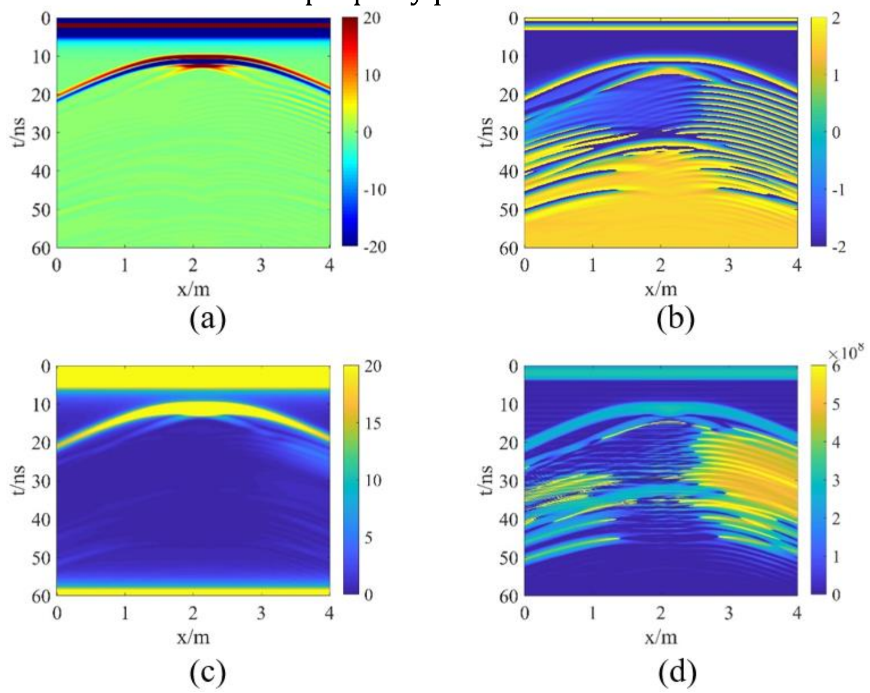

Figure 3. Ground penetrating radar image profile: (a) B-Scan record section; (b) Instantaneous phase profile; (c) Instantaneous amplitude profile; (d) Instantaneous frequency profile.

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In the identification of hidden dangers of underground voids in urban roads, by combining 200 sets of B-Scan maps and attribute analysis, the dielectric constant mutation interface can be directly reflected, and the spatial position of underground voids in roads can be more accurately analyzed. The contradiction between resolution and detection depth of a single method is solved, and the positioning accuracy is improved to centimeter level, thus improving the recognition accuracy. The accuracy rate reaches 90%, which can achieve accurate positioning and promote the transformation of global underground space governance from 'experience-driven' to 'data-driven'. It provides an innovative paradigm for the refined governance of underground space in global cities.

2.2. MobileNet convolutional neural network to realize intelligent recognition of cavity

Underground abnormal target recognition and high-precision positioning are the core technical challenges in the fields of geological exploration and urban underground space safety monitoring[17,18]. Aiming at the problems of insufficient accuracy and weak anti-interference ability of traditional electromagnetic wave data interpretation methods in complex geological structure recognition, this study proposes an intelligent recognition framework based on deep learning. The framework takes the improved MobileNet neural network as the core architecture, breaks through the dependence of traditional inversion methods on artificial empirical features through complex feature fusion and dynamic perception mechanism, and realizes the end-to-end intelligent mapping from electromagnetic wave signal to underground dielectric constant distribution. At the technical implementation level, this study systematically optimizes the MobileNet infrastructure for the complex morphological characteristics such as branch bifurcation and nested structure unique to underground cavities. Firstly, the channel-space dual attention mechanism (SE-CBAM module) is introduced. In the channel dimension, the feature response is adaptively calibrated through the Squeeze-and-Excitation operation. At the same time, the attention heat map is constructed in the spatial dimension, so that the network focuses on the key areas of the abnormal reflection signal concentration. Secondly, the deep residual jump connection structure is constructed, and the shallow high-resolution texture information and deep semantic features are fused through cross-layer feature splicing, which effectively solves the problem of positioning deviation caused by blurred boundary of underground target body[19-22]. Aiming at the multi-complex spatial distribution characteristics of underground holes, a multi-level dilated convolution module is designed to extract context information in parallel through dilated convolution kernels with different dilation rates. This structure expands the effective sensing range to 4.8 times that of conventional convolution while maintaining the resolution of the feature map, which significantly improves the network's ability to characterize irregular extended structures. In order to enhance the robustness of the model in the actual complex electromagnetic environment, the adversarial training mechanism is innovatively introduced to construct a GAN training framework composed of generator-discriminator. The generator is responsible for the conversion of the electromagnetic wave signal to the dielectric constant distribution, and the discriminator distinguishes the real geophysical data from the network output by adversarial learning, forcing the generator to reconstruct the medium distribution that is more in line with the physical law.

The improved MobileNet network greatly improves the pixel-level recognition accuracy of geological radar data. In terms of spatial positioning error, the average intersection over union (mIoU) between the network output and the real medium boundary reaches 0.873. Especially for the tubular cavity structure with a diameter of less than 0.5 meters, the positioning accuracy error is controlled within 8 centimeters. Through the visual feature activation map, it can be seen that the network can accurately capture the dielectric constant mutation interface between the underground cavity and the surrounding rock medium, and the topological reduction degree of the multi-level bifurcation structure is more than 89 %. This technology has been successfully applied to engineering scenarios such as urban underground pipeline leakage detection and karst geological survey. Future research will integrate complex radar array data to further expand the reconstruction ability of the network in three-dimensional space and provide key technical support for the digitization of underground space in smart cities.

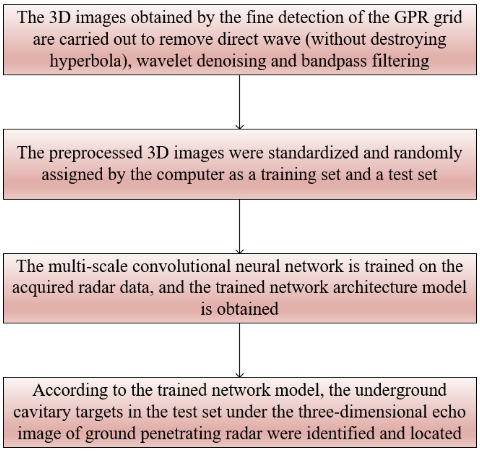

Figure 4. Data flow processing diagram.

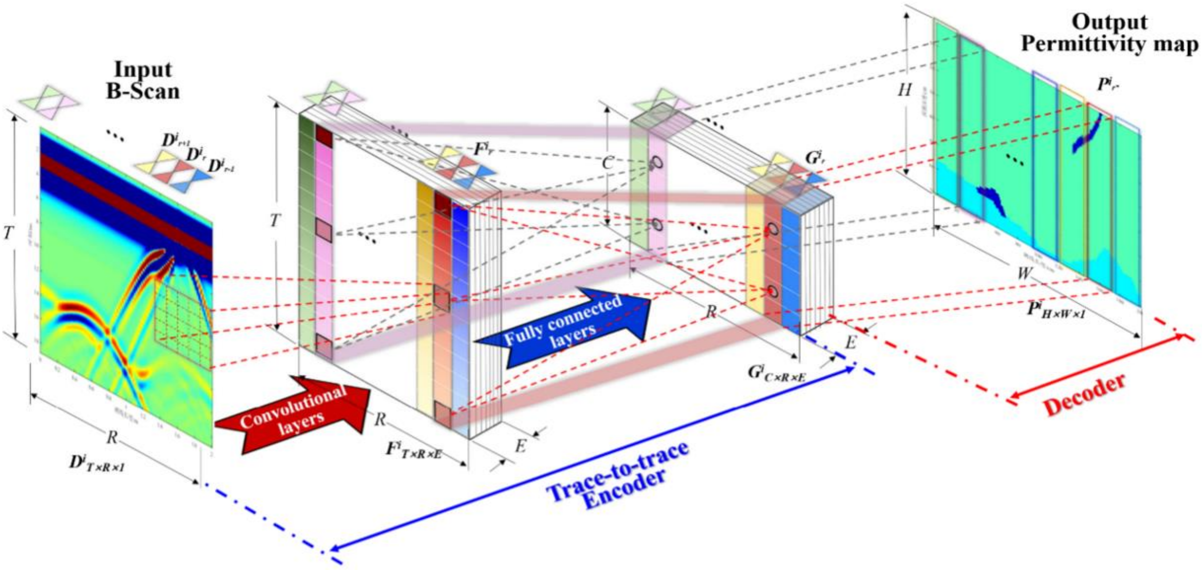

Figure 5. Neural network recognition diagram.

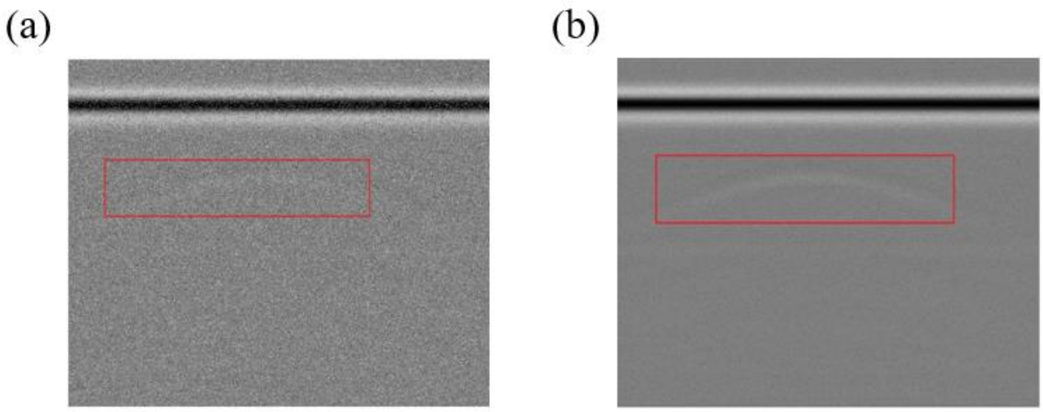

Figure 6. (a) Original radar data; (b) Radar data after neural network recognition.

With its lightweight design and deep separable convolution structure, MobileNet convolutional neural network shows significant advantages in hole intelligent recognition tasks[20,21]. The model reduces the computational complexity to 1/8 to 1/9 of the traditional convolution while ensuring the recognition accuracy and feature extraction ability by compressing the parameter quantity and computational complexity. Compared with the 25.6M parameter of ResNet-50, the volume of the model is compressed by nearly 86%, and the single-frame inference speed can be as low as 50 ms on the edge computing device, which meets the real-time processing requirements of terminal equipment such as tunnel detection robot and portable ground penetrating radar. This lightweight feature enables it to operate stably in scenarios with limited computing power (such as the Jetson Nano platform carried by the mine underground inspection vehicle), which significantly reduces the deployment cost of the geological disaster monitoring system.

Combining transfer learning and complex feature enhancement strategies, MobileNet effectively overcomes the problems of hole morphological diversity and background interference[23]. Aiming at the recognition challenge brought by the diversity of underground cavity morphology, MobileNet constructs dynamic perception ability through complex feature enhancement strategy. The inverted residual structure is introduced into the network architecture, and the 1×1 convolution is used to first increase the dimension and then reduce the dimension. The cross-channel information fusion is realized in the low-dimensional space, and the contour features of different scale holes are effectively captured. At the same time, in order to overcome the complex electromagnetic interference in the underground environment, MobileNet adopts the collaborative optimization scheme of transfer learning and confrontation data enhancement to achieve high-precision cavity identification and positioning. In addition, Random Frequency Masking and Elastic Deformation are used to simulate the signal distortion caused by the fluctuation of dielectric constant of different rock and soil layers, and improve the robustness of the model. MobileNet provides an efficient and low-consumption solution for cavity hidden danger identification in underground engineering, mines, tunnels and other scenarios[24], and promotes the prevention and control of geological disasters to the direction of intelligence and lightweight.

3. Application example of ground penetrating radar underground engineering identification

3.1. Classification and identification of underground pipelines in a municipal engineering project in Zhengzhou City

The measured data used in this detection come from an underground space safety hazard investigation project in Zhongyuan District of Zhengzhou City. As the core development area of the city, the underground pipeline network is dense and there are problems left over from multi-period construction. The GR-2 ground penetrating radar system independently developed by the Key Laboratory of China University of Mining and Technology (Beijing) is used for data acquisition. The system is equipped with a 400 MHz center frequency shielded antenna. Its -3dB bandwidth covers 200-600 MHz, and has a high-precision acquisition capability with a 12ns time window width and a 0.1ns sampling interval. The excitation source adopts an optimized seven-term Blackman-Harris window modulated pulse waveform. Compared with the conventional Rake wavelet, the main lobe width is compressed by 18%, and the side lobe level is reduced to -65dB, which effectively improves the resolution of shallow targets. The field detection adopts the grid data acquisition mode, and the final detection requirement is to generate the dielectric constant profile. The detection process is shown in the figure. The results of underground pipeline detection are shown in Figure 7.

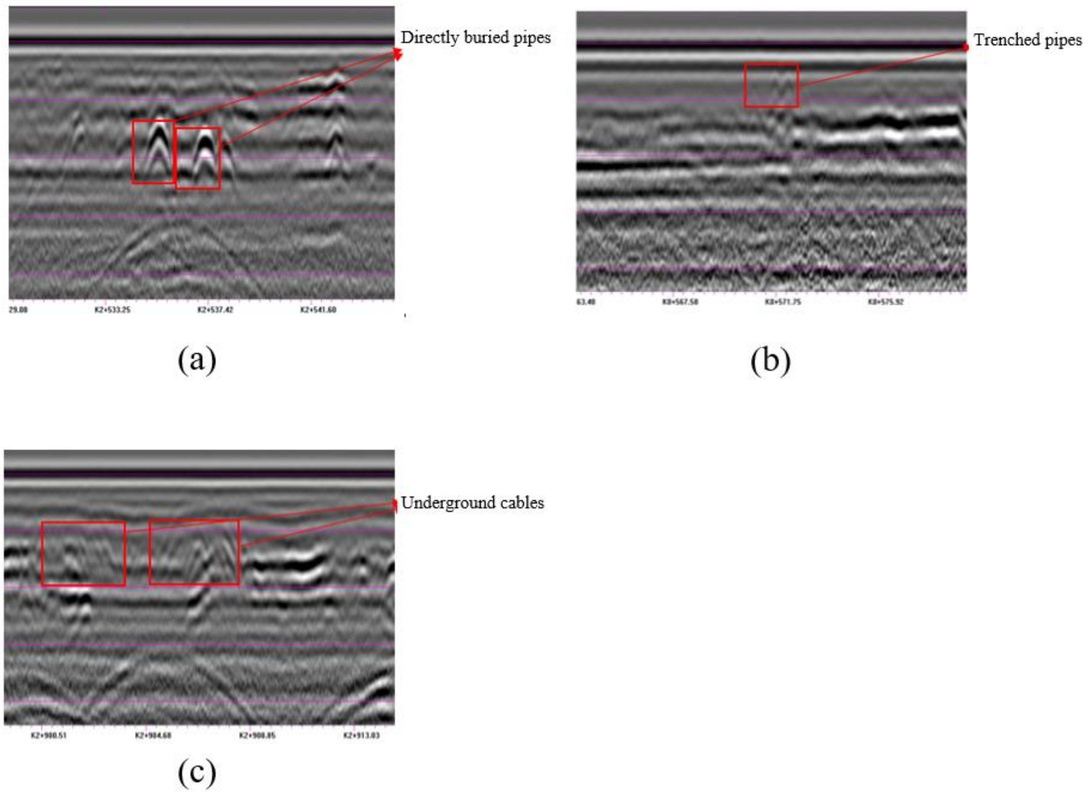

Figure 7. Underground pipeline detection schematic diagram: (a) MobileNet recognition result diagram of directly buried pipeline; (b) MobileNet recognition result of buried pipeline; (c) MobileNet recognition result of underground cables.

The original B-Scan data is obtained by arranging the survey lines along the longitudinal direction of the road (spacing of 1m). The cumulative scanning mileage is 35.6 kilometers, and the original radar profile data is 2.3TB. Aiming at the electromagnetic interference problem in complex urban environment, a multi-level data processing flow is constructed. Firstly, the adaptive threshold method is used to eliminate the baseline drift caused by vehicle vibration, and then the Daubechies wavelet basis (db6) is used for 5-layer decomposition and reconstruction to effectively separate high-frequency noise and effective signals. The 50-800 MHz band-pass filter is designed to suppress the subway clutter interference, and the exponential gain algorithm (gain coefficient $\alpha = 0.12$) is used to compensate the attenuation effect of the medium. In order to improve the generalization ability of the model, the data enhancement strategy is used to expand the pipeline feature image. By randomly rotating (±15°), mirror flipping, adding salt and pepper noise (SNR=25dB) and generating an adversarial network (GAN) to synthesize abnormal samples, the data set size is expanded from the initial 200 groups to 2000 groups. Based on the improved MobileNet network architecture, the channel attention mechanism (SE module) is introduced to strengthen the pipeline edge feature response. The transfer learning strategy is used to fine-tune the ImageNet pre-training model. The initial learning rate is set to 0.001 and the training period is 30. The Adam optimizer is used to update the parameters. The test results show that the classification and recognition accuracy of the system for three types of underground pipelines is 95.6%, and the single-frame image recognition takes only 38 ms (NVIDIA Jetson Nano platform). Compared with the traditional YOLO V5 model, the calculation amount is reduced by 72% while maintaining similar accuracy, which provides efficient and reliable technical support for the safe operation and maintenance of urban underground space. The accuracy of pipeline target training and recognition is shown in Figure 8.

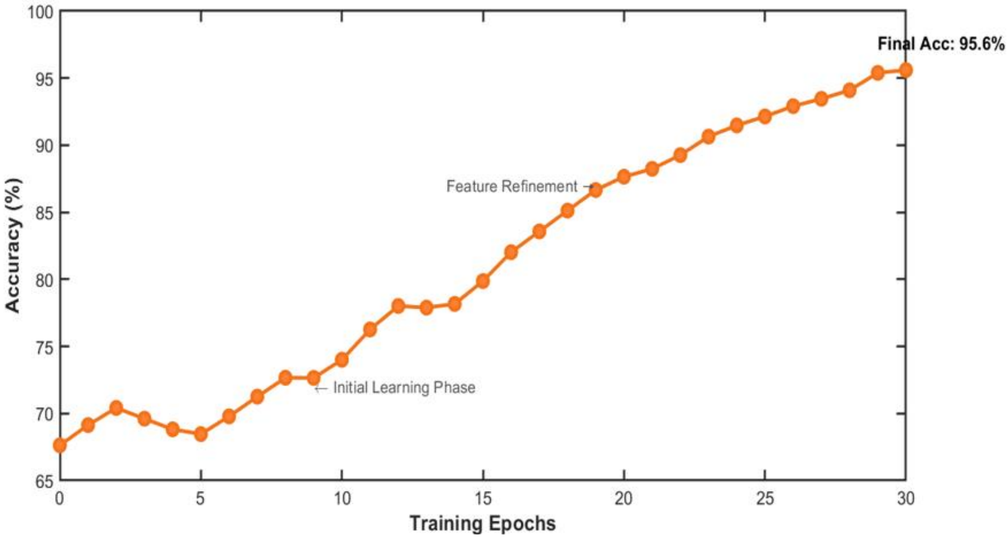

Figure 8. Pipeline target training recognition accuracy chart.

3.2. Accurate identification of underground cavities in a road in Beijing

In order to comprehensively improve the safe operation level of urban infrastructure and ensure urban safety, Beijing has launched a special investigation action on hidden dangers of underground cavities since 2022, focusing on the implementation of high-precision detection in the surrounding areas of urban main roads, transportation hubs and major activities. As the core technology application, ground penetrating radar mainly includes detecting the leakage of road gene pipeline, the cavity or loose area formed by soil loss, and exploring the potential collapse risk sources such as underground pipeline damage and old civil air defense works. Two main types of risk sources are accurately identified by three-dimensional tomography technology : one is the hidden cavity formed by soil erosion caused by leakage of water supply/heating pipelines, which can detect loose soil areas with a diameter of ≥30cm and a vertical resolution of 5cm; the other is the hidden cavity formed by soil erosion caused by leakage of water supply/heating pipelines. The second is the coverage of corrosion leakage of old cast iron gas pipeline network. The detection range of the project includes more than 500 kilometers of urban roads within the third ring. The results of underground road cavity detection are as follows

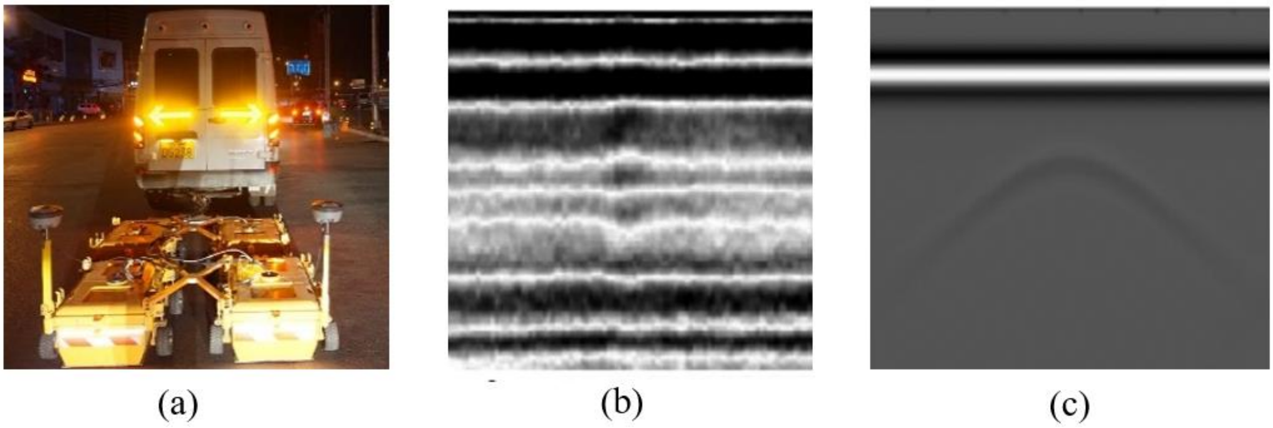

Figure 9. (a) Underground road cavity detection diagram; (b) Void measured result diagram; (c) Hollow MobileNet recognition result diagram.

Therefore, ground penetrating radar technology and MobileNet convolutional neural network identification provide an efficient and accurate hidden danger screening method for underground voids in Beijing roads. Relying on a 400 MHz high-frequency antenna array radar vehicle, the system achieves continuous detection within a depth range of 10m below the road at a speed of 80km/h, and the single-day detection mileage exceeds 50km. Combined with polarization direction optimization and adaptive noise suppression algorithm, it still maintains an abnormal detection rate of more than 90% in a complex electromagnetic interference environment. Through the improved MobileNet network architecture (embedded SE channel attention module), multi-scale feature extraction and classification of 2000 sets of radar B-Scan images after preprocessing are carried out to accurately distinguish the reflection wave mode differences of voids, trenches and gravel layers. The model volume is compressed to 9.3MB, and millisecond real-time analysis is realized on the end side of the edge computing device. The training period is 30, and the recognition accuracy is 96.8%(As shown in Fig.10). At the same time, the 'hidden danger heat map' within the depth of 10 m underground is constructed, and the risk level (high/medium/low) is automatically marked through the MobileNet network. Based on this, the dynamic database of underground diseases is established, which can effectively carry out dynamic prediction and guide targeted reinforcement construction, saving about 12 million yuan in treatment costs, and strongly supporting the urban safety guarantee system during major events. This system not only builds a strong urban security defense line, but also forms a new infrastructure operation and maintenance paradigm that can be replicated and promoted, and contributes to the 'China plan' for the risk management and control of underground space in global megacities.

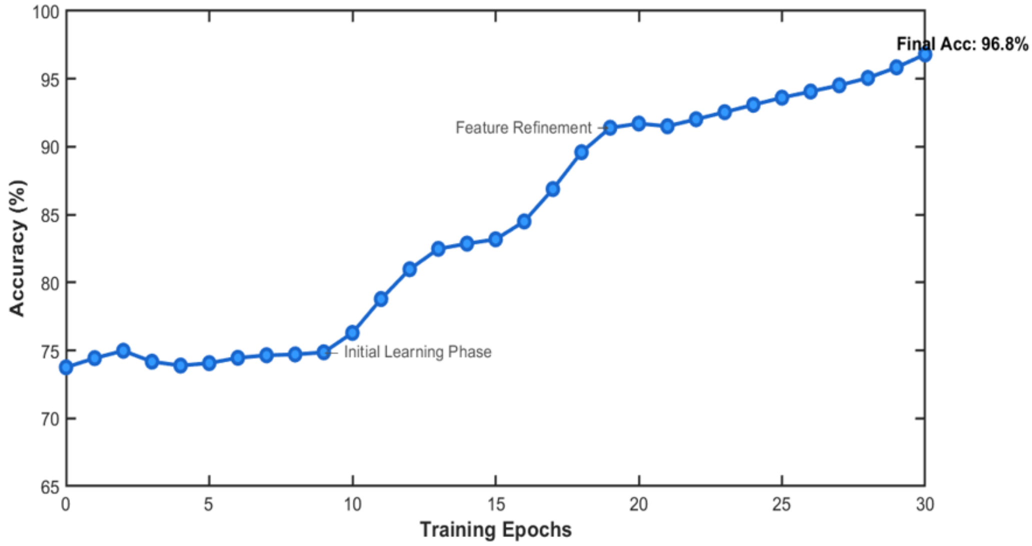

Figure 10. Underground cavity training recognition accuracy map.

4. Conclusion

Ground penetrating radar technology has non-destructive and high-resolution characteristics. It is highly compatible with the needs of road underground cavity detection in terms of principle, performance and application scenarios, and has become the core technical means for road underground cavity detection. Its working principle is based on the difference of electromagnetic wave propagation in different dielectric constant media: the transmitting antenna radiates high-frequency pulse electromagnetic wave (50MHz-2.5GHz) to the ground, and generates reflected echo when encountering dielectric constant abrupt interfaces such as voids and loose areas. The two-way travel time and amplitude information are recorded by the receiving antenna, and the underground medium distribution can be reconstructed by combining the time-depth conversion algorithm. Aiming at the demand of road cavity detection, 400-900MHz antenna combination can achieve the best balance between 5cm vertical resolution and 3m detection depth, effectively identify abnormal bodies with diameter≥30cm, and the detection accuracy in engineering applications can reach 90%.

In the field of intelligent detection of underground cavities, this study innovatively combines the improved MobileNet network with the attention mechanism to construct a lightweight and high-precision recognition model. By embedding the channel attention module in the network bottleneck layer, the system can dynamically calibrate the feature channel weight. Firstly, the channel statistics are obtained by global average pooling to compress the spatial dimension, and then the channel attention vector is generated through two fully connected layers, so that the network can focus on the high-frequency reflection characteristics of the dielectric mutation region, and effectively improve the sensitivity to the void boundary (dielectric constant difference≥5). After structural optimization, the number of model parameters is compressed from 4.2M of the original MobileNet to 0.98M, and the volume is only 8.7MB. Millisecond-level image analysis is realized on the end side of the embedded device, and the holes are accurately identified and located. The accuracy can reach more than 95%.

The deep fusion of ground penetrating radar technology and MobileNet convolutional neural network constructs a full-chain prevention and control system of 'intelligent detection-accurate identification-dynamic early warning'. The hidden danger identification results are transmitted back to the urban safety brain in real time, and the time response mechanism is shortened within 10 minutes, which greatly improves the accuracy and efficiency. Based on this, a dynamic database of underground diseases was established to effectively predict risks and realize the paradigm shift of underground diseases from passive disposal to active prevention and control.

Acknowledgements

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