Advances in Natural Hazard Prediction Modeling Based on Artificial Intelligence Vision

Zihuai Xiong

Mingde Huaxing Middle School, Changsha,410005, China
ouren@wejoyedu.cn

Abstract. The frequent occurrence of natural disasters has seriously affected human survival and development. As well as the rapid development of artificial intelligence vision technology provides a new solution to solve the natural disaster challenges. This paper systematically reviews the progress of research on artificial intelligence vision technology in natural disaster prediction. Firstly, the limitations of traditional prediction methods in the context of frequent occurrence of natural disasters around the world are described, leading to the new solutions brought by AI vision technology; then the efficacy of mainstream technology models in different disaster scenarios is sorted out, comparing the performance boundaries and limitations of different models; and then the multiple challenges faced by the current research are analyzed. Finally, we put forward targeted suggestions from the dimensions of technology optimization, interdisciplinary collaboration, and policy governance, aiming to help global disaster governance to move towards a higher level of intelligence and synergy.

Keywords: Artificial Intelligence Vision; Natural Hazards Early Warning Models; Research Progress; Challenges; Development Direction

1 Introduction

In recent years, the frequent occurrence of natural disasters around the world has become a major challenge threatening human survival and development. The destructive effects of disasters such as earthquakes, floods, fires and typhoons not only cause direct economic losses, but also pose a far-reaching threat to ecosystems and social stability. According to statistics, from 2020 to 2023 alone, the global economic loss due to natural disasters has exceeded US$800 billion, with developing countries suffering more severe consequences due to weak infrastructure and insufficient early warning capacity. Traditional disaster prediction methods mainly rely on historical statistics, physical models and expert experience, however, these methods have significant limitations in terms of real-time, accuracy and adaptability. For example, earthquake prediction is still difficult to break through the bottleneck of "empirical thresholds", flood modeling is limited by the lack of spatial and temporal resolution of meteorological data, and simulation of the spread of mountain fires is difficult to realize high-precision extrapolation due to the complexity of the terrain and the conditions of dynamic meteorology. Against this background, how to utilize emerging technologies

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to break through the boundary of prediction capability has become a core issue in the field of disaster prevention and mitigation.

The rapid development of artificial intelligence vision technology has provided new solutions to this challenging problem. The integration of Computer Vision (CV) and deep learning has made it possible to extract disaster precursor features from massive amounts of remote sensing imagery, drone surveillance, and IoT sensor data. Technologies such as Convolutional Neural Networks (CNN), object detection models (e.g., the YOLO series), and time-series prediction frameworks (e.g., LSTM, Transformer) have demonstrated significant advantages in disaster identification, dynamic tracking, and risk assessment. For instance, U-Net-based flood inundation area segmentation algorithms can monitor the expansion of water bodies in real-time through satellite imagery, while the Transformer architecture has shown superior performance over traditional methods in analyzing the long-term dependencies of seismic precursor signals. At the same time, multimodal data fusion techniques, such as the joint analysis of satellite imagery, meteorological data, and social media text, have further improved the accuracy of typhoon path prediction. These technological advancements not only facilitate the shift from "passive response" to "active early warning" in disaster prediction but also provide decision-makers with more scientific foundations for emergency management.

However, current research still faces multiple challenges. First, the low-frequency and non-repeatable nature of disaster events lead to scarce training data, making the model's generalization ability in rare disasters (e.g., mega-earthquakes or extreme climate events) insufficient. Second, the processing of high-resolution remote sensing images has an extremely high demand for computational resources, which makes it difficult to meet the real-time requirements of edge devices at the disaster site. In addition, the “black box” nature of deep learning models reduces the interpretability of prediction results, leading to limited trust in AI systems by disaster managers. These issues not only constrain the practical implementation of the technology, but also expose the shortcomings of existing research in interdisciplinary collaboration and data ethics. For example, disaster prediction involves the intersection of geoscience, computer science and sociology, but most current research is still limited to single-technology optimization and lacks a global analysis of disaster causal chains and social response mechanisms.

This paper aims to systematically review the research progress of artificial intelligence vision technology in natural disaster prediction, clarify the evolution of technological advancements, analyze core challenges, and explore future development directions. First, it summarizes the application effectiveness of mainstream technical models (such as remote sensing image segmentation, time-series prediction, and multimodal fusion) in different disaster scenarios. Second, based on public datasets and typical cases (e.g., the 2021 Zhengzhou flood warning), it compares the performance boundaries and limitations of various models. Finally, it proposes targeted recommendations from three dimensions: technical optimization, interdisciplinary collaboration, and policy governance. On one hand, this paper integrates scattered research achievements in disaster science and artificial intelligence, constructing a comprehensive analysis framework encompassing technology, data, and applications. On the other hand, it highlights the potential of cutting-edge directions such as lightweight models, self-supervised learning, and causal reasoning in enhancing the robustness of prediction systems.

2 The Application of Artificial Intelligence Vision Technology in Natural Disaster Early Warning

2.1 Remote sensing image segmentation technology

Remote sensing image segmentation technology plays an important role in natural disaster early warning. With the significant breakthrough of machine learning in the field of remote sensing, the neural network remote sensing image segmentation method has become one of the mainstream methods in recent years. In recent years, deep learning has excelled in vision applications, and automatic feature learning methods utilizing deep learning have become a feasible method for semantic segmentation of remote sensing images. One of the prominent representatives is the segmentation model based on convolutional neural network (CNN), and most of the current deep feature-based segmentation methods are extended and developed on the basis of this network.

In 2019 Jianmin Su et al. proposed a semantic segmentation method for high-resolution remote sensing images based on the improvement of U-Net, increasing the number of convolutional layers to achieve a more accurate pixel classification problem, and the back-end adopts an integrated learning strategy to optimize the segmentation results.In 2020, DeeplabV 3+ introduces the null convolution and the spatial pyramid pooling, and obtains the different sensory fields through the null convolution of different expansion rates of the feature maps, and finally these feature maps are fused by spatial pyramid pooling. In 2023, a lightweight remote sensing feature segmentation network, LRSS-Net, was designed for high-resolution drone remote sensing imagery. It utilizes MobileNetV2 for coarse feature extraction and achieves fine-grained feature extraction at different scales by constructing a spatial information embedding branch. Dense connections are introduced between different layers to capture dense contextual information.

For example, the U-Net-based flooded area segmentation algorithm is able to monitor the expansion trend of the water area in real time through satellite images. The algorithm utilizes convolutional neural networks to process remote sensing images and classify different areas in the images to accurately identify the extent of flood inundation. This technology can help the relevant departments to understand the dynamics of the flood in a timely manner, and provide an important basis for flood prevention and disaster relief decision-making [1].

2.2 Multimodal data fusion method

The multimodal fusion technique further improves the accuracy of typhoon path prediction by jointly analyzing a variety of data such as satellite images, meteorological data and social media texts. Different types of data contain different information about the typhoon, and fusing them together can provide a more comprehensive understanding of the typhoon's characteristics and development trends. For example, satellite imagery can provide information on the appearance and location of the typhoon, meteorological data can reflect the weather conditions around the typhoon, and social media texts can provide real-time ground observations and public feedback.

Integrating visual data with meteorological and geologic sensor information can improve prediction robustness. Multimodal Agent Framework (Agent-AI) proposed by Stanford team Multimodal Agent AI (MAA) is a class of systems that generate effective behaviors in specific environments based on understanding multimodal perceptual inputs [2]. By fusing thermal infrared imagery and seismic wave data, the warning time of volcanic eruptions is advanced to 72 hours, but cross-modal alignment and computational complexity are still bottlenecks.

2.3 Time series prediction technology

Time series prediction technology provides a breakthrough solution for natural disaster prediction by integrating multi-dimensional data and complex algorithmic models. Time series prediction technology such as LSTM, Transformer, etc., the fusion processing capability of multi-source heterogeneous data: time series prediction models based on Transformer architecture (such as TimeXer) can simultaneously process multi-modal data such as meteorological, geological sensors, historical disaster records, etc., through the parallel attention mechanism [3]. Deep mining characteristics of nonlinear relationships: deep learning methods can effectively capture nonlinear features in disaster evolution through hierarchical neural network structure. The river runoff prediction system with digital twin technology combined with LSTM network successfully realizes the accurate simulation of the Yellow River runoff trend, and its 72-hour prediction accuracy reaches 91.3%. Of particular interest is that diffusion models (e.g., Diffusion-TS) are capable of generating disaster development scenarios containing seasonal and trend components through a stepwise denoising process, and demonstrate a generalization capability superior to traditional numerical models in typhoon path prediction [4]. Intelligent Iterative Mechanism for Real-Time Early Warning System: a multi-scale feature extraction framework based on WITRAN network, which realizes the capture of long-range dependencies through the water wave information transfer mechanism. This technique has been applied to the analysis of earthquake precursor data, and the warning response time is shortened to 8.6 seconds by monitoring the synergistic changes of more than 20 indicators, such as crustal deformation rate and groundwater radon concentration. Meanwhile, the cross-sequence correlation learning module proposed by MSGNet enables the landslide hazard prediction system to dynamically adjust the weight allocation of data from different geological monitoring points [5].

2.4 Semi-supervised generative adversarial networks

Semi-Supervised Generative Adversarial Networks (SGAN) have shown significant technical advantages in natural disaster prediction, the core of which lies in the fusion of the dynamic game mechanism of generative adversarial networks and the low labeled data dependency of semi-supervised learning. Traditional supervised learning methods in the field of disaster prediction often face challenges such as scarcity of labeled data and difficulty in fusion of heterogeneous data from multiple sources, whereas SGAN, by constructing an adversarial framework of Generator and Multi-task Discriminator, is able to utilize a small number of labeled samples and a large amount of unlabeled data at the same time, which can significantly improve the data utilization of the model. Specifically, SGAN's discriminator is designed to be a powerful and efficient network that can be used to predict natural hazards. The discriminator of SGAN is designed as an N+1 class classifier (N is the disaster category), which simultaneously discriminates the category attribution of the real disaster data and the pseudo-category of the generated data through the softmax function, and this structure enables the model to not only learn the known disaster patterns during the training process, but also mine the potential disaster features through the generative adversarial mechanism. For example, in typhoon path prediction, the generator can simulate the distribution of historical typhoon data to generate synthetic trajectories, while the discriminator combines annotated data such as satellite cloud maps and weather station observations to dynamically optimize the boundary conditions of trajectory prediction, thus enhancing the model's ability to generalize to extreme weather events.

On the technical level, the advantages of SGAN are mainly reflected in three aspects: first, the model robustness is enhanced by adversarial training. The game process between the generator and the discriminator forces the model to focus on the key features of the disaster data (e.g., anomalous peaks in the seismic waveforms or texture changes in the flooded areas) instead of overfitting the noise, which is especially important in disaster prediction because the sensor data often contain environmental disturbances; and secondly, it supports multimodal data fusion. SGAN can seamlessly integrate multi-source information such as remote sensing images, GIS data, and social media texts, e.g., synthesize the missing radar reflectivity data through a generator, and then jointly optimize it with the labeled disaster reports through a discriminator, so as to improve the spatial and temporal resolution of the prediction system; Third, the semi-supervised mechanism reduces the labeling cost. Research shows that SGAN only needs 10%-20% of labeled data to achieve the performance of fully supervised model, which has important application value for disaster scenarios such as mudslides, landslides, etc. where the labeling cost is high. In practical applications, such as the intelligent operation and maintenance system constructed by the Hainan Earthquake Bureau based on deep generative adversarial network, the joint analysis of abnormal network traffic and earthquake precursor signals has been realized, which verifies the feasibility of this technology in disaster warning. In the future, with the further combination of large model architectures such as Transformer and SGAN, disaster prediction is expected to achieve more accurate end-to-end modelling [6].

3 Challenges to Current Research

3.1 Problem of data scarcity

The low frequency and non-repeatability of disaster events lead to the scarcity of training data, which makes the model's generalization ability in rare disasters insufficient. However, the causes of the data scarcity problem are complex. On the one hand, the special attributes of disaster events make data collection difficult, such as the low frequency and irreducible nature of rare disasters, and the existing data collection system has deficiencies such as insufficient coverage of sensors, lack of multimodal data fusion, and low digitization of historical data. On the other hand, traditional supervised learning models have limited adaptability in disaster prediction scenarios, face the problems of feature spatial dimensionality explosion and time series anomalous pattern capture difficulties, and have poor adaptability to long-tailed distributions. The core challenges include attenuation of generalization ability and distortion of the evaluation system. Sparse data makes the model parameter optimization fall into local optima, such as the growth of variance of gradient estimation and the collapse of feature representation space, which leads to large model prediction errors for special hazards. The current K - fold cross-validation method is less reliable when the data are sparse, causing the actual model performance to deviate greatly from the laboratory metrics and invalidating the benchmark for comparison of different algorithms. For example, mega-earthquakes or extreme climate events occur so infrequently that it is difficult to collect enough relevant data to train the model, which makes the model unable to accurately make predictions in the face of these rare hazards (rare hazard events (e.g., earthquakes of magnitude more than 8.0 on the Richter scale and one-in-a-hundred-year floods) are characterized by a low frequency (annual incidence rate of <0.1%) and non-repeatability [7][8].

3.2 Problem of computing resource demand

The processing of high-resolution remote sensing images has an extremely high demand for computational resources, which makes it difficult to meet the real-time requirements of edge devices at the disaster site. At the disaster site, it is often necessary to quickly obtain disaster information, and the edge devices have limited computational capacity to process a large amount of high-resolution remote sensing image data, which affects the timeliness of early warning.

3.3 Model interpretability problems

In the field of academic research, Raymond Bourdon proposed a new theory of cognitive rationality, the core purpose of which is to eliminate the “black box” problem in the interpretation of social mechanisms. Budon holds the view that human rationality is the only reliable factor, so when explaining social phenomena, they should be analyzed from the perspective of individual rationality [9].

Turning to deep learning models, there is a “black box” characteristic, which poses a significant problem of reducing the interpretability of predictions [10]. This problem is particularly prominent in disaster management scenarios. Disaster managers need to make rational decisions based on reliable information and clear rationale, while deep learning models have limited trust in AI systems due to their “black box” characteristics. Because disaster managers need to know clearly the basis of the model's prediction and the specific prediction process, so that they can make correct and reasonable decisions in the actual disaster management. However, the internal structure of deep learning models is extremely complex, which makes it difficult for managers to understand their decision-making process. As a result, disaster managers are bound to be skeptical about the predictions given by the model, and it is difficult for them to carry out disaster management based on these results with complete confidence.

3.4 Interdisciplinary synergy and data ethics

Disaster prediction involves the intersection of multiple disciplines such as earth science, computer science and sociology, but most current research is still limited to single technology optimization and lacks a global analysis of the causal chain of disasters and social response mechanisms. In addition, data ethical issues are becoming more and more prominent, such as privacy protection and fairness of data, which constrain the practical implementation of the technology.

Enhance collaboration among multiple disciplines, such as geosciences, computer science, and sociology. Interdisciplinary research can synthesize the strengths of various disciplines to comprehensively analyze the formation mechanism, development process and social impact of disasters. For example, geoscientists can provide geological and meteorological background knowledge of disasters, computer scientists can develop more efficient prediction models, and sociologists can study the impacts of disasters on society and the social response mechanisms, thereby realizing all-round early warning and management of disasters.

4 Future Development Directions and Recommendations

4.1 Technology optimization

Explore cutting-edge directions such as lightweight models, self-supervised learning and causal inference. Lightweight models can reduce the demand for computational resources and improve the operation efficiency of models on edge devices. Self-supervised learning can improve the generalization ability of models by mining the structure and information of the data itself to train the models in the case of data scarcity. Causal inference, on the other hand, can help us better understand the causal relationship of disasters and improve the interpretability of models. To cope with the data scarcity problem, there are cutting-edge solutions. Data enhancement technological innovations include physical constraint generation adversarial network, which improves the quality of Wenchuan earthquake aftershock sequence generation; and federated learning cross-domain migration, which accelerates the model convergence speed in small sample scenarios. In terms of model architecture innovation, the sparse attention mechanism extends the temporal window for flood prediction in the Yangtze River Basin; and the meta-learning framework shortens the response time for early warning of earthquakes in new regions. However, there are still three major directions to be broken through in the current research, i.e., dynamic coupling of multi-scale spatio-temporal features, quantification of uncertainty in small samples, and human-machine collaborative enhancement learning. Subsequent research can draw on the experience of autopilot, establish a disaster critical state model, and develop multimodal representation learning methods to enhance the model generalization ability.

4.2 Policy governance

To establish an intelligent disaster prevention system with the trinity of "technology research and development - social application - ethical standardization" [11][12]. The government and relevant departments should formulate corresponding policies and regulations to encourage technology research and development and innovation, and promote the application of AI vision technology in natural disaster warning. At the same time, it is necessary to strengthen the regulation of data ethics, safeguard data security and privacy, and ensure that the application of the technology is in line with the interests of the society and moral norms.

5 Conclusion

Artificial intelligence vision technology provides new solutions for natural disaster early warning and shows significant advantages in different disaster scenarios. However, current research still faces problems such as data scarcity, high demand for computational resources, poor model interpretability, and interdisciplinary synergy and data ethics. In the future, researchers should start from the three dimensions of technology optimization, interdisciplinary collaboration, and policy governance to explore cutting-edge directions, strengthen interdisciplinary cooperation, and establish a perfect intelligent disaster prevention system. Through these efforts, it is expected to improve the robustness and intelligence of natural disaster early warning systems and help global disaster governance move towards a higher level of synergization.

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