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Tailings Pond Classification Based on Satellite Images and Machine Learning: An Exploration of Microsoft ML.Net

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Abstract: Mine pollution from mining activities is often widely recognised as a serious threat to public health, with mine solid waste causing problems such as tailings pond accumulation, which is considered the biggest hidden danger. The construction of tailings ponds not only causes land occupation and vegetation damage but also brings about potential environmental pollution, such as water and dust pollution, posing a health risk to nearby residents. If remote sensing images and machine learning techniques could be used to determine whether a tailings pond might have potential pollution and safety hazards, mainly monitoring tailings ponds that may have potential hazards, it would save a lot of effort in tailings ponds monitoring. Therefore, based on this background, this paper proposes to classify tailings ponds into two categories according to whether they are potentially risky or generally safe and to classify tailings ponds with remote sensing satellite images of tailings ponds using the DDN + ResNet-50 machine learning model based on ML.Net developed by Microsoft. In the discussion section, the paper introduces the environmental hazards of mine pollution and proposes the concept of "Healthy Mine" to provide development directions for mining companies and solutions to mine pollution and public health crises. Finally, we claim this paper serves as a guide to begin a conversation and to encourage experts, researchers and scholars to engage in the research field of mine solid waste pollution monitoring, assessment and treatment.

Keywords: mine geology; computational intelligence; remote sensing; environment management

MSC: 68T20

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1. Introduction

1.1. Research Background

With the increasing frequency of mining activities worldwide, mine discharge brings plenty of environmental problems. Among these, mine solid waste discharge is considered one of the most serious environmental problems, and as mine solid waste has a low reuse rate compared to other solid waste, tailings ponds generally need to be built to stockpile mine solid waste [1,2].

There is no doubt that the construction of tailings ponds, while allowing for the storage of mine solid waste, is not a good thing for the environment and human beings: the construction of tailings ponds takes up a lot of land and causes damage to vegetation cover, while the leachate from the ponds can have a serious negative impact on the environment and public health. There are many cases (as shown in Table 1) which confirm this.

In 2003, Agrawal, A. et al. [3] introduced the world to the environmental impact and damage caused by solid waste discharge from the non-ferrous metal industry in India, such as leachate pollution; their research showed that metal recycling of solid waste from the non-ferrous metals industry would be effective in mitigating environmental pollution, and Shengo's [4] review endorsed this practice of recovering metal resources from solid waste. In 2016, Liu, Y. et al. [5] suggested that solid waste discharges can lead to damage to the surface landscape, for example, tailings pond stockpiles, which not only occupy surface space but also bring a major safety hazard that would result in serious human casualties at the mine site in the event of a tailings pond failure; in the same year, 2016, Asif, Z. and Chen, Z. [6] argued that the land occupation of tailings pond stockpiles is indeed a nuisance, and therefore they advocated the use of mine solid waste for land reclamation.

Table 1. Research cases on the mine solid waste pollution.

Pollution Issue	Research Cases	Research Area	Research Purpose	Research Findings
Mine Solid Waste Pollution (Tailings Ponds)	Agrawal, A. et al., 2004 [3]	India: Non-ferrous metals Industry	To study solid waste pollution and management in the non-ferrous metals industry in India.	The results showed that solid waste polluted surface water as well as groundwater, primarily through leachate, thus affecting farmland, rivers and public health. Additionally, the authors advocated that mines should commit to metal recycling of non-ferrous solid waste, which would mitigate solid waste pollution.
	Liu, Y. et al., 2016 [5]	China: Mining Industry	To study the pollution of industrial solid waste in general (mining solid waste in particular) and to make recommendations related to solid waste management based on the current state of the resource and environmental development in China.	The authors suggested that the problem of land occupation by solid waste (tailings pond stockpiling) from mines is very serious, especially in China; at the same time, tailings ponds are a major safety hazard that would result in serious human casualties at the mine site in the event of a tailings pond failure.
	Asif, Z. et al., 2016 [6]	North America: Mining Industry	To discuss the challenges of environmental management, particularly solid waste management, in the North American mining industry.	The author highlighted the hazards of land occupation from tailings pond accumulation, and the author recommended the use of non-hazardous mine solid waste for land reclamation.
	Shengo, L. M. 2021 [4]	Democratic Republic of the Congo: Mining Industry	In order to explore the environmental issues related to the management of mineral waste in the mining industry in the Democratic Republic of the Congo.	The recycling and reuse of non-ferrous solid waste were very important, not only to mitigate the problem of solid waste pollution but also to bring potential resource value.

In addition to the potential environmental pollution and health risks associated with tailings ponds, they are also a potential source of danger and can lead to potential safety incidents. If a tailings pond were to fail, it would be a huge disaster for the environment and the people living in the vicinity of the mine. In Brazil, serious tailings pond failures occurred in 2015 and 2019 [7], causing massive damage to homes and vehicles. In China, a tailings pond failure accident occurred in 2008 in Xiangfen Country, Shanxi, resulting in a large number of casualties and environmental damage [8,9].

Since 2010, the safety and environmental pollution hazards of tailings ponds have received increasing attention from researchers [10,11]. Based on the Google Scholar database (https://scholar.google.com; accessed on 14 November 2022), using "tailings ponds and safety" and "tailings ponds and environment" as the keywords, the number of studies related to both keywords for each three-year period from 2010 to 2020 was found, as shown in Figure 1. The number of related literature results in the last 10 years clearly has an upward trend, showing that the safety and environmental pollution hazards of tailings ponds are receiving the public's increasing attention.

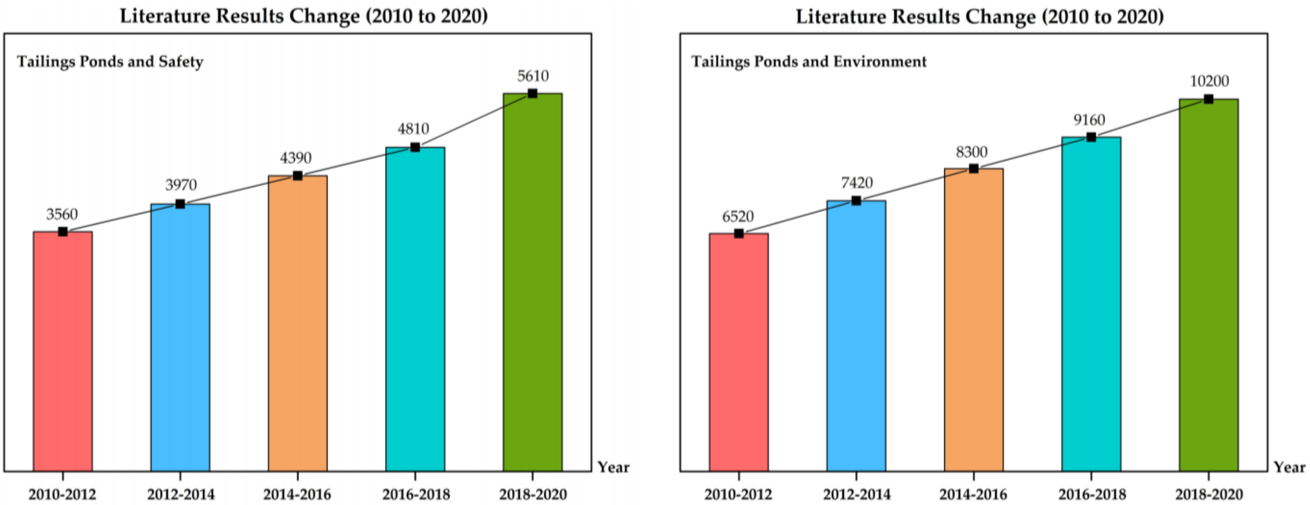

Figure 1. Literature results change of keywords "tailings ponds and safety" and "tailings ponds and environment".

1.2. Research Purpose and Significance

Monitoring and management of tailings ponds are particularly important in order to avoid environmental pollution and safety accidents in tailings ponds [12]. However, monitoring tailings ponds is often very time-consuming and labour-intensive [13]; if remote sensing images and machine learning could be used to determine whether a tailings pond might have potential pollution and safety hazards and then mainly monitoring tailings ponds that may have potential hazards, it would save a lot of effort in tailings ponds monitoring [14,15].

As a result, this paper divides tailings ponds into two categories according to whether they are potentially risky: 1# Tailings Pond, which has potential environmental and safety hazards, and 2# Tailings Pond which has no obvious potential environmental and safety hazards. Combining the remote sensing images (satellite maps) with the results of the field surveys (as shown in Figure 2): it defines that 1# Tailings Pond is an unclosed tailings pond that has significant surface water leaching, thus posing a potential contamination and safety hazard (as shown in Figure 2A); it defines that 2# Tailings Pond is generally a closed (almost closed) tailings pond or a dry stockpile pond with no significant surface water leaching, which may show signs of land reclamation and can generally be considered to have no obvious potential environmental and safety hazards (as shown in Figure 2B).

Based on the features of the two categories of tailings ponds, this paper planned to implement the image identification and classification function of tailings ponds by building a machine learning model via ML.Net developed by Microsoft [16]. At the same time, this paper planned to explore the accuracy of the ML.Net machine learning framework and its machine learning model in classifying and identifying the two types of tailings ponds with different characteristics, providing a starting point for future remote sensing techniques to monitor tailings pond risk and pollution.

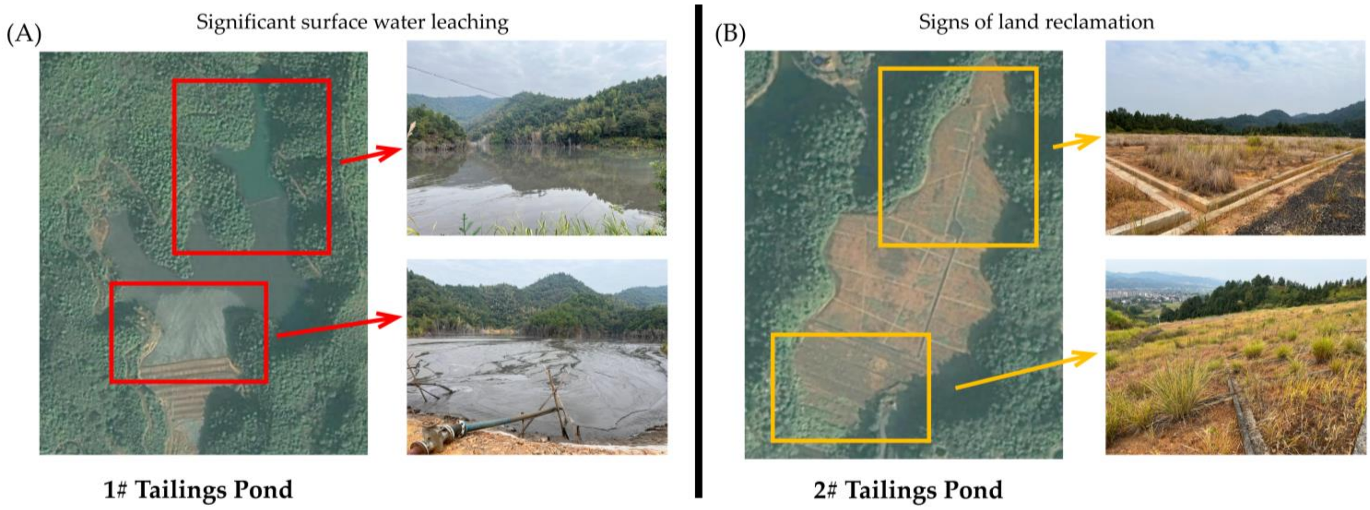

Figure 2. Examples: (**A**) 1# Tailings Pond; (**B**) 2# Tailings Pond. Satellite images from tianditu.gov.cn (accessed on 10 November 2022).

2. Materials and Methods

2.1. Machine Learning Model

The training environment used was local training on a computer using a CPU (Intel Core i7-9750H; Memory: 16 GB). Additionally, the study was carried out on Visual Studio 2022 Professional, based on ML.Net developed by Microsoft [17]:

ML.Net is a machine learning framework developed by Microsoft for the new ".Net" platform and provides a low-code development tool called "Model Builder", an intuitive graphical Visual Studio extension for generating, training and deploying custom machine learning models [18]. Therefore, for ".Net" platform developers, using the ML.Net machine learning framework is an excellent choice in terms of ease of use, performance and accuracy [19]. The ML.Net machine learning framework uses a DNN (Deep Neural Network) and Resnet-50 model (DNN + Resnet-50) to implement image classification functions so the study was based on DNN and the ResNet-50 model to categorise two types of tailings ponds with different features:

ResNet-50 is a residual network that uses a shortcut connection to connect the inputs directly to the outputs (as shown in Figure 3A), which effectively solves the problem of performance degradation due to the deepening of the network as the shortcut connection does not increase the amount of computation [20].

In essence, the idea of residual network learning can be understood as a block, which can be defined by Equation (1) [21], where y represents the output, $F(x, \{W_i\})$ represents the residual component and x represents the sample:

$$y = F(x, \{W_i\}) + x. \quad (1)$$

As a result, the ResNet-50 residual network is well suited for feature extraction of the data sets [22]. Additionally, regarding structure, the ResNet-50 network is divided into six parts, of which Stage 1 is the input module, consisting of Conv and Max Pool, Stage 2 to Stage 5 are the residual modules, containing both Conv Block and Identity Block, and Stage 6 is the output module [22,23]. The structure of ResNet-50 is shown in Figure 3B.

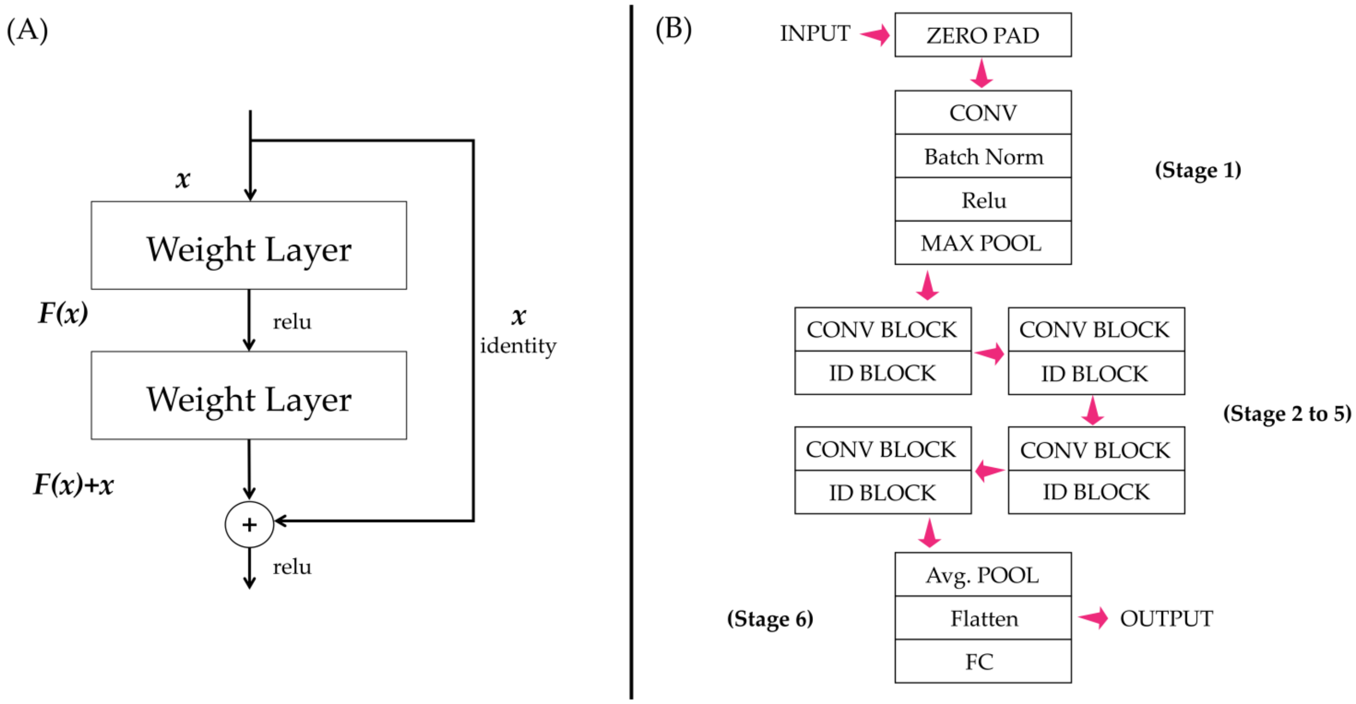

Figure 3. (**A**) The structure of the shortcut connection; (**B**) the structure of the ResNet-50 network.

2.2. Training Set and Test Set

The data chosen for the study were satellite images of tailings ponds within China from Geovis (http://www.geovis.com.cn/ (accessed on 10 November 2022) and Tianditu (https://www.tianditu.gov.cn/ (accessed on 10 November 2022), with a total of 30 sets of both the 1# tailings pond (15 sets) and the 2# tailings pond (15 sets). The two different categories of data in the training set have their own distinctive features: the data in the category 1# Tailings Pond are all unclosed tailings ponds, with significant surface water leaching on the satellite images; the data in the category 2# Tailings Pond are generally closed (or almost closed) tailings ponds or dry storage tailings ponds, with no significant surface water leaching on the satellite images and signs of land reclamation. For data set details, please refer to http://dx.doi.org/10.13140/RG.2.2.26494.87367 (accessed on 10 November 2022).

2.3. Validation Methods

To further validate the accuracy of the image recognition and classification function of the ML.NET machine learning framework [24,25], the cross-validation method was chosen to randomly disrupt the data from training sets and the test sets, re-train the new training sets with DDN + ResNet-50 machine learning framework, test with the new test sets and repeat another 19 times (total 20 times) to find the mean value of the accuracy as an estimate of the accuracy [26]. The entire study process is shown in Figure 4.

After training, the accuracy was tested with the test sets in the intuitive graphical Visual Studio extension module of ML.Net. If the model determines that a satellite image of a tailings pond has a greater than 50% probability of belonging to its original category, then the model is considered to have correctly identified and categorised the tailings pond for this time (as shown in Figure 5).

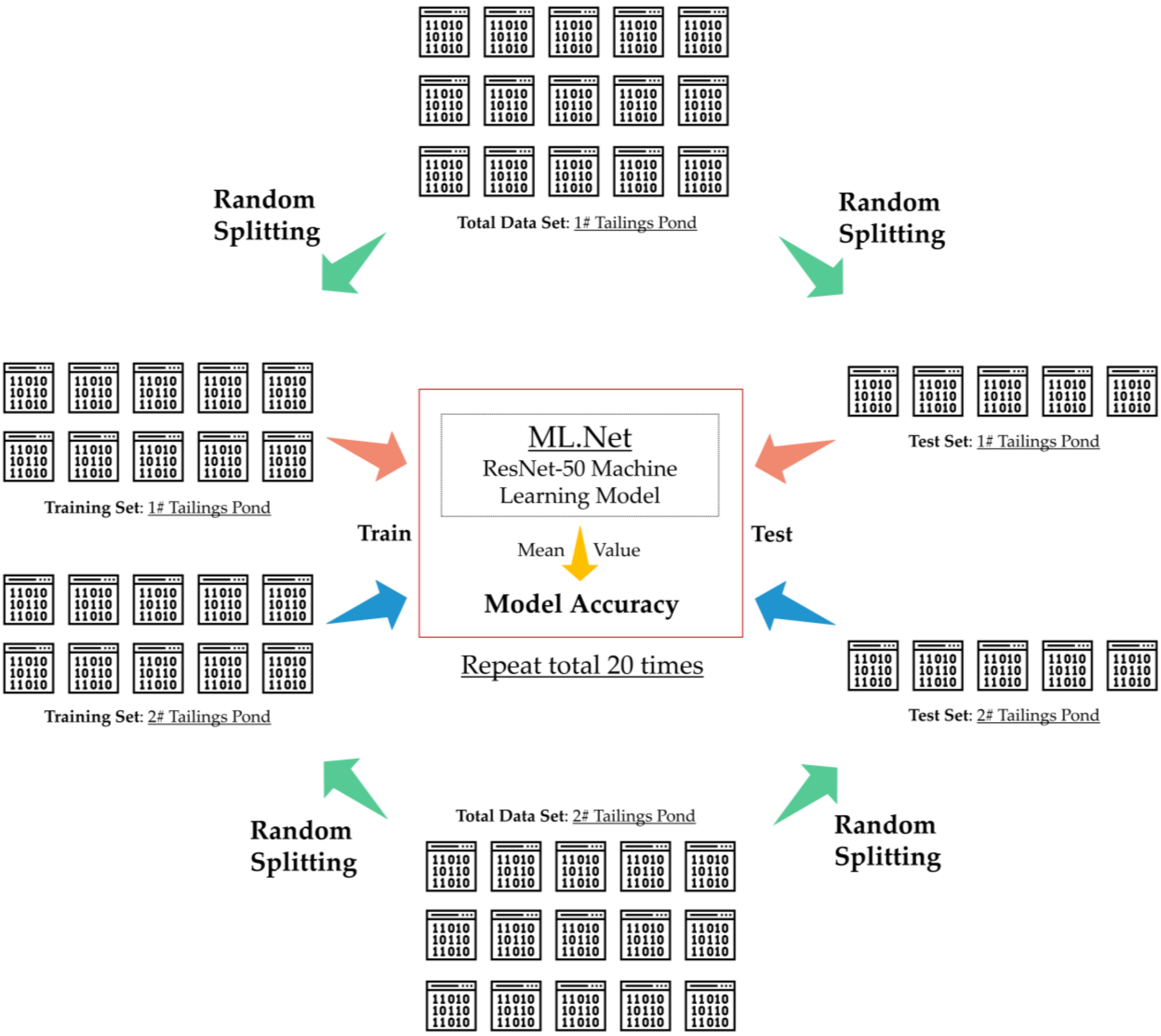

Figure 4. The cross-validation of the machine learning model.

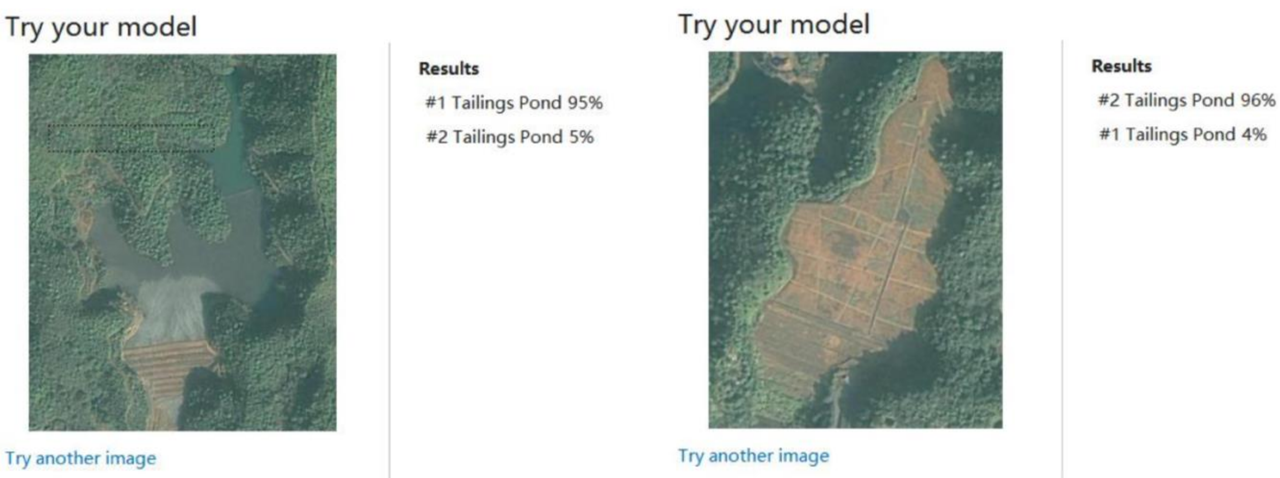

Figure 5. The intuitive graphical Visual Studio extension module of ML.Net. Satellite images from tianditu.gov.cn (accessed on 10 November 2022).

3. Results and Discussion

3.1. Test Accuracy

According to Figure 4, each dataset of the 1# Tailings Pond and 2# Tailings Pond was randomly divided into a training set (10 sets of data) and a test set (5 sets of data), respectively, and each training set was trained by the built DDN + ResNet-50 machine learning model. The model was then tested through the intuitive graphical Visual Studio extension module of ML.Net using the test set according to Figure 5. The whole process was repeated a total of 20 times.

After 20 times cross-validation, the DDN + ResNet-50 network model was found to perform well for the identification and classification of satellite images of tailings ponds, with an average test accuracy of 83.5%: 84% for the 1# Tailings Pond and 83% for the 2# Tailings Pond. The test accuracy data for the 20 times cross-validation are shown in Figure 6.

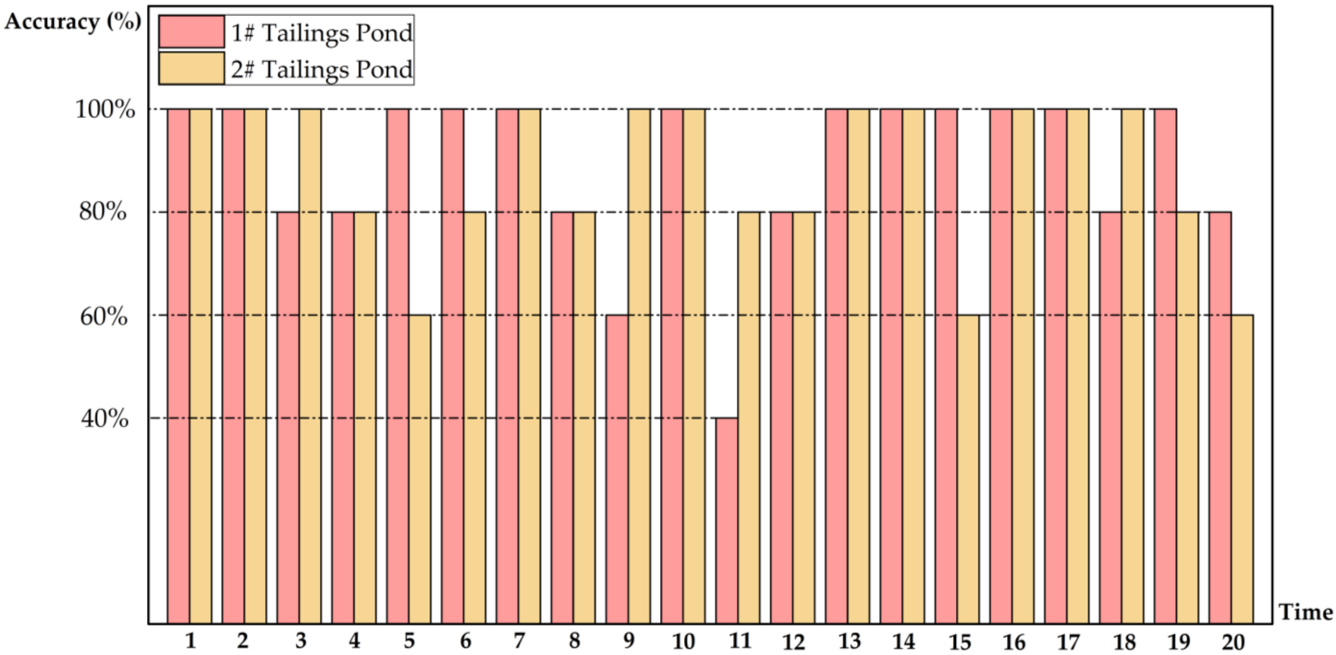

Figure 6. The results of the cross-validation.

3.2. Analysis

The results show that the test accuracy of identification and classification of satellite images of tailings ponds based on the DDN + ResNet-50 machine learning model can reach 83.5%; however, in the cross-validation, the identification accuracy of test sets under different training sets has a relatively large difference. For example, as shown in Figure 6: in the 1st, 2nd, 7th, 10th, 13th, 14th, 16th and 17th time of the cross-validation, the identification accuracy of both categories reached 100%; however, in the 4th, 8th, 11th and 20th time of the cross-validation, the identification accuracy for both categories was lower, with a low identification rate of 40% for the 1# Tailings Pond and a low identification rate of 60% for the 2# Tailings Pond.

This may occur because of the presence of data with insignificant features in the dataset, resulting in insufficient generalisation of the model [27]. For example, in Figure 7, Tailings Pond A below has no significant surface water leaching compared to Tailings Pond B, although it belongs to the category of the 1# Tailings Pond. However, cross-validation solved this problem well; as the number of cross-validation times increased, the test accuracy reached closer to the true value.

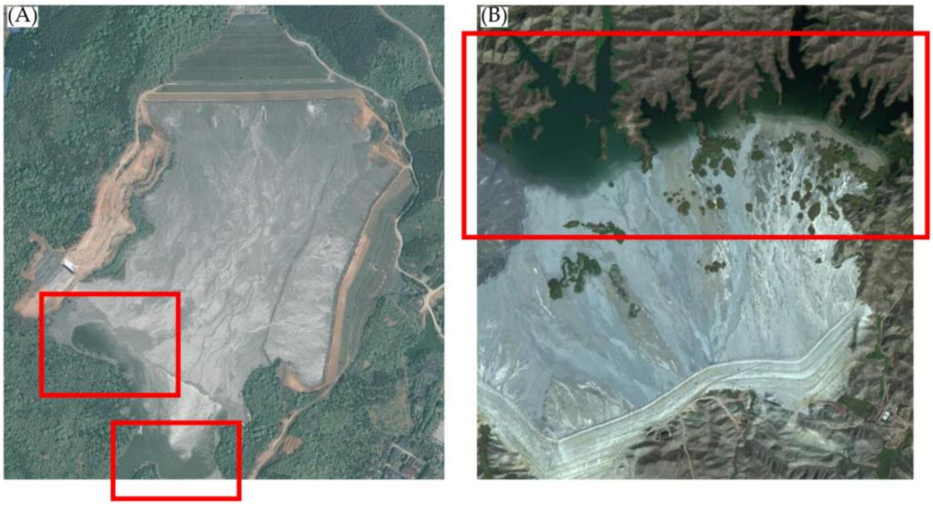

Figure 7. Tailings ponds in the datset. (**A**): Source from tianditu.gov.cn; (**B**) source from geovis.com.cn (accessed on 10 November 2022).

Therefore, if further validation and improvement of the accuracy of machine learning models are required, the following measures are worth considering.

- Using the cross-validation method, the total data set is split and combined into different training and testing sets, with the training set being used to train the model and the testing set being used to evaluate how well the model identifies and categorises, which further reflects the accuracy of the model [28]. S-fold cross-validation is a common form of cross-validation in which the total data set is randomly divided into S mutually exclusive subsets of equal size, and each time S-1 copies are randomly selected as the training set and the remaining 1 copy as the test set [29]. When the round is completed, S-1 copies are randomly selected again to train the data [30].
- Expanding the dataset to allow the model to be more aware of the features of the data in the training set can improve the accuracy of the model. Among the ways to expand the dataset may be finding more relevant data, as well as data augmentation [31,32].

3.3. Optimisation

In order to further validate the accuracy of the image recognition and classification functions of the ML.NET machine learning framework and to optimise the original method of cross-validation, in this part, the three-fold cross-validation method was chosen to be used by randomly dividing the total data set into three equally sized sets, randomly selecting two each time as the training set and the remaining one as the test set, and the cycle was repeated three times to determine the accuracy mean value as the accuracy estimate. The three-fold cross-validation method was also repeated three times by randomly disrupting the data inside the A/B/C/D/E/F sets three times, as shown in Figure 8.

After three times three-fold cross-validation, the DDN + ResNet-50 network model was still found to perform well for the identification and classification of satellite images of tailings ponds, with an average test accuracy of 87.8%: 88.9% for the 1# Tailings Pond and 86.7% for the 2# Tailings Pond. The test accuracy data for the three times three-fold cross-validation are shown in Figure 9.

We then explored further and improved the accuracy of the ML.NET machine learning framework and its DNN + Resnet-50 model for the identification and classification of tailings ponds by expanding the dataset (training set and test set). The data for the new dataset were satellite images of tailings ponds within China, Australia and Malaysia from Geovis (http://www.geovis.com.cn/ (accessed on 10 November 2022), Tianditu (https://www.tianditu.gov.cn/ (accessed on 10 November 2022) and Google Earth (https://earth.google.com/ (accessed on 10 November 2022), with a total of 42 sets of both the 1#

tailings pond (21 sets) and 2# tailings pond (21 sets). For data set details, please refer to http://dx.doi.org/10.13140/RG.2.2.27124.01928 (accessed on 10 November 2022).

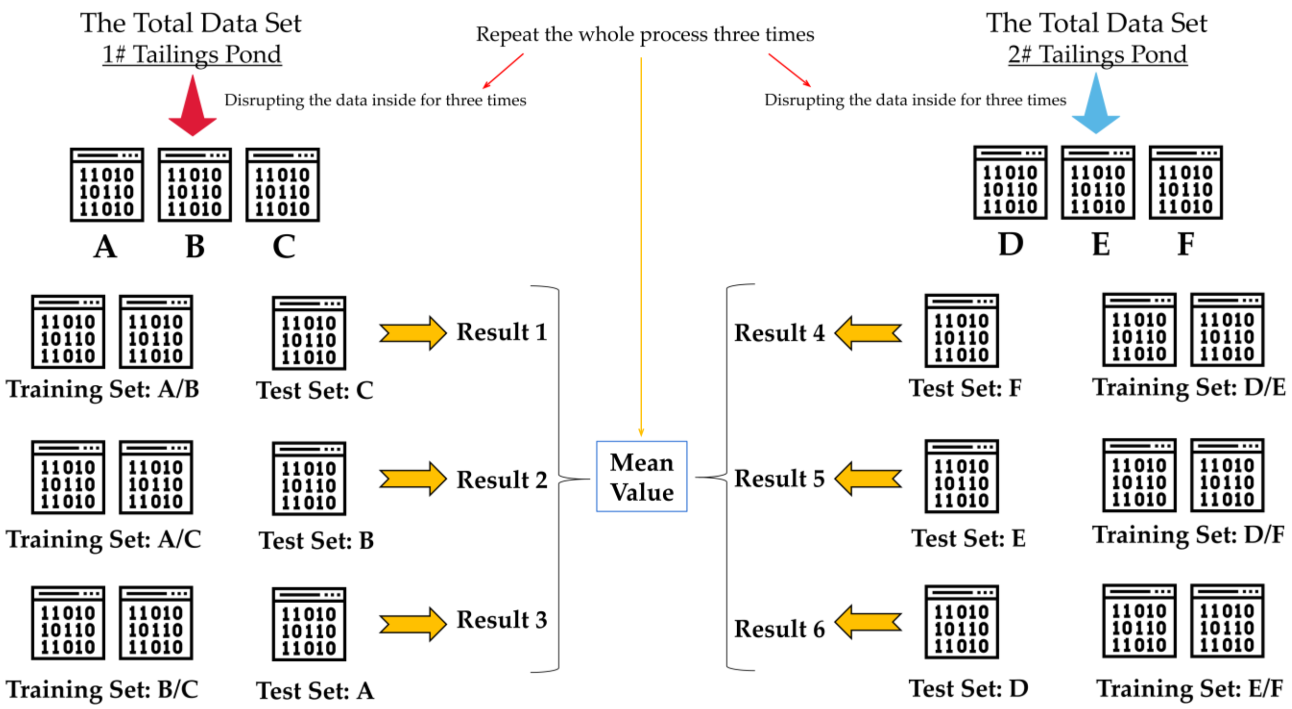

Figure 8. The 3-fold cross-validation schematic diagram.

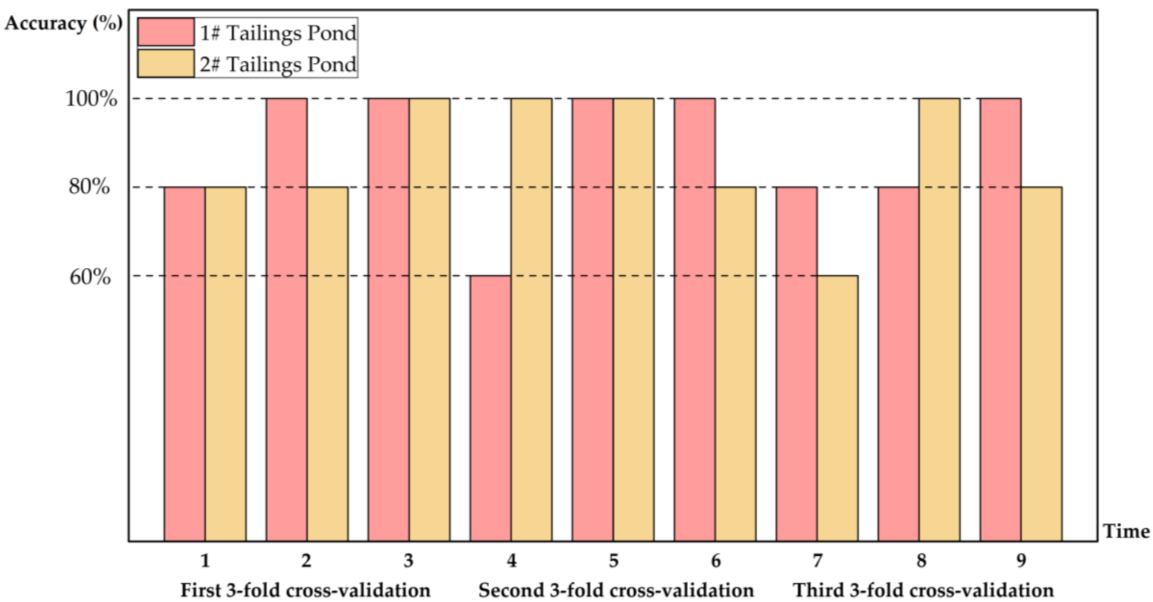

Figure 9. The results of the 3-fold cross-validation.

The new dataset likewise underwent three times three-fold cross-validation (as shown in Figure 8). The DDN + ResNet-50 network model was still found to perform well for the identification and classification of satellite images of tailings ponds, with an average test accuracy of 87.3%: 90.5% for the 1# Tailings Pond and 84.1% for the 2# Tailings Pond. The test accuracy data for the three times three-fold cross-validation are shown in Figure 10.

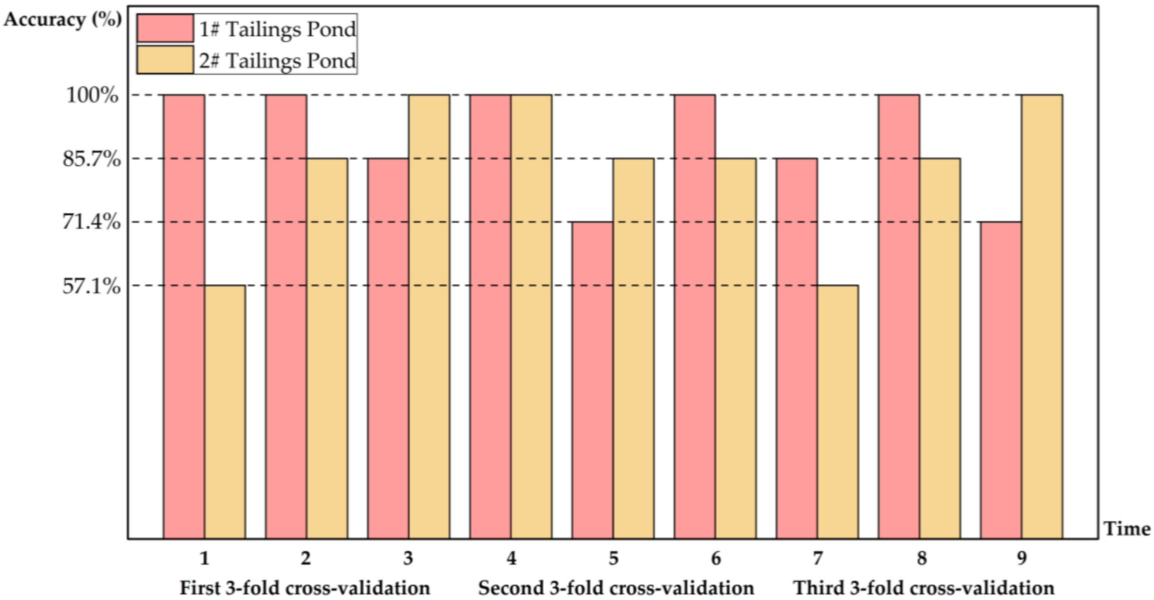

Figure 10. The results of the 3-fold cross-validation for the expanded dataset.

The results showed that the ML.Net machine learning framework and its DDN + ResNet-50 machine learning model performed very well in the recognition and classification of satellite images of tailings ponds, with accuracies above 80% for all three validations (including the validation after expanding the database). However, the identification accuracy for the 2# Tailings Ponds was slightly lower than that for the 1# Tailings Ponds in all three validations. This may be due to the fact that the 2# Tailings Pond is not well characterised, which is exactly the case: some 2# Tailings Ponds, which are about to be closed or have just been closed, are not very different from 1# Tailings Ponds; while some 2# Tailings Ponds, which has been closed for some time, generally already show signs of extensive land reclamation, which are all different. This problem may need to be solved in the future by other methods, but there is no doubt that ML.Net has done an excellent job of identifying and classifying tailings ponds.

4. Discussion: Research Implications and Other Types of Mine Pollution

The monitoring and management of tailings ponds are particularly important in order to avoid environmental pollution and safety accidents in tailings ponds. However, monitoring tailings ponds is often very time-consuming and labour-intensive. This paper explored the accuracy of the ML.Net machine learning framework and its machine learning model in classifying and identifying the two types of tailings ponds with different characteristics, providing a starting point for future remote sensing techniques to monitor tailings pond risk and pollution [33,34].

It is also important to introduce the public to the severity of the current worldwide mine pollution and its hazards to the environment and public health because, in addition to mine solid waste pollution, mine wastewater and mine dust are also serious threats to the environment and the health of residents [35,36]: Mine wastewater pollution causes serious environmental problems (e.g., heavy metal pollution) to rivers, agricultural soils, the surrounding environment and drinking water for people living nearby; mine dust pollution can affect the safety of mining production and can also have a negative impact on the health of miners, for example by causing them to suffer from occupational diseases such as pneumoconiosis [37].

With the introduction of "Sustainable Development" [38] and "One Health" [39], issues related to mine pollution, environmental damage and public health are receiving increasingly widespread attention worldwide that more and more people are becoming aware of the negative health effects of mine pollution and they are trying to take precautions, while researchers are noticing the ecological and public health risks posed by mine pollution, so more and more research related to mine pollution, environmental damage and public health is being carried out. Additionally, many experts in the field of environmental engineering and public health have proposed measures based on their research expertise to address the problems associated with environmental pollution and health crises in mining; they have mostly focused their research on their own single area of study. For example, Li, S. et al. [40,41] have been working on Green Mine Construction and the elimination of mine pollution, but their research has remained focused on improving mining methods and thus mitigating mine pollution, without taking into account emissions pollution and the impact of emissions on public health; furthermore, Sahu, K et al. [42,43] were among the first researchers to propose the reuse of metal mine solid waste for metal resource recovery as well as to mitigate mine solid waste pollution, but their research was limited to chemical recovery processes, and no further research or discussion of mine pollution or public health threats was undertaken [44,45].

Consequently, in the discussion, we propose the concept of a “Healthy Mine” to provide a direction for development and solutions to the mine pollution and public health crises for mining companies to follow and to raise public awareness of mine pollution.

We define a “Healthy Mine” as a mine that actively addresses and mitigates the impact of mine environmental pollution from the mine discharge (water, solid and dust) on the ecological environment, residents’ health and the occupational health of miners through company management, pollution treatment technologies and employee education in the process of resource development. We advocate all existing mines in the world today should be moving in this direction so that environmental pollution problems and public health crises can be well alleviated.

By definition, a mine is considered a “Healthy Mine” if it meets the following basic conditions: (A) Wastewater and Leachate Treatment: the wastewater and leachate generating from mine solid waste should be treated, so the mine should actively introduce wastewater treatment technology, and the quality of discharged wastewater and leachate should meet the emission standard; (B) “Healthcare”: the mine should ensure that the surrounding population is not affected by pollution from the mine wastewater pollution and the leachate pollution; (C) Solid Waste Management: the mine should have strict management of solid waste discharge sites, and actively implement the land reclamation; (D) Solid Waste Recycle: the mine should be active in the reuse of mine solids, for example in the preparation of construction (or backfill) materials; (E) Dust Control: the mine should actively introduce dust control measure, such as spraying covering agents on the surface of dusty materials; (F) Company Management and Employee Education: the mine should make regulations to strictly manage pollution and discharge control during the mining process, and also strengthen health education for mine employees, for example by strictly requiring them to wear dust filtering masks during mining operations. Thus, the concept diagram of the “Healthy Mine” is as follows in Figure 11:

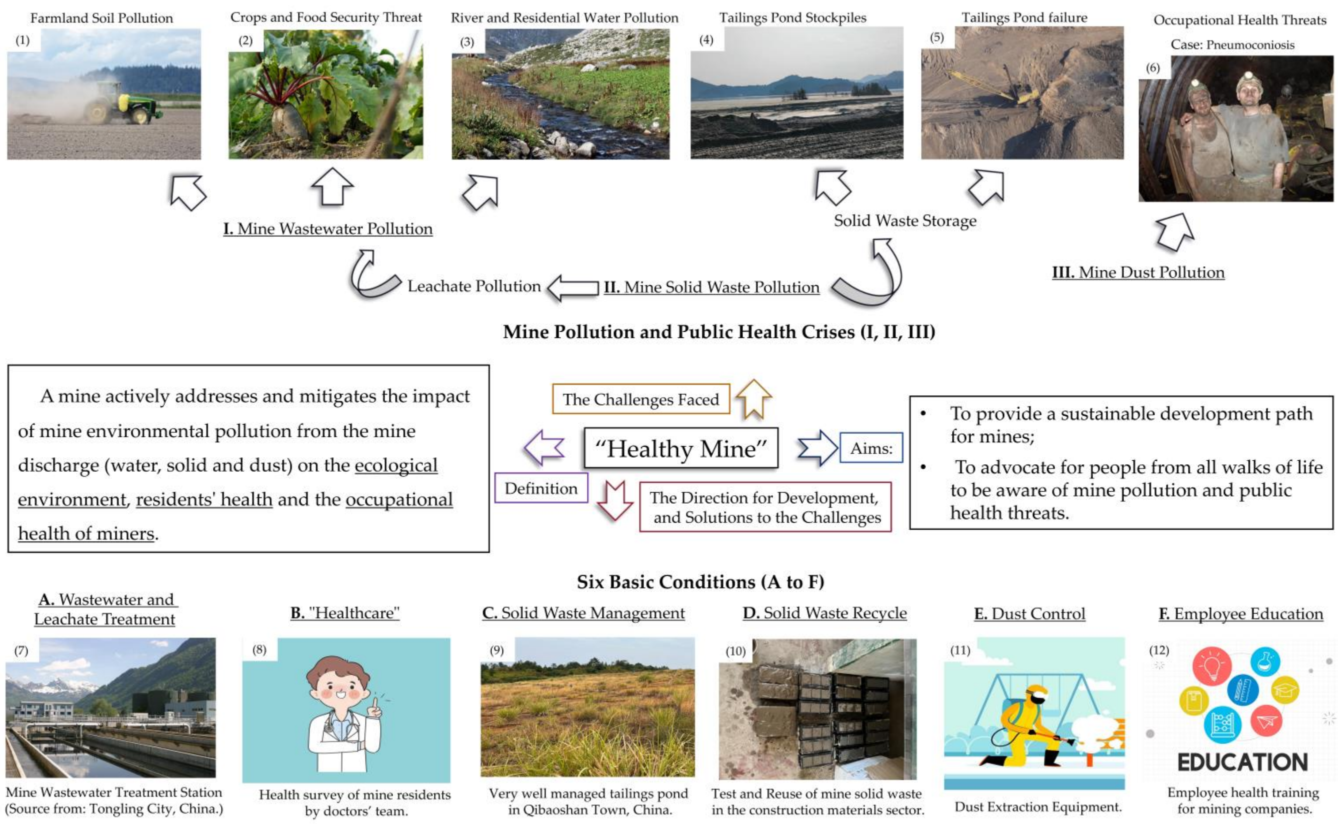

Figure 11. The concept diagram of the "Healthy Mine".

5. Conclusions

As the construction of tailings ponds is a potential environmental and safety hazard, their monitoring is very necessary. Against this background, this paper proposes to classify tailings ponds into two categories according to whether they are potentially risky or generally safe and to classify tailings ponds' remote sensing satellite images using DDN + ResNet-50 machine learning model based on ML.Net developed by Microsoft. Meanwhile, this paper also explored the accuracy of the ML.Net machine learning framework and its machine learning model in classifying tailings pond types according to the different characteristics of the 1# Tailings Pond and 2# Tailings Pond.

The conclusions we have drawn are as follows:

- ResNet-50 is a residual network that uses a shortcut connection to connect the inputs directly to the outputs. Its classification is more accurate, solves the problem of deep network degradation and is well suited to studying the identification and classification of tailings ponds' satellite images.
- DDN + ResNet-50 was found to perform well in the identification and classification of satellite images of tailings ponds. The ML.Net machine learning framework and its model achieved an accuracy of 83.5% for the identification and classification of tailings ponds in the case of 20 times cross-validation, achieved an accuracy of 87.8% for the identification and classification of tailings ponds in the case of three-fold cross-validation and achieved an accuracy of 87.3% for the identification and classification of tailings ponds in the case of three-fold cross-validation after expanding the dataset.
- In this study, the identification accuracy of the 2# Tailings Ponds was slightly lower than that of the 1# Tailings Ponds. This may be due to the fact that the characteristics of 2# Tailings Ponds are not obvious on the satellite maps: some 2# Tailings Ponds that are about to be closed or have just been closed do not differ much from 1# Tailings Ponds on the satellite maps, while some 2# Tailings Ponds that have been closed for

some time generally already show signs of extensive land reclamation on the satellite maps, which are different from each other.

In a nutshell, we claim that this research serves as a guide to starting a conversation, and we hope more and more experts, researchers and scholars will be interested and engage in research in this field of mine pollution assessment using remote sensing technologies and machine learning models.

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