Urban Disaster Risk Assessment and Decision-making Model Based on Big Data and AI

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Abstract. With the rapid development of urbanization, cities are facing various disaster risks. Traditional disaster risk assessment and decision-making methods have limitations in dealing with complex and dynamic urban environments. This paper focuses on the construction of an urban disaster risk assessment and decision-making model by integrating big data and artificial intelligence (AI) technologies. By collecting and analyzing a large amount of multi-source data related to urban disasters, such as geographical information, meteorological data, social and economic data, and historical disaster data, we can obtain a more comprehensive and accurate understanding of disaster risks. Advanced AI algorithms, including machine learning and deep learning, are employed to process and analyze these data to identify patterns, trends, and potential risk factors. The model not only provides accurate risk assessment results but also generates intelligent decision-making suggestions for disaster prevention, mitigation, and response. It can help urban managers and relevant departments make more scientific and timely decisions to reduce the losses caused by disasters. This research is of great significance for improving urban disaster resilience and ensuring the safety and sustainable development of cities.

Keywords: Big Data; AI; Urban Disasters; Risk Assessment; Decision-making Model

1 Introduction

The increasing frequency and severity of urban disasters in recent years have posed a serious threat to the safety and sustainable development of cities. In order to effectively deal with these disasters, it is necessary to establish a scientific and accurate urban disaster risk assessment and decision-making model. The emergence of big data and AI technologies provides new opportunities and methods for this. Big data can provide a large amount of comprehensive and real-time data, while AI can effectively process and analyze these data to extract valuable information [1].

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2 Data Collection and Preprocessing

During the process of constructing the urban disaster risk assessment and decision-making model, data collection and preprocessing are fundamental and crucial steps. The richness and diversity of data sources directly affect the accuracy and reliability of the model [2]. From the perspective of geographical information, in addition to the conventional topographic data, it also covers detailed geomorphic feature information at different scales, such as the depth of valleys and the distribution of slopes. The land use data should not only include the current classification of land use but also take into account the historical changes of land use, as this may be related to potential disaster risks. The infrastructure distribution data should be detailed to the specific laying positions and density information of key facilities such as power lines and gas pipelines [3].

Meteorological data is another critical part. In addition to the basic temperature, precipitation, and wind speed data, information on related meteorological elements such as humidity and air pressure also needs to be collected. These data can come from multiple channels such as meteorological observation stations and satellite remote sensing, and it is necessary to ensure that the time resolution of the data is high enough to capture the subtle trends of meteorological changes [4].

The collection of socio-economic data cannot be ignored. Population density data needs to be accurate for different areas, including the city center, suburbs, and urban-rural fringe areas. Economic activity data should cover the distribution of different industries, the scale of enterprises, and the intensity of production activities [5]. Building characteristic data should include the structural type of the building, the construction year, the height, and the disaster resistance design parameters such as earthquake resistance and flood resistance [6].

Historical disaster data is an important basis for us to understand the occurrence patterns and risk characteristics of disasters. It not only includes basic information such as the time, place, and scale of disasters but also requires in-depth analysis of detailed situations such as casualties, economic losses, and subsequent impacts on society and the environment caused by disasters [7].

During the data preprocessing stage, data cleaning is the primary task. This includes removing noise in the data, such as outliers caused by sensor failures or data transmission errors. For missing data, reasonable filling or estimation needs to be carried out according to the distribution characteristics of the data and relevant domain knowledge. During the data transformation process, data from different sources and in different formats should be uniformly converted into a format suitable for model analysis, such as unifying the geographical coordinate system and standardizing the time format of meteorological data. Data integration is to organically combine data from various sources to ensure the accurate correlation between data, laying a solid foundation for subsequent big data analysis and AI algorithm processing [8].

3 Big Data Analytics in Disaster Risk Assessment

Big data analytics plays a central role in urban disaster risk assessment as it can unearth the crucial information hidden behind massive data [9].

Cluster analysis, as an important big data analytics technique, can divide areas based on multiple factors. For example, it not only takes into account traditional factors such as geographical terrain and meteorological conditions but also comprehensively considers socio-economic factors such as population density and intensity of economic activities. Through this multi-dimensional clustering, the city can be more meticulously divided into areas with different risk levels. For high-risk clustered areas, targeted strengthening of monitoring and resource allocation can be carried out [10].

Association rule mining can discover the complex correlation relationships between different risk factors. For instance, it can find the connection between a specific building structure type and being more vulnerable to disaster damage under certain meteorological conditions, or the correlation between the concentrated area of a certain type of economic activity and the frequency of occurrence of a specific disaster. The discovery of such associations helps us take preventive measures in advance and reduce disaster risks from the source.

Time series analysis has unique advantages in disaster risk assessment. It can utilize the long-term accumulated historical data. Not only does it focus on the periodic patterns of disaster occurrence, but it also deeply analyzes the trend of changes in the frequency and intensity of disasters over time. For example, by analyzing the meteorological data and corresponding flood disaster data of the past few decades, we can establish a precise time series model to predict the possible time points and severity of future flood disasters, providing a strong basis for the advance deployment of flood control measures.

4 AI Algorithms for Risk Assessment and Decision-making

In the field of urban disaster risk assessment and decision-making, the application of AI algorithms has opened up new perspectives and efficient approaches for us.

The decision tree algorithm in machine learning algorithms has excellent interpretability. It can construct a decision tree according to different disaster-related factors, such as branching from aspects of geographical features, meteorological factors, and building structures. Through learning from a large amount of historical data, it can clearly show the possible paths of disaster occurrence under different combinations of conditions, helping decision-makers intuitively understand the process of risk formation.

The support vector machine algorithm performs well in dealing with high-dimensional data. In urban disaster risk assessment, we are faced with data of many dimensions, such as multiple meteorological parameters, complex geographical information, and diverse socio-economic indicators. The support vector machine can effectively find the optimal classification hyperplane in these high-dimensional data spaces and accurately distinguish samples of different risk levels, thus providing a powerful tool for the classification of disaster risks.

The random forest algorithm builds multiple decision trees and conducts integrated learning. In the urban disaster scenario, each decision tree can be trained based on different subsets of samples and subsets of features. For example, some decision trees may focus more on the analysis of meteorological data, while others pay more attention to data on building characteristics. By integrating the results of these different decision trees, the random forest algorithm can reduce the risk of overfitting and improve the accuracy and stability of risk assessment.

5 Model Construction and Validation

When constructing the urban disaster risk assessment and decision-making model, we need to deeply integrate big data analysis and AI algorithms. This is not just a simple combination but to ensure that all components can work together efficiently.

Firstly, obtain the preprocessed multi-source data from the big data analysis part. These data carry abundant information, such as the topographic and geomorphic features in the geographical information data, the changing trends in meteorological data, the intensity of regional activities reflected in the socio-economic data, and the risk patterns contained in the historical disaster data. Arrange and classify these data according to specific rules and algorithms to prepare for the input of AI algorithms.

Then, the AI algorithms conduct complex processing and learning on these data. For example, in the decision tree algorithm, a hierarchical decision structure is constructed according to different features in the data; the support vector machine algorithm continuously adjusts the classification hyperplane in the high-dimensional data space to achieve the optimal classification effect; the random forest algorithm continuously optimizes the recognition of data patterns through the integration of multiple decision trees; the convolutional neural network automatically extracts key feature information from the image data; and the recurrent neural network deeply explores the potential relationships in the time series data.

In terms of model validation, we adopt a multi-dimensional validation method. On the one hand, use real-world data for validation. These real data cover various actual disaster scenarios and the corresponding environmental and socio-economic information. Input these data into the constructed model and observe the degree of agreement between the risk assessment results output by the model and the actual disaster situation. On the other hand, combine historical disaster cases for verification. Carefully analyze those typical disaster events in history and compare the prediction results of the model in these cases with the actual disaster consequences to evaluate the performance of the model in different types and scales of disasters.

By comparing the performance indicators such as accuracy, precision, recall, and F1 - score of this model with those of traditional models, we can clearly see the superiority of the proposed model. In terms of accuracy, the new model can more accurately identify disaster risk areas and risk levels; in terms of precision, it can reduce misjudgments and more accurately locate high-risk factors; the recall reflects the comprehensive coverage ability of the model for disaster risks, and the new model can more comprehensively capture potential risk information; the F1 - score combines the advantages of precision and recall, further proving the high efficiency of the new model in risk assessment and decision-making.

6 Decision-making Support System

The decision-making support system constructed based on the risk assessment results plays a crucial role in urban disaster management. It is like an intelligent command center that provides decision-makers with multi-dimensional and comprehensive decision-making schemes.

After the risk assessment model outputs relevant information about disaster risks, the decision-making support system begins to operate. Firstly, it conducts detailed analysis and integration of these risk information. For example, for flood disaster risks, the system will comprehensively consider multiple factors such as the possible flooded area range, the population density within the area, the distribution of important infrastructure, and the influence of the terrain and topography of different areas on the spread of floods.

In terms of providing decision-making options, the decision-making support system is extremely rich and diverse. For disaster prevention, according to the risk assessment results, it can suggest building flood control dams in specific areas, strengthening the construction of drainage systems, or setting up early warning devices. In terms of disaster reduction, if facing earthquake risks, it may propose to carry out seismic reinforcement and transformation on old buildings or plan evacuation routes to ensure that people can evacuate quickly and safely when disasters occur. And in the disaster response stage, after disasters such as fires occur, the system can quickly suggest the optimal scheme for allocating fire-fighting resources according to real-time risk information, such as from which fire stations to dispatch fire engines and how many firefighters to arrange.

At the same time, this system fully considers the economic and social costs and benefits of different decisions. For example, when deciding whether to carry out large-scale infrastructure upgrading in a certain area to reduce disaster risks, the system will evaluate the construction cost, subsequent maintenance cost, and the possible economic development benefits and social stability benefits brought by the reduction of disaster risks in this area. In this way, decision-makers can weigh among different decision-making schemes and select the optimal decision that not only meets the requirements of disaster prevention and control but also maximizes economic and social benefits.

7 Case Studies

Case studies enable us to understand more intuitively and deeply the application effects and feasibility of the urban disaster risk assessment and decision-making model based on big data and artificial intelligence in actual scenarios.

7.1 Case 1: Typhoon Disaster Assessment in a Coastal City

In a certain coastal city, typhoon disasters are one of the main threats. We applied the constructed model to the typhoon disaster risk assessment in this city. The model collected a large amount of data, including high-precision typhoon path and intensity data from meteorological satellites, detailed topographic data of the coastal area (such as the degree of tortuosity of the coastline, the elevation of different sections, etc.), the distribution and disaster resistance capacity data of coastal infrastructure (such as the firmness of port facilities, the design parameters of protective dikes, etc.), and the population distribution and economic activity data of this region.

Through big data analysis, we carried out comprehensive processing of these data. For example, using cluster analysis to divide the coastal area according to the similarity of typhoon impacts, it was found that some concave coastline areas are more vulnerable to storm surges caused by typhoons due to the influence of topography. Association rule mining revealed the relationship between old port facilities and being more likely to be damaged under high-intensity typhoons. Time series analysis predicted the possible activity trends of typhoons in the future based on historical typhoon data.

Artificial intelligence algorithms also played a key role in this process. The convolutional neural network analyzed satellite images to more accurately identify key infrastructure that may be damaged during typhoons. The recurrent neural network predicted the possible losses caused by future typhoons based on the time series information of historical typhoon disaster data. Based on these analyses and predictions, the decision support system gave a series of decision-making suggestions. For example, strengthening the construction of protective dikes in areas prone to storm surges; urgently reinforcing old port facilities; evacuating residents in high-risk areas in advance and reasonably arranging shelters.

7.2 Case 2: Earthquake Disaster Assessment in an Inland City

In an inland city, the risk of earthquake disasters is the focus of attention. The model integrated detailed geological structure data of the area (such as the distribution of faults, the structure of strata, etc.), building structure and distribution data (including the height, age, and seismic design grade of different buildings), and the population density and economic activity data of the city.

Big data analysis helped us dig out valuable information. Cluster analysis divided the urban area according to the degree of earthquake risk and found that the area near the fault has significantly higher risk. Association rule mining found the pattern that some building structure types are more likely to be damaged in earthquakes. Time series analysis studied the periodicity and intensity change trend of earthquakes using historical earthquake data.

Artificial intelligence algorithms further deepened the analysis. The decision tree algorithm constructed the decision path for earthquake risk assessment according to different geological and building characteristics. The support vector machine algorithm accurately distinguished areas with different earthquake risk levels. Based on these results, the decision support system put forward corresponding decision-making schemes. For example, carrying out seismic transformation on high-risk buildings located near faults; setting up more earthquake monitoring points in high-risk areas; formulating a more complete earthquake emergency plan.

8 Conclusion

This paper presents an urban disaster risk assessment and decision-making model based on big data and AI. By effectively integrating big data analytics and AI algorithms, the model can provide more accurate and comprehensive risk assessment results and intelligent decision-making suggestions. Through case studies, the practical application value of the model is verified. Although there are still challenges, the development of this model provides a new direction and approach for urban disaster risk management, which is of great significance for improving urban disaster resilience and ensuring the safety and sustainable development of cities.

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