Early Warning of Regional Landslide Disaster and Development of Rural Ecological Industrialization Based on IoT Sensor

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Regional landslide disaster is actually the instability caused by the movement of ground or slopes, etc. If a landslide occurs in a habitat area where people live, it can cause a great deal of damage. So, in order to improve the early warning effect of regional geological landslide disaster, the study abandoned the conventional geological probe data, directly used the tilt photography data provided by the fixed camera, introduced the camera clock synchronization control system supported by the high-sensitivity atomic clock timing function, and used the data warehouse hardware and computing host hardware. Combined with the spatial convolution neural network, fuzzy neural network (logarithmic depth iterative regression neural network, polynomial depth iterative regression neural network, transfinite learning machine, and binary neural network) and other technologies finally realize high geological disaster early warning sensitivity and long early warning advance. The system will become an alternative to the previous geological disaster early warning system based on the direct data of geological embedded probes.

1. Introduction

Zeng said in his study that rural ecological agriculture and ecotourism industry are important ways to realize new agriculture. However, the planting area and tourism reception area of ecological agriculture are generally located in mountainous landforms, and the quaternary development layer is thick in mountainous areas with good planting effect, which is easy to form landslides in extreme weather and extreme groundwater environment [1]. Sun and Zhang said in their study that common landslide types include collapse type, fault block type, creep type, layer displacement type, debris flow, and barrier lake [2]. Relevant studies provide accurate landslide early warning in large advance for data collection, data analysis, and data early warning of regional landslides.

In relevant studies, various machine learning algorithm modules are selected to perform in-depth mining on geological monitoring data so as to realize geological landslide early warning with sufficient advance, sensitivity, and specificity. Wang et al. used the combination model to analyze the susceptibility of landslide disasters and gave the susceptibility parameter factors so as to realize high-precision landslide early warning [3]. Liu et al. designed a big data model of a landslide disaster direct early warning factor and used the model to form a machine learning algorithm to realize landslide early warning with high sensitivity and large advance [4]. The research on regional landslide monitoring Internet of Things system is rare. Only one document has been published in mainstream journals in the recent 10 years. This document is the application suggestion of geological disaster monitoring and early warning sensor network technology proposed by Zhou [5]. That is, around 2011, the domestic geological disaster monitoring and early warning Internet of Things system has been basically matured, and the relevant technologies have been used to this day. Wang et al. took the Bailong River Basin as the research area, the evaluation model of regional landslide susceptibility was constructed, and its applicability and result rationality were explored [6]. Zhu et al. for landslides in the western mountainous areas, regional landslide sensitivity analysis was designed and validated, and evaluated it using environmental factor spatial features and heuristic fuzzy logistic model correlation [7]. Fang et al. used the logistic
regression algorithm to establish an early warning model for the regional landslide disasters in Qingchuan County, Sichuan Province [8,9]. Li et al. use data mining technology. The model was constructed by the artificial neural network algorithm to evaluate and predict the regional landslide [10].

Under the traditional Internet of Things signal system, this research focuses on the model combination mode of the machine learning algorithm, verifies its availability and reliability, and then discusses the engineering value of early warning data to ecological agriculture.

The rest of the paper is organized as follows: Section 2 focuses on the hardware design of regional landslide disaster early warning Internet of Things system, Section 3 throws light on innovation of the big data early warning algorithm based on machine learning, and Section 4 is about the simulation evaluation of the effectiveness of big data early warning algorithm. Similarly, Section 5 enlightens the importance of significance of a regional landslide disaster early warning system to the development of the rural ecological industry. Finally, Section 6 is the conclusion.

2. Hardware Design of Regional Landslide Disaster Early Warning Internet of Things System

The geological disaster early warning system for regional landslide uses the displacement and vibration data of rock stratum and soil layer to obtain relevant data in the traditional mode. However, in the principle of geology, stratum displacement can cause the displacement and vibration of rock stratum and soil layer, but the displacement and vibration of rock stratum and soil layer are difficult to have a logical relationship with the subsequent geomechanical changes. Therefore, although this kind of data is relatively direct, it is difficult to form an effective early warning. After the popularization of UAV tilt photography 3D modeling technology, considering the dependence of UAV on weather, fixed tilt photography probes are arranged at most key observation positions. Because the coordinates of the fixed tilt photographic probe can be accurately positioned by the total station and other measuring equipment, the monitoring modeling accuracy can reach the submillimeter level, which can intuitively show the subtle changes of the mountain surface, and the amount of data is much larger than the direct data monitoring results. This technology has become an important technical means of geological disaster monitoring in key areas. Moreover, the rock stratum monitoring data under the traditional mode have not been eliminated but entered the data warehouse as auxiliary data. The logic of the above data acquisition system is shown in Figure 1.

In Figure 1, we have the following: RD Meter: a probe device for obtaining geological monitoring data by analyzing the relative displacement between rock stratum and soil layer. Seismograph: equipment for receiving ground microvibration and obtaining geological monitoring data. Visible camera: the real-time photographing equipment based on visible light can be controlled by a remote clock synchronization signal to form three-dimensional modeling of multangle tilt photography. Infrared camera: the equipment that cooperates with a visible camera to realize ground temperature data acquisition and synchronous three-dimensional modeling, and the equipment control mode is the same as that of the visible camera.

The above main data acquisition process based on camera involves clock synchronization control, data mining analysis, data warehouse, and other hardware functions, so the relationship between hardware devices (host, database, timer, etc.) is shown in Figure 2.

In Figure 2, we have the following: Red: the hardware equipment of the data warehouse is configured with a raid-based high-speed read-write high-capacity solid-state disk system, and the corresponding streaming media data management software is installed. Green: the data analysis host is configured with multiple high-performance CPU computing cores, the maximum capacity allowed by the motherboard is configured with a high-speed dynamic storage system, and multiple high-performance GPU computing cores are configured at the same time to form a multiboard floating-point computing support hardware. Blue: specially marked data processing thread. Brown: data input/output interface.

It should be emphasized that the timer module needs to provide a clock signal with a higher degree of synchronization to improve the observation accuracy. This accuracy needs to take into account the interference factors such as the time-consuming data transmission of the clock trigger signal line. In submillimeter measurement, the clock accuracy directly determines the modeling accuracy. Therefore, when conditions permit, the cesium atomic clock is used to control the core clock signal generator and the antineural network is used to control the transmission advance of the clock signal, which is limited by the length. Although the signal is important, this study focuses on the processing scheme of geological disaster monitoring and early warning signal, which is not discussed here.

3. Innovation of Big Data Early Warning Algorithm Based on Machine Learning

3.1. 2D Still Image Processing Part. The two-dimensional spatial convolution neural network combined with the log depth iterative regression fuzzy neural network is used to generate the fuzzy evaluation value of a single frame image, and the two-dimensional image on the time series generates the time series of fuzzy evaluation value. On this sequence, the transfinite learning machine is used to extract the comprehensive evaluation value of the static image. The logic of the big data algorithm is shown in Figure 3.
In Figure 3, we have the following: SNN: the two-dimensional spatial convolution neural network module is used to strengthen the detailed information of the two-dimensional image. LNN: the log depth iterative regression neural network is used to amplify the data details of high-density landing points near the zero point of the number axis, and compress and convolute the two-dimensional array data into a double precision floating-point data. ELM: it is used for the feature extraction of periodically changing data, fully known as extreme learning machine, which continues to compress and convolute multiple variables on the time series into a double precision floating-point variable.

The core algorithm function of the SNN module is the 2D spatial convolution function, as shown in the following formula:

\[ y(d, e) = \int_{-\infty}^{\infty} g(x) d(u - x) e(u - x) du . \]  

(1)

Among them, \( g(x) \) denotes the convolution kernel; \( d(u - x) \) denotes the convoluted array expression of the first dimension; \( e(u - x) \) denotes the convoluted array expression of the second dimension; \( x \) denotes the convolution control factor; \( u \) denotes the convolution pointer factor.

In the node of the log depth iterative regression neural network, the log depth iterative regression algorithm is used to construct the node basis function, as shown in the following formula:

\[ y = \sum_{i=1}^{n} (A \cdot \log x_i + B). \]  

(2)

Among them, \( x_i \) denotes the output value of the function node; \( A \) and \( B \) are the coefficient to be regression of the base function; \( n \) is the number of nodes of the upper neural network; before using the ELM, the above data needs to be converted, which calculates the ratio of the difference between two adjacent sequence elements and the previous element, which is shown in the following formula:

\[ \tilde{A}_n = \frac{A_n - A_{n-1}}{A_{n-1}}. \]  

(3)

Among them, \( \tilde{A}_n \) denotes the n-th element of the difference sequence; \( A_n \) denotes the n-th element of the original sequence.

The essence of ELM is the depth iterative regression neural network based on trigonometric function. Although there are abundant selection objectives of ELM’s basis function in relevant studies, the most basic trigonometric function depth iterative regression algorithm is adopted in this study, and its basis function is as follows:

\[ y = \sum_{i=1}^{n} [A \cdot \sin(B \cdot x_i + C) + D]. \]  

(4)

Among them, \( A, B, C, D \) denote the coefficients to be regressed; \( n \) denotes the number of nodes of the upper layer neural network. The meanings of other mathematical symbols are the same as those above.

3.2.3D Model Comparison Processing Part. The comparative analysis algorithm of the three-dimensional model is basically similar to the comparative analysis algorithm of the above two-dimensional still image. Firstly, the double precision floating-point data sequence of deep iterative regression convolution is obtained by using the spatial convolution method and the logarithmic neural network method, and then the transfinite learning machine algorithm is used to further convolute the data sequence. Finally, a double precision floating-point variable is formed as the evaluation value of the three-dimensional
model. At the basis function selection level, the only difference is that the three-dimensional space convolution is used to replace the two-dimensional space convolution. The basis function of the three-dimensional space convolution neural network is shown as follows:

\[ y(d, e, f) = \int_{-\infty}^{\infty} g(x) d(u-x) e(u-x) f(u-x) du. \]  

Among them, \( g(x) \) denotes the convolution kernel; \( d(u-x) \) denotes the convoluted array expression of the first dimension; \( e(u-x) \) denotes the convoluted array expression of the second dimension; \( f(u-x) \) denotes the convoluted array expression of the third dimension; \( x \) denotes the convolution control factor; \( u \) denotes the convolution pointer factor.

### 3.3. Fuzzy Neural Network Analysis

The logarithmic depth iterative regression neural network and transfinite learning machine neural network in the previous paper belong to the category of the fuzzy neural network. The fuzzy neural network forms a double precision floating-point variable by the convolution compression of bulk data, but the logarithmic neural network focuses on feature amplification and extraction of the high-density part of uneven data. The neural network of the transfinite learning machine focuses on the periodic change feature extraction of periodic variables. After two-dimensional image analysis and three-dimensional model analysis, the two outputs are double variable floating-point variables. The fuzzy neural network for subsequent data fusion adopts the FNN general mode, i.e., multinomial deep iterative regression neural network. Its data logic is shown in Figure 4.

In Figure 4, both FNN and FNN-pro use the sixth-order polynomial depth iterative regression function to design the neural network node basis function, as shown in formula (6), and the output function of the final early warning result adopts the binary fuzzy neural network node function as follows:

\[ y = \sum_{i=1}^{n} \sum_{j=0}^{5} A_j x_i^j, \]  
\[ y = \sum_{i=1}^{n} \frac{1}{A_i \cdot e^{x_i} - B} \]

Among them, \( A, B \) denote the coefficients to be regressed; \( A_j \) denotes the coefficient to be regressed of the \( j \)th order polynomial; \( n \) denotes the number of nodes of the upper layer neural network. The meanings of other mathematical symbols are the same as those above.

The output result of the FNN module and the binarization module is a data located in \([0, 1]\) interval and infinitely close to 0.000 or 1.000. When the data is near 0.000, it is considered that the corresponding early warning has not been issued. When the data is near 1.000, it is considered that the corresponding early warning has been issued. At this time, the alarm control system is used to trigger audible and visual early warning; at the same time, the mobile Internet is used to inform relevant managers and heads of management departments.

From the above algorithm analysis, it can be seen that the system belongs to a general neural network system, that is, the machine learning module driven by the neural network. By observing the camera information, it can judge the possible probability of regional landslide. The algorithm does not involve any calculation module of geology and geotechnical mechanics, so the system needs to use more data for training; however, it is not subjected to any current geological and geotechnical theory.

Different early warning directions, such as dividing different landslide early warning areas and setting different landslide early warning amounts, can build independent algorithm modules, each module can be trained independently, and finally, independent judgment is given. In the following study, the early warning efficiency of different early warning targets will be simulated and analyzed.

### 4. Simulation Evaluation of the Effectiveness of Big Data Early Warning Algorithm

The Simulink component is loaded under MATLAB to form a simulation environment. According to the above algorithm design, the early warning software for common early warning targets is constructed. The data source is all the available data of 26 deep mountain and deep valley ecological agriculture bases available in China from January 1, 2020 to December 31, 2021. Among them, 146 real landslide disasters were involved, and the prediction and early warning effectiveness of relevant landslide disasters were compared. The reference group provides the early warning results of the geological disaster early warning system based on the direct data of stratum monitoring provided by the State Seismological Bureau.

Firstly, the data before 146 geological landslides are classified according to the types of landslides, and the simulation software formed by the algorithm designed in this study is used to analyze and make early warning in the simulation environment. Compared with the early warning results of the previous system, Table 1 is obtained.

In Table 1, we have the following: Early warning advance: the interval between the issuance of early warning and the occurrence of disaster. Caving type here is no displacement of mountain foundation rock stratum, but there is large rock or a large amount of earthwork collapse. Displacement type: the basic rock stratum of the mountain is displaced and stripped, but the earthwork after stripping basically maintains the previous sequence. Torsion type: the basic rock stratum of the mountain body is displaced and stripped, and the earthwork after stripping disrupts the previous sequence. Debris flow type: the interaction of surface runoff and groundwater causes large-area erosive displacement of rock stratum.

In order to more intuitively observe the data in Table 1, visual processing is performed to obtain Figure 5.

According to the threshold requirements for industrial application of machine learning proposed by the Ministry of Industry and Information Technology, machine learning
software can be used as a grid connected data source for industrial application only when the sensitivity reaches more than 95%. In Figure 5, the sensitivity of the original system based on the direct data of geological monitoring decreases sharply with the increase of early warning, while the sensitivity of the simulation software formed by the algorithm designed in this study in the simulation environment does not decrease significantly with the increase of early warning. It is proved that the simulation system formed by the algorithm has higher availability than the original system.

Under the 120 s and 5 s early warning demand, the regional landslide that forms outside the collapse landslide is investigated, the sensitivity, specificity, and accuracy of the algorithm simulation system are compared and analyzed with the previous system, and Table 2 is obtained.

In Table 2, we have the following: Sensitivity: the ratio of the number of true positive early warning to the number of positive samples. Specificity: the ratio of the number of true negative warnings to the number of negative samples. Accuracy: the ratio of early warning data consistent with reality to all early warning data. $T$: in SPSS big data analysis software, the value of bivariate $t$ check output is considered to be statistically different when $T < 10.000$. $P$: the log value of bivariate $t$-check output in SPSS big data analysis software is considered to have credible statistical significance when $P < 0.05$ and significant statistical significance when $P < 0.01$.

It can be seen that when the early warning advance is 120 s, there is a very significant statistical difference between the two groups of data, $T < 0.001$, $P < 0.001$; when the early warning advance is 5 s, there is a believable small statistical difference between the two groups of data, $T < 10.000$, 0.01 < $P < 0.05$; It can be considered that the previous system focuses more on short advance geological disaster early warning, and the system shows better early warning effect than the previous system under any advance conditions, especially with the increase of early warning advance.
5. Significance of Regional Landslide Disaster Early Warning System to the Development of Rural Ecological Industry

All eco agricultural production parks and tourism parks located near high mountains and deep valleys need to face the impact of geological disasters. Of the 146 landslides discussed in this study, they have caused direct economic losses, including 22 casualties (63 injuries and 2 deaths) and 37 losses of buildings and property, and the total number of abandoned or collapsed houses has reached 679 square meters. Regardless of the secondary losses caused by the decline in the number of tourists and insufficient reception capacity caused by the destruction of the landscape after the landslide disaster, only the direct economic losses are enough to bring economic burden to the operator.

In the research at home and abroad, when geological landslide disaster occurs, the early warning advance is about long and the emergency disaster relief capacity is about strong. Cooperating with the early warning mechanism (evacuation mechanism and protection mechanism) and optimizing the early warning algorithm to improve the advance of effective early warning is an important technical way to reduce the loss of ecological agriculture operators.

Sun Liming used the tilt photography method to quickly model the geological hazards of the barrier lake and realize the geotechnical analysis [11]. Yu Jiayong et al. used the tilt photography modeling method in the prediction and evaluation of geological disasters along a highway [12]. The above related studies show that the tilt photography method is an important method in the current geological disaster assessment and early warning. In particular, the tilt photography data acquisition system with fixed cameras is used in this study. Each camera is accurately positioned by the total station, and the shutter control of all cameras uses a high-precision timing synchronization system. With the support of big data and cloud computing hardware system, it can form submillimeter real-time 3D modeling with higher accuracy. Data analysis is based on a high-precision model, and the full use of the advantages of machine learning helps in analyzing incomplete data and hidden logic data to finally achieve the algorithm efficiency in the previous simulation.

The algorithm can basically achieve more than 95% of the early warning sensitivity under the demand of 120 s early warning advance. In the actual engineering implementation of domestic geological disaster early warning, it can be considered as having engineering value if it reaches 60% of the early warning data. In the simulation, under the 60% sensitivity target, the actual early warning advance of the system can reach more than 900 s, which is enough for the operator to organize effective evacuation of tourists.

6. Conclusion

This research comprehensively uses spatial the convolution neural network and the fuzzy neural network, and forms a multimodule deep iterative convolution neural network machine learning system based on the static image data and tilt photography data collected by visible light camera and infrared camera. Finally, it realizes the high early warning sensitivity and specificity of underground in the early stage of long early warning advance. However, the relevant algorithms in this research do not form packaged software but run in the simulation environment. The follow-up research will develop the application software for the algorithm and try it in the ecological agricultural industrial park with high geological disaster risk.

6.1. Future Work. This work can be further extended onto a major level using the spatial convolution neural network and the fuzzy neural network to form a multimodule deep iterative convolution neural network machine learning system based on the static image data and tilt photography data collected by visible light camera and infrared camera. This work can be useful as it realizes the high early warning sensitivity and specificity of underground at very early stages.

Data Availability

The data underlying the results presented in the study are included within the manuscript.

Conflicts of Interest

The author declares that there are no conflicts of interest.

Authors’ Contributions

The author has read the manuscript and approved submit to your journal.

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