sustainability

MDPI

Article

A Machine Learning-Based Decision Support System for Predicting and Repairing Cracks in Undisturbed Loess Using Microbial Mineralization and the Internet of Things

Yangyang Yue and Yiqing Lv *

College of Mining Engineering, Taiyuan University of Technology, Taiyuan 030024, China; yueyangyang0769@link.tyut.edu.cn
* Correspondence: lvyiqing@tyut.edu.cn

Abstract: Recent years have seen a significant increase in interest across several sectors in the application of learning techniques to extract ground object information, such as soil cracks, from remote sensing high-resolution images. Out of the many technologies, the microbial-induced carbonate deposition (MICP) technology is used to inject bacteria and cementation liquid containing specific bacteria into the cracks of soil to be repaired. Calcium carbonate types of cement are produced by bacterial metabolism so that cracks in the soil could be repaired for disaster management. However, detection of cracks and taking appropriate decisions for repairing are the most fundamental issues that researchers' attention. Machine learning algorithms can be trained to detect and predict cracks in undisturbed loess using various data sources, such as images captured using the internet of things (IoT), devices, drones, and/or ground-based sensors. These algorithms can be designed to identify different types of cracks based on their shapes, sizes, and orientations, and can be trained on large datasets of labelled crack images to improve their accuracy over time. In this paper, we propose a decision support system (DSS) that detects and predicts cracks and recommends a suitable crack repair methodology. Our results show that our system is highly accurate. Our system provides real-time recommendations to engineers working on crack repair projects in undisturbed loess, guiding them on where and how to apply microbial mineralization treatments based on the predicted crack locations and treatment effectiveness. We noted that the accuracy of the crack detection and prediction can be increased significantly (up to 9.57%) when the proposed DSS approach is considered. Moreover, if PSO is implemented as the optimization model, then we can see that the accuracy can be significantly improved by as much as 21.67% to no DSS approach and 11.32% to the DSS approach.

Keywords: decision support system; IoT; mineralization reaction; undisturbed loess; uniaxial compression; particle swarm optimization; machine learning; disaster management

check for updates

Citation: Yue, Y.; Lv, Y. A Machine Learning-Based Decision Support System for Predicting and Repairing Cracks in Undisturbed Loess Using Microbial Mineralization and the Internet of Things. *Sustainability* **2023**, *15*, 8269. https://doi.org/10.3390/su15108269

Academic Editors: Thippa Reddy Gadekallu and Saqib Iqbal Hakak

Received: 24 April 2023
Revised: 12 May 2023
Accepted: 17 May 2023
Published: 18 May 2023

1. Introduction

The collapse of unstable slopes and landslides is a relatively common geological disaster in Shanxi Province, such as the collapse of Dongyue Temple and Cuiping Mountain Panshan Highway in Pu County, Linfen City, with a damage range of up to kilometers. The main reason is that the rainfall enters through the cracks of the soil body, causing the loess body to lose its sink, and the road surface is overhead until it collapses. Therefore, the main cause of this disaster is the loess body's own fissures and structural characteristics leading to wet subsidence. With the continuous progress of science and technology, the technology of crack management-related measures is becoming more and more exquisite, and the current methods for crack repair are the fill method, the plugging method, the grouting method, etc. However, these treatment methods are based on passive repair after the formation of large cracks, the operation is inconvenient and ineffective, and the follow-up safety hazards are large. Based on this phenomenon, domestic and foreign scholars have introduced microorganisms into this, slowly forming the concept of self-healing.

Particle self-healing means that microorganisms can carry out biomineralization on their own when the environment allows so that microfractures in geotechnical bodies can be repaired in time to prevent expansion leading to damage. The full name of this technology is MICP (microbiologically induced calcite precipitation), which is microbially induced calcium carbonate precipitation technology [1–4]. It refers to the metabolism of bacteria under alkaline conditions to produce CO_2 and ammonia. CO_2 and ammonia are further hydrolyzed in the extracellular fluid to obtain H^+/OH^- anion neutralization to obtain ${CO_3}^{2-}$, and ${CO_3}^{2-}$ combined with Ca^{2+} to obtain $CaCO_3$ mineralized deposition [5]. This technique is currently mostly used in concrete, sandy soil, and chalky soil. Whiffin et al. [6] conducted indoor tests of microbial cemented sand columns by injection. Similarly, Harkes et al. [7] and Van et al. [8] used a stepwise grouting method to successively infuse a bacteriological solution, a low-concentration $CaCl_2$ solution (fixing solution), and a cementing solution (urea-$CaCl_2$), thus allowing microorganisms to form calcium carbonate gels.

The MICP is a process in which bacteria are used to precipitate calcium carbonate in soils. This process has a wide range of engineering applications, including soil stabilization, groundwater remediation, and construction. From an engineering point of view, various applications of the MICP technology include (i) soil stabilization—the process's microbes generate calcium carbonate, a binding substance that helps to stabilize the soil; (ii) construction —calcium carbonate can precipitate when bacteria are added to the concrete mixture, filling up any gaps and enhancing the overall strength of the concrete [9]. In addition, MICP may also be used for repairing infrastructure in the context of bridges and tunnels, as well as other existing infrastructure. The soil may be stabilized and the structure reinforced by adding calcium carbonate and bacteria to the soil around the structure [10]. By stabilizing the soil and reducing the effect of waves, MICP can be used to stop coastal erosion. In regions vulnerable to hurricanes or other natural catastrophes, this can be very helpful.

After many scholars at home and abroad have explored the microbial-induced carbonate deposition technology in depth, various influencing factors of microbial mineralization reaction were found, such as carbon source type [11], bacterial solution concentration, calcium ion concentration, pH, temperature [12,13], grouting frequency, grouting time, the grouting method [14], soil particle size [15], calcium source type [16], and bacterial carrier type. Moreover, all these have been conducting indoor experimental analysis. However, the inhomogeneity of $CaCO_3$ deposition produced by mineralization is still a difficult problem to be solved. Perhaps, the reasons include the uneven distribution of colloidal concentration, the distribution of bacterial solution and the distribution of dissolved oxygen caused by the uneven distribution. In addition, there is less research on the nature of the geotechnical body itself, which has its own particle size gradation, permeability, compactness, mineral composition, freeze–thaw properties, etc., on the strength and improvement effect. The soil itself has an important influence on the strength and improvement effect that is most important for soil crack detection and repair. However, these methods are passive and can only take the repairing action once cracks occur. On the other hand, machine learning-based methods along with decision support systems can help in detecting the cracks and an automatic decision support system can be designed to look after the entire process of the above discussed disasters.

In this paper, pseudo-in situ indoor fracture repair tests were conducted on collapsed loess bodies in Pu County, Linfen City, China. Therefore, the experiment was carried out on loess bodies with different viscous particle contents and different concentrations of the cementing solution to explore the crack repair and the best concentration of cementing solution for different types of soil bodies. Machine learning algorithms can be trained to detect and predict cracks in undisturbed loess using various data sources, such as images captured using drones or ground-based sensors. These algorithms can be designed to identify different types of cracks based on their shapes, sizes, and orientations, and can be trained on large datasets of labelled crack images to improve their accuracy over time.

Machine learning can be used to develop a decision support system that integrates crack detection, prediction, and treatment optimization models. This system can provide real-time recommendations to engineers and technicians working on crack repair projects in undisturbed loess, guiding them on where and how to apply microbial mineralization treatments based on the predicted crack locations and treatment effectiveness. The major contributions of our work are as follows:

- We design and develop a decision support system (DSS) that integrates crack detection, prediction, and treatment optimization models to manage cracks and take appropriate decision;
- We use the particle swarm optimization (PSO) method to improve the working mechanism of the treatment optimization module;
- We implement different machine learning methods (CNN, LSTM, and U-Net) to test the accuracy of the proposed decision support system. We noted that the accuracy of the crack detection and prediction can be increased significantly (up to 9.57%) when the proposed DSS approach is considered.

The remaining parts of this paper are structured in the following manner. A brief overview and summary of the related works are presented in Section 2. In Section 3, we discuss the test preparation. In Section 4, we propose a machine learning-based decision support system that can be used to detect cracks and recommend suitable methodology for repairing cracks. In Section 5, the experimental process and the optimization module are discussed. Moreover, the particle swarm optimization algorithm is also elaborated in this section. In Section 6, the attained results are deliberated. Finally, Section 7 concludes this paper.

2. Related Work

Pei et al. [17] studied the mineralization mechanism and application of Bacillus sp. and pointed out that the urease microorganisms such as Bacillus sp. hydrolyze urea model is the easiest and most direct. Furthermore, the authors observed that the suggested model deals with lower operational difficulty and cost than other mineralization models such as nitrate reduction model, sulfate model and denitrification model, and the surface of Bacillus sp. has more negative charge and is easier to be used as. The factors that affect the mineralization effect are mainly the concentration ratio of the cements, and the factors that affect the size, morphology and crystallinity of the mineralization products are: pH, calcium source type and concentration, bacterial concentration and urea concentration. Firstly, this technique was applied to the repair of concrete cracks as investigated in the work proposed in [18], where scholars injected microorganisms into concrete cracks through polyurethane foam wrapping.

Wang et al. [19] mixed the concentrated bacterial solution and the crystalline solution and nutrient solution with concrete sand-based material and injected them into the cracked concrete area, which effectively stopped the cracking process and repaired the concrete from the inside out; however, all the above-mentioned repair methods are based on the passive type of repair after the material is cracked. However, the repair methods described above are based on passive repair after the cracking of the material, which is tedious, labor intensive and costly, so scholars at home and abroad proposed the concept of self-healing concrete [20], that is, microcracks can be effectively repaired by themselves at the early stage of formation, and the repair material is calcium carbonate crystals, which have good compatibility with the original concrete matrix. Zhang et al. [21] compared Bacillus cereus with the screened aerobic, anaerobic and partly anaerobic by comparing the mineralization deposition ability of Bacillus cereus with the screened aerobic, anaerobic and partly anaerobic hybrids, and using expanded perlite as the carrier of the strain. This was concluded that different mineralized microorganisms have good remediation ability, but aerobic hybrids present the best remediation effect. This may, probably, because the carbonate crystals formed by aerobic hybrids are in aragonite crystal form, while other bacteria form calcite crystal form, and aragonite crystals Ca^{2+} and ${CO_3}^{2-}$ follow the most closely packed regular repetitive arrangement, structural compactness than calcite crystal morphology.

Zhou et al. [22] by testing the effect of the restorative agent and the silica fume admixture of encapsulated expanded perlite (CEP) on the compressive strength of concrete, it was concluded that the optimal amount of the silica fume admixture is 7%, the CEP admixture has a greater effect on the concrete, the compressive strength decreases with the increase in the admixture. Sookis et al. [18] used polyurethane (PU) new material foam to fix Bacillus cereus whole cells and compared the calcite precipitation and ammonia production rate produced by free and by PU-fixed Bacillus cereus cells repairing concrete, and found that the tensile strength of PU-fixed microorganisms increased by 42% after repairing, indicating that PU both protects the strain and can be used as a nucleation site for calcite crystals. Recent years have seen a significant increase in interest across several sectors in the application of learning techniques to extract ground object information, such as soil cracks, from remote sensing high-resolution images. The mechanisms, materials, and technical qualities related to each application of MICP, as well as their different engineering applications, have all been covered in-depth by Yuze et al. [9]. Furthermore, Kuan et al. [10] have also discussed an addressed the principles of MICP technology as it examines the viability of MICP in several industries including geotechnical, geological, and environmental engineering.

All of the above works have discussed and proposed various methods for one factor of the soil cracks and repairing them; however, the other side is left behind and is not well studied in the existing literature and state-of-the-art articles. It is rarely discussed how soil cracks can be detected and predicted and, once detected, which methodology should be adapted to repair the cracks. In fact, a decision support system that is operated by the machine learning methods and where various IoT devices are used to monitor the entire environment is essential for efficient disaster management systems. In Table 1, we offer a comprehensive summary of various approaches and how our work fits well with the state-of-the-art methods.

Table 1. Summary of the related works and approaches in terms of advantages and disadvantages.

Work	Methodology	Advantage	Disadvantage
[11]	Microbial-induced carbonate deposition	Carbon source type	Passive only after cracks occur
[17]	Mineralization mechanism	Lower operational difficulty and cost	No repair of concrete cracks
[18]	Microorganisms and polyurethane (PU)	Repair of concrete cracks	Approach is based on the passive type of repair after the material is cracked, i.e., tedious, labor intensive and costly
[19]	Concentrated bacterial and crystalline solution	Effectively stopped the cracking process and repaired the concrete	Tedious, labor intensive and costly
[20]	Self-healing concrete	Microcracks can be effectively repaired by themselves at the early stage of formation	No automatic detection and prediction
[21]	Bacillus cereus and screened aerobic	The aerobic hybrids present the best remediation effect	No automatic detection and prediction
This Work	Microbial-induced carbonate deposition (MICP), DSS, and machine learning	Automatic detection and prediction of cracks and recommendation for crack repairing method	Computation intensive

3. Test Preparation

3.1. Specimen Selection

The in situ soil was selected from the internal soil of a section of collapsed rock and soil of Dongyemiao Pangshan Highway in Pu County, Linfen City, and the soil of the leading edge of a landslide in Yuzi Haojiagou, Taiyuan City. The main physical property indexes are shown in Table 2. The data samples were collected randomly so that a mix of various characteristics and properties of the soil can be considered for the evaluation and experimental documentation. Further details about the collection and preprocessing of the dataset are given in Section 5.1.

Table 2. Physical properties of the soil.

Region Indicators	Depth (m)	Weight Capacity	Specific Gravity	Porosity	Porosity Ratio	Plasticity Index (%)	Internal Friction Angle (Degree)	Cohesion kg/cm^3
Linfen	2.0	1.8	2.70	45.4	0.8	13.5	32°42′	0.26
Yuzhi	2.0	1.973	2.71	37.7	0.606	12.7	29°7′	0.9

3.2. Test Materials

3.2.1. Activation and Culture of Strains

In this experiment, the Bacillus cereus was selected because it is an aerobic bacterium and can survive under high temperatures, high pressure, and high pollution, which can meet the complex outdoor soil environment [20,23]. Each medium contains 1.0 g of peptone, 0.6 g of beef extract, 4.0 g of urea, and 200 mL of distilled water, while the pH is adjusted to 7.3 [11]. After the configuration is completed, the medium is sterilized in an autoclave at 121 °C for 15 min, cooled, and placed on the bench for UV sterilization for 20 min, the strain is inoculated into the liquid medium in a sterile environment and placed in an oscillating incubator (30 °C, 150 r/min) for 0–48 h. and incubated for 0–48 h. The growth curve of microorganisms was obtained by measuring the transmission ratio every 4–12 h [24], as shown in Figure 1.

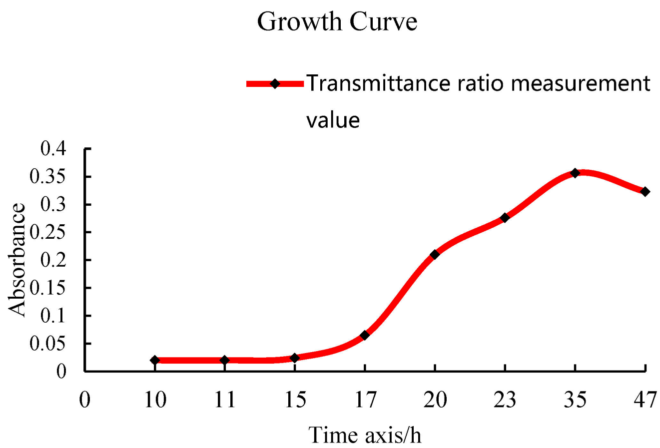

Figure 1. Growth curve of microorganism.

According to the growth curve, the microbial growth will enter the decay period after approximately 35 h, and the growth and metabolism will be slowed down so that the remediation effect will be reduced. Therefore, the culture microorganism control time is best at 20–35 h so that it can carry out the growth and metabolism mineralization when at the strongest vitality, and the concentration of the bacterial solution is controlled at OD600 = 1.0–2.0.

3.2.2. Caking Solution

Combined with the findings of various scholars, acetic acid and nitric acid have inhibitory effects on the mineralization reaction of Bacillus. Therefore, the cementing solution used in this experiment was a mixture of calcium chloride ($CaCl_2$) and urea in three groups of different concentrations. As a result, the concentration gradient of the cementing solution was set as anhydrous $CaCl_2$/urea: A: 0.5 mol/L/0.5 mol/L, B: 1.0 mol/L/1.0 mol/L, and C: 1.0 mol/L/2.0 mol/L.

Crystallization process: The growth and metabolism of Bacillus cereus produce urease to breakdown urea into NH_3 and CO_2, CO_2 dissolves in water under an alkaline environment to form ${CO_3}^{2-}$, which in turn binds with Ca^{2+} in the colloid to produce $CaCO_3$ crystals and adheres to the bacterial surface for accumulation. The crystallization principle is as follows in the following Equations (1).

$$\begin{array}{l} Ca^{2+} + Cell \rightarrow Cell - Ca^{2+} \\ CO(NH_2)_2 + H_2O \rightarrow CO_2 + 2NH_3 \\ CO_2 + OH^- + NH_3 \rightarrow NH^{4+} + CO_3^{2-} \\ Cell - Ca^{2+} + CO_3^{2-} \rightarrow Cell - CaCO_3 \downarrow \end{array} \quad (1)$$

When calcium carbonate cement ($CaCO_3$) is combined with the soil, then it combines with water to produce calcium carbonate crystals and calcium silicate hydrates, which fill the spaces between soil particles. The soil particles are successfully glued together by these crystals, acting as a binding agent, resulting in a stronger and more cohesive soil structure. By strengthening the link between soil particles and boosting the soil's stiffness and compressive strength, the addition of $CaCO_3$ cement to the filled pores of soil particles helps to improve strength and displacement.

4. The Proposed Decision Support System

Machine learning can play a significant role in enhancing the efficiency and effectiveness of crack repair in undisturbed loess using microbial mineralization technology, by providing accurate crack detection, prediction, treatment optimization, decision support, and monitoring capabilities. Machine learning can be used to develop a decision support system that integrates crack detection, prediction, and treatment optimization models. This system can provide real-time recommendations to engineers and technicians working on crack repair projects in undisturbed loess, guiding them on where and how to apply microbial mineralization treatments based on the predicted crack locations and treatment effectiveness. By enabling more focused and effective restoration techniques, the combination of fracture detection, prediction, and treatment optimization models can result in more efficient crack healing processes in undisturbed loess. The severity of discovered fractures and the chance that they may widen can both be learned from the crack detection and prediction modules. The decision-making module may then utilize these data to decide which cracks need to be repaired first and in what order. For instance, if the prediction module predicts that a crack is likely to spread quickly and cause structural collapse, the decision-making module can give that crack priority over less serious cracks when it comes to repair. The overall framework of the proposed decisions support system is shown in Figure 2. The decision support system consists of several components, including (i) crack detection; (ii) crack prediction; (iii) optimization module; (iv) the decision-making module.

1. **The Crack Detection Module:** This module uses machine learning algorithms to analyze data from various sources, such as images captured by drones or ground-based sensors, to detect cracks in undisturbed loess. It can identify different types of cracks based on their shapes, sizes, and orientations.
2. **The Crack Prediction Module:** This module utilizes machine learning models trained on historical data to predict the likelihood of crack formation in undisturbed loess. It considers environmental and geospatial factors such as weather conditions, soil properties, and other relevant parameters to estimate the probability of crack occurrence in different areas. Additionally, the crack detection and prediction modules can offer continuing monitoring information for managing cracks over time. For instance, if a crack is found and repaired, the prediction module may keep an eye on it to make

sure it does not widen further. If the crack does start to reappear, the system may notify maintenance staff so they can respond appropriately and prevent the crack from worsening. The system can offer a more thorough approach to crack management that can ultimately save time and costs by incorporating continual monitoring data into the decision-making process.

3. **The Treatment Optimization Module:** This module employs machine learning algorithms in order to optimize the application of microbial mineralization technology for crack repairing. In fact, it analyzes the collected data on the effectiveness of microbial mineralization treatments, and based on crack type, soil conditions, and treatment parameters, it provides recommendations on the most suitable treatment methods, dosages, and application timings. This module may gather and analyze information on the pH, organic matter content, and nutrient levels of the soil and water in the region to be treated. Additionally, characteristics of the concrete fractures, information on how microbes behave, and information on environmental factors such as temperature, moisture, and sunlight exposure may all be gathered and studied.
4. **The Decision-Making Module:** This module integrates the outputs of the crack detection, prediction, and treatment optimization modules to make informed decisions about the crack detection and repair. Generally speaking, the decision-making module will utilize the outputs of each of the other modules to help it decide whether to find and fix cracks. The severity of the fracture, the crack's anticipated future behavior, the expense and practicality of mending the crack, and other considerations may all be taken into consideration throughout this decision-making process. It combines the crack detection results with the crack prediction probabilities to identify high-risk areas that require priority attention. It also considers the treatment optimization recommendations to determine the most appropriate course of action for crack repair.

The crack detection module receives input data and detects cracks in undisturbed loess. The crack prediction module uses various factors to predict the likelihood of crack formation. The treatment optimization module provides recommendations on various treatment methods based on crack type, soil conditions, and treatment parameters. The decision-making module integrates the outputs of the previous modules to make informed decisions [25]. For instance, the crack detection module may provide information to the decision-making module indicating that a crack has been found at a certain point on a structure. It could then decide based on the output of the prediction module as to whether the fracture is likely to widen and perhaps cause structural failure. The decision-making module may use the results of the treatment optimization module to identify the most affordable and practical approach for patching the crack if the forecast indicates that it is likely to continue expanding.

The integration of crack detection, prediction, and treatment optimization models can result in a more efficient crack repair process, as treatment efforts can be targeted to areas with the highest crack formation likelihood. This can lead to faster and more effective repair of cracks in undisturbed loess, minimizing further damage to structures and infrastructure built on such soils. By optimizing treatment strategies and minimizing trial-and-error approaches, the decision support system can potentially result in cost savings in terms of materials, labor, and equipment used for crack repair in undisturbed loess. This can lead to more cost-effective solutions and better allocation of resources.

Here is an example of how the module integrates the findings of crack detection, crack prediction probabilities, and treatment optimization suggestions to establish the best course of action for crack repair so that you can better grasp the overall DSS framework. The prediction module determined a modest chance of crack growth after the crack detection module identified a crack in a specific region of a structure. Assume that the treatment optimization module has suggested a variety of treatments, each with unique costs and advantages. With this knowledge, the decision-making module may assess the costs and advantages of each treatment method in light of the anticipated likelihood of crack expansion and other criteria (such as the resources at hand and potential safety hazards). It may then decide on the course of treatment that offers the most affordable and practical way to fix the fracture while lowering the likelihood of a subsequent structural breakdown.

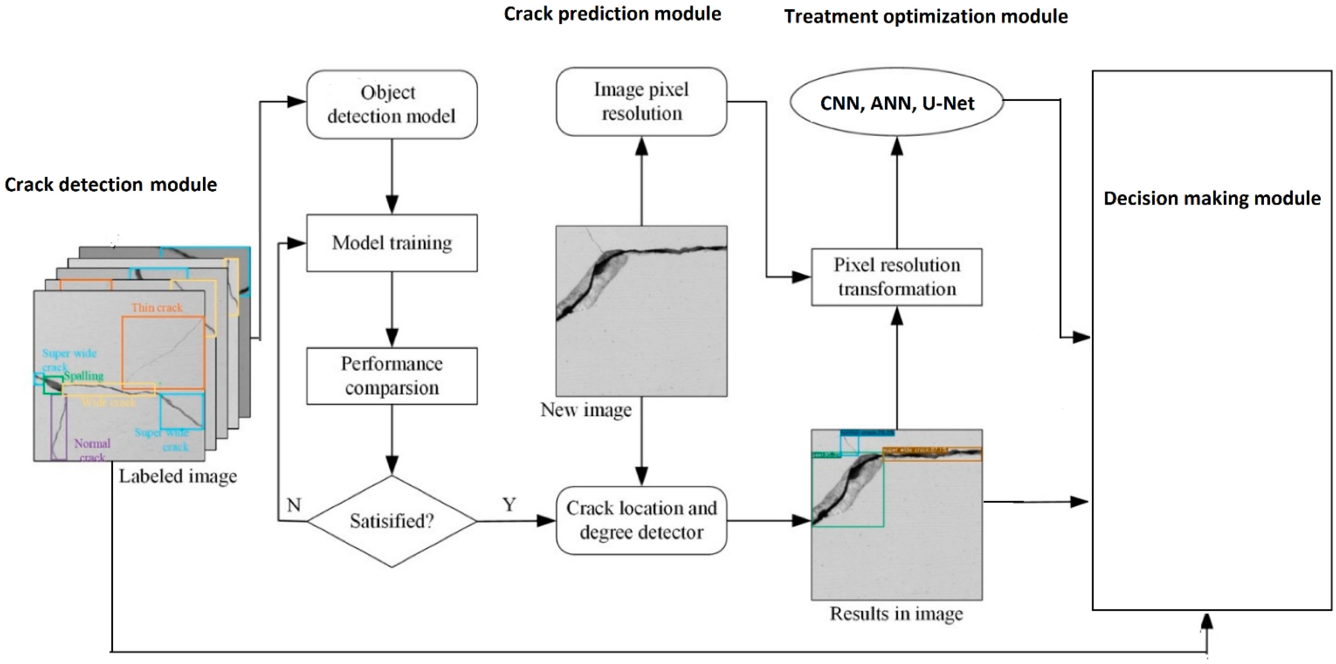

Figure 2. The proposed decision support system for cracks detection and prediction.

5. Experimental Process

5.1. Specimen Preparation and Processing

A cubic in situ soil sample with a side length of 300 mm was taken, wrapped in a black plastic bag, transported back to the laboratory, and cut by a wire cutter to obtain several 50 mm $\times$ 100 mm cylindrical soil samples. The test was divided into two different groups. The first group was a restoration test of different soils in two regions with different clay content. Moreover, soil materials were set up as 1, 2, 3, and 4; among them, groups 1 and 2 were brittle soils with less clay content, and groups 3 and 4 were soils with more clay content. Similarly, the second group was a restoration test of loess soils in the same region with different colloid concentrations. In this group, the soil materials were set up as 5, 6, 7, 8, 9, and 10. Groups 5, 6, 7, 8, 9, 10, and 8, 9, and 10 were collected from Pu County, Linfen City, and Yuzi Haojiagou.

The amount of clay present in soil samples can have a big impact on how well microbial remediation techniques work and the results of cleanup. A highly adsorptive substance with the ability to bond with pollutants and reduce their availability for microbial breakdown is clay. This implies that toxins may be harder to reach and degrade in soils with a high clay percentage, decreasing the efficacy of microbial remediation techniques. The treated groups of soils were placed in the lower tray of the indoor universal testing machine (the soils were coated with petroleum jelly on the top and bottom of each), and the process was as follows. The strength growth ratio and stress–strain curves of undisturbed loess are obtained by laboratory restoration and the strength test to compare the overall results showing that the loess body with less clay content has a better strength foundation and experimental restoration foundation. The restoration of loess body by microbial mineralization basically closed the loess pores and acted as the rock skeleton, improved the integrity of the soil and increased its mechanical strength fundamentally.

To a certain extent, the medium concentration of cementing fluid is conducive to the microbial mineralization reaction, resulting in more $CaCO_3$ cementation precipitation. The application of in situ soil mixing methods is one typical strategy for soil restoration. This entails enhancing the existing soil's features and traits by adding additions or amendments. Depending on the particular requirements of the soil, the additives used in this procedure might vary, although they frequently include substances such as cement, lime, or organic waste. In general, soil restoration may raise the mechanical strength of in situ soil by enhancing its physical and chemical characteristics using a variety of methods such soil mixing, soil reinforcement, and soil stabilization. The overall process of the restoration technique is described below.

- Place the soil in the center of the lower disk of the universal testing machine, operate the computer software so that the upper disk just touches the upper part of the soil, and adjust the software parameters and the loading rate of 0.2 mm/min.
- After observing the graph depicted by the software to reach the peak position, continue to pressurize so that the deformation variable reaches 1/3 of the peak deformation variable when the pressurization is stopped (after that, each soil body is pressurized according to this over peak deformation variable standard to ensure that the pressurization factor remains unchanged).
- Finally, control the upper plate of the testing machine through the aforementioned software to rise slowly and unload slowly to prevent the specimen from breaking due to sudden unloading, and then the soil is slowly taken out and placed on the table to wait for the next test.

5.2. The Microbial Remediation Process

The experimental grouting equipment was selected from a peristaltic pump (to control the injection speed), and the injection ratio was a bacterial solution, i.e., a cementing solution = 1:2, with an interval of 4 h between each injection [26]. Note that the operation was repeated every 24 h until the cracks were completely blocked, with each drip injection lasting for approximately 1 h at minimum. In subsequent discussions, we describe these results in more detail.

The first group of the test grouting method adopts the step-by-step drip injection method, in which the bacterium solution and the cementing solution are dripped into the soil cracks. This is achieved through the drip tube, respectively, i.e., the bacterium solution is injected once and then two equal amounts of cementing solution are injected, respectively (the concentration of the cementing solution is selected as group B) so that they can infiltrate naturally. Similarly, the amount of solution for each drip injection is shown in the following Table 3, and the interval of each drip injection is approximately 12 h, depending on the degree of soil subsidence. The specific grouting amount is shown in Table 3. Note that the left side of the table shows the amount of bacterial solution used, while the right side of the table shows the amount of adhesive solution used. The unit of liquid usage is mL.

Table 3. Amount of the first group of grouting solution.

Time/h Group	1	2	3	4	Time/h Group	1	2	3	4
0	6	6	12	14	0	12	12	24	28
7	5	5	6	6	7	10	10	12	12
19	5	5	6	6	19	10	10	12	12
42.5	4	5	4	6	42.5	8	10	8	12
92.5	6	6	6	8	92.5	12	12	12	16

The second group of the experimental grouting method still adopts the step-by-step drip injection method, with the difference that the injection time of bacterial liquid and cementing liquid is separated. Exactly 4 h after the first injection of bacterial liquid, an equal amount of cementing liquid is injected, and 4 h later, an equal amount of cementing liquid is injected again. The 24 h is a cycle until the soil pores are blocked. Note that the whole grouting process lasts for four days, and the specific grouting dosage is shown in Tables 4 and 5.

Table 4. Dosage of the second group of grouting bacterial solution.

Time/d Group	A 5	B 6	C 7	A 8	B 9	C 10
1	15	14	14.5	13.5	13.5	15.5
2	12.4	14.6	12.55	13.5	13.0	14.5
3	11.4	11.5	10.7	10.3	9.5	10.5
4	11.6	10.75	9.6	10.6	11.0	11.1

Table 5. Dosage of the second group of grouting adhesive solution.

Time/d Group	A 5	B 6	C 7	A 8	B 9	C 10
1	30	28	29	27	27	31
2	26.5	21.8	22.5	21.4	22.5	23.6
3	20.9	22.8	19.1	20.8	20.75	21.3
4	21.6	22.75	22.45	22.65	21.5	22.4

It should be noted that: ① priority drip injection cracks and pores, followed by drip injection of the part with the tendency of fragmentation; ② drip speed should be slow, accurate, as close as possible to the crack or pore mouth, slow drip injection, to avoid too fast blowing the soil particles lead to poor bonding conditions; ③ in principle, each addition should be consistent, but the soil is different from the concrete, soil particles are more loose, unstable, so take into account the problem of saturation of the soil particle gap, to the actual as the standard. (Avoid too many drops of the solution, so that the soil wet sink is too large or the pore structure collapses, leading to early destruction of the soil structure.)

5.3. The Strength Test

After the slurry is completely injected, it should be left for more than 7 days to wait for the mineralization reaction to complete and the calcium carbonate crystallization to harden [27], then the moisture content of each soil sample is adjusted to the same moisture content as the original soil sample by drying method and water spraying method, and then the soil is tested for strength. The strength test was conducted using a universal testing machine, and the process is as follows: ① transfer the diameter size of the specimen into the corresponding parameters of the software of the universal testing machine; ② coat the upper and lower surface of the soil sample with the appropriate amount of petroleum jelly, place it vertically in the lower compression disk of the universal testing machine, adjust it just within the center circle of the lower disk, and adjust the upper disk to just touch the top surface of the soil sample; ③ set the test compression rate to 0.2 mm/min in the software, start the equipment, and observe the stress–strain curve in the software at the same time., when the curve decreases after the peak, the strength of the specimen can be judged to be decreasing, continue to apply pressure until the specimen is destroyed, and get the uniaxial compression soil stress–strain curve.

The repair process mentioned in this experiment is the grouting process in the indoor repair experiment. When the bacterial solution is dripped into the soil cracks together with the cementing solution, the microorganisms will carry out metabolic activities to precipitate the calcium ions in the cementing solution to produce calcium carbonate cement, which acts as a cement to bond the unstable particles of the soil together to maintain stability in the early stage, and acts as the soil skeleton to enhance the overall strength after solidification in the later stage. The process, the change in calcium carbonate in the internal soil particles, can not observe the specific changes, only the results of the strength of the change to assess.

5.4. The Optimization Algorithm

The proposed particle swarm-based optimization algorithm is presented in Algorithm 1. The algorithm takes a set of outcomes from crack detection and prediction modules and finds an optimal position in the form of the repairing decision. In the first step, we initialize all particle dimensions, positions, and modules. In the second step, we try to balance all the particle position using the prediction technique. From step 3 to step 9, the particle positions are updated according to a particular fitness function. The fitness function here ensures a balance decision, i.e., the one that has more efficiency in terms of resource utilization and prediction durations. Each particle in the suggested PSO algorithm (Algorithm 1) represents a potential crack repair solution, and its location in the search space reflects a collection of possible fracture repair options. Each particle's position in the search space is assessed using the fitness function, and a fitness score is given depending on how well the particle meets the requirements laid out in the fitness function. When the process iterates, particles with higher fitness ratings are more likely to be kept while those with lower scores are destroyed. The fitness function is computed according to the following Equation (2).

$$F_v = \frac{cost}{Average_{utilization}} \times P_{detection} \tag{2}$$

Throughout the development phase, the velocity and location of the jth particle on dimension D are updated using the following Equations (3) and (4), respectively:

$$\mathrm{v_j(k + 1) = w \times v_j\ (k) + c_1 \times rand_1 \times (pbest_j\ (k) - x_j\ (k)) + c_2 \times rand_2 \times (gbest_j\ (k) - x_j\ (k)} \tag{3}$$

$$\mathrm{x_j\ (k + 1) = x_j\ (k) + v_j\ (k + 1)} \tag{4}$$

The scaling factor w, one of the key factors, regulates how the prior velocity affects the current one. Additionally, c_1 and c_2 are the respective cognitive and social acceleration coefficients, while $rand_1$ and $rand_2$ are two uniformly distributed random values drawn from the range [0, 1]. Note that $Pbest_j$ and $Gbest_j$ are representations of the best solution recognized by particle jth, known as pbest, and the best solution discovered by the whole swarm, known as gbest. The process is shown in Algorithm 1.

In order to guarantee that the most effective and efficient technique is chosen for each unique crack repair scenario, the fitness function can be a useful tool for balancing the decision-making process in fracture repair. Accuracy, efficiency, and cost-effectiveness are all factors that must be balanced for the system to be efficient in maximizing resource use and reducing the time and expense needed for crack repair. For instance, the accuracy of crack detection, the propensity for crack prediction, the effectiveness of treatment optimization, and the cost and viability of repair procedures are just a few examples of factors that may be used to construct the fitness function. The decision-making module may then evaluate various combinations of crack detection, prediction, and treatment optimization models using this fitness function and choose the best course of action for fixing a specific crack.

Algorithm 1: PSO-based optimization technique

Begin Input: Set of outcomes from crack detection and prediction modules
Output: Find the optimal position
1. Initialize particle dimensions, particle positions, and velocities.
2. For each particle, balance the particle position using the prediction algorithm.
3. For all particles,
4. Compute the fitness value using Equation (2): $F_v = \frac{cost}{Average_{utilization}} \times P_{detection}$
5. If Fv <= pbest, update pbest with the obtained value.
6. Select the particle position as gbest.
7. Choose the best particle as gbest.
8. Calculate velocity and update particle positions using Equations (3) and (4).
9. Repeat these steps until the maximum iteration criteria is satisfied.
10. Return the best position
End

6. Results and Analysis

The system is implemented on a Windows 10 Home 64-bit computer using the Python programming language and the Keras package. An Intel Core i7 7700HQ running at 2.8 GHz and 16 GB of RAM make up the gear. In different ratios, we split the soil data into training (70%) and testing (30%) halves. We selected 10 different samples. In order to verify the detection and prediction accuracy using the RMSE and MAPE evaluation metrics, various machine learning methods were applied. Different soil samples were repaired by soil samples with different moisture contents and concentrations of cementing solution. Their strength curves were obtained after uniaxial compression strength tests on the repaired soil. The stress–strain curve was observed and decreased when the curve reached the peak strength when the soil sample was crushed, and the complete comparative strength data and stress–strain curve of the soil sample were obtained. This relationship is shown in Table 6 and Figures 3 and 4 below.

Table 6. Comparison of the strength of each group of soil samples before and after restoration.

Soil Sample Number	In Situ Soil Strength σ/kPa	Repair Soil Strength σ/kPa	Intensity Growth Rate p/%
1	619.66	1129.83	82.33
2	579.73	1102.35	90.15
3	523.38	827.63	58.13
4	553.35	971.33	75.54
5-A	482.61	1021.07	111.57
6-B	518.83	1364.08	162.91
7-C	589.37	1496.17	153.86
8-A	789.75	1261.80	59.77
9-B	865.71	1849.66	113.66
10-C	1082.07	1989.66	83.88

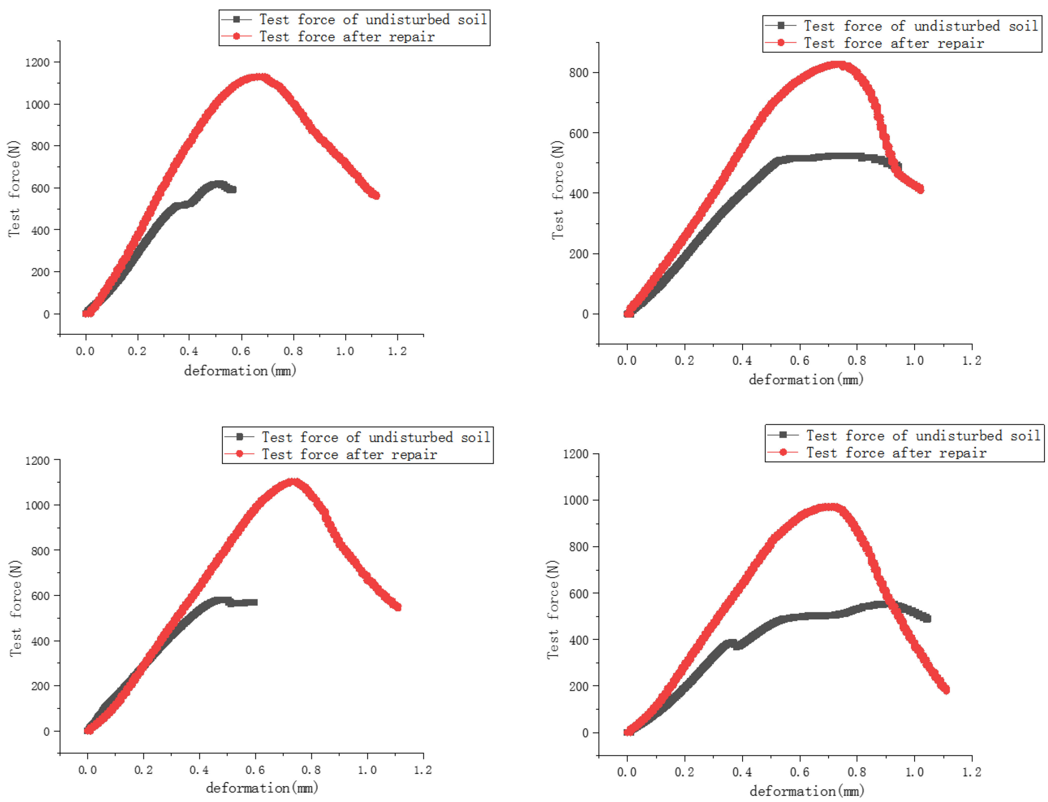

Figure 3. The first group of strength curves of the soil before and after restoration.

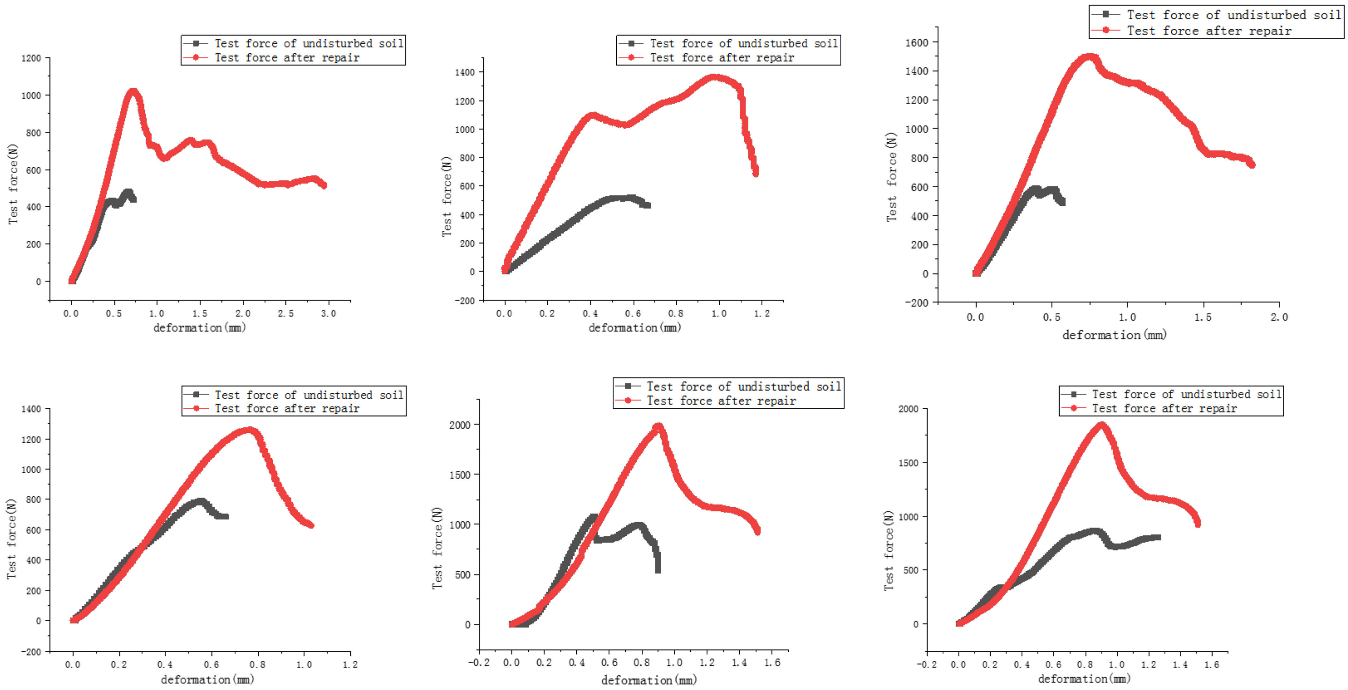

Figure 4. The second group of strength curves of the soil before and after restoration.

From the strength and growth rate of each group of soil samples before and after remediation in Table 4, it can be seen that this microbial mineralization and sedimentation technology has a good effect on the remediation of the soil at this site. From the experimental data of the first group (the first four groups of soil samples), we can see that all four groups of soil samples have obvious restoration growth, but the strong growth rate of soil samples 1 and 2 after restoration is greater than that of soil samples 3 and 4, $\overline{p_2} > \overline{p_1} > \overline{p_4} > \overline{p_3}$; while soil samples 1 and 2 are soils with fewer clay particles, soil samples 3 and 4 soil with more clay particles, so it is inferred that the soil with more clay particles has more free water between the clay particles and less permeability so that the bacterial solution has fewer attachment points between the particles and the mineralization reaction of microorganisms lacks attachment points and thus the aggregation site of $CaCO_3$ is reduced. As such, the reduction in the produced cement directly affects the restoration effect; therefore, it is considered that this technology is more suitable for soils with fewer clay particles. The strength growth ratio data in Table 5 and the changes in the strength curves in Figure 3 show that the strength growth rate of the soil specimens with more clay particles is obviously not as large as that of the soil with fewer clay particles after the microbial mineralization treatment, and the difference in strength growth rate due to the difference in clay particle content can only be compared from a macroscopic point of view; due to the limited test conditions, transmission and irradiation tests in microscopic aspects could not be conducted, and the specific restoration effect of the particles inside the soil could not be observed.

From the experimental data of the second group (the last six groups of soil samples), it can be seen that the restoration effect of the six groups of soil samples is greater compared with the first four groups. The possible reason is that the time point of grouting is different, and it is inferred that microorganisms need a period of time to adapt to the environment when they enter the soil, and then the nutrient solution is added for microorganisms to metabolize, which can make the activity of microorganisms and the mineralization restoration effect better. Comparing the strong growth rate of soil samples from groups 5, 6 and, 7 or 8, 9 and, 10, it can be seen that the strong growth rate B > C > A. This indicates that the concentration of cementing solution should not be too low or too high, and 1 mol/L + 1 mol/L is the most suitable, and the lower concentration of group C compared to group B may be due to the high urea content which affects the pH value and thus the microbial activity, and this factor needs to be further explored.

From the point of view of restorability, it can be seen from any of the graphs in Figures 2 and 3 that the mechanical strength of the in situ soil is greatly increased after restoration, and the curve characteristics are also changed; from the soil samples of groups 1 and 2 in Figure 2, it can be seen that the peak strength displacement of the in situ soil is smaller and the ductility is lower, and after restoration, not only the strength is greatly increased, but also the displacement is greatly increased, probably because there are filled pores of soil particles $CaCO_3$ cement, on the one hand, acts as a skeleton and on the other hand, it can increase the adhesion between the particles; Figure 3, the peak of the original soil samples of groups 3 and 4 are not obvious and the ductility is obviously stronger than groups 1 and 2. However, the peak strength increase is not as big as the growth of groups 1 and 2, and the peak strength displacement does not increase obviously.

This probably happens because the clay content of the soil samples is greater, which leads to the generation of carbonic acid cement to play a cementing role. It is possible that because of the high clay content in the soil samples, the carbonic acid cement produced did not play a big role in cementing, and the cement only played the role of a skeleton after solidification; this indicates that the amount of clay content is applicable to this microbial remediation method, but the remediation effect of soil samples with more clay content is not as good as that of brittle soil samples. The double-peak phenomenon in Figure 4 (Group 5 and 6) is normal and is due to the soil body being under pressure. This is due to the uneven treatment of the top of the soil specimen, the upper pressure plate and the top of the soil body in contact with the phenomenon of uneven stress. So when the stress curve reaches the peak and continues to press until the raised side of the small pieces of soil fall off, and the stress curve reaches the stage of destruction. The upper plate continues to press, the remaining flat part of the top of the soil specimen and the upper plate in full contact, the stress curve starts to rise again until it reaches the peak, at which time the double-peak phenomenon of the stress curve occurs; however, it is also obvious that the test force and displacement of the strength curve have increased in all six figures.

To further investigate the performance of the proposed decision support system (DSS), we implemented the model shown in Figure 1. We used MATLAB and the experiments were conducted on the same machine with a 2.6 GHz CPU and 8 GB of RAM. Different algorithms such as CNN, LSTM, and U-Net were implemented and the model accuracy in terms of RMSE and MAPE values was observed. The outcome demonstrates that the effect will be better the longer the repair time. The cracked sandstone's porosity falls by 29.69%, its impermeability rises by 89.98%, and its compressive strength rises by 22.87% after 35 days of repair. As shown in Figure 5, the accuracy of the U-Net model is higher than that of the CNN and LSTM models, but the RMSE and MAPE values are not in line with the attained outcome. The CNN and U-Net models [28] are almost of comparable accuracy but considering the RMSE and MAPE indexes, the CNN is better than the other two.

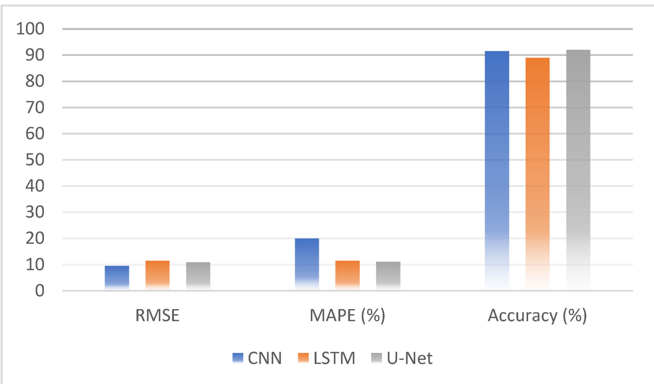

Figure 5. The RMSE and MAPE values along with accuracy using CNN, LSTM, and U-Net.

In Figure 6, an evaluation was performed for the proposed decision support systems (DSS) in terms of the RMSE and MAPE indexes for various machine learning algorithms. Note that the machine leaning techniques are used in two different modules of the DSS and we assume that both are the same to keep consistency in the outcomes. We observed the efficiency of the U-Net model which was significantly increased with the DSS systems both in terms of RMSE and MAPE values. It should be noted that lower values for the RMSE show more efficiency while higher values for the MAPE characterize more efficiency and vice versa. The training and prediction times are shown in Figure 7. The model training times look comparable as these are the averages, and the same argument is also true for the prediction times when the algorithm accuracy is considered. However, we noted variations that sometimes were significant amongst the training and prediction times and the machine learning technique, the complexity of the datasets, and the accuracy of the approach. On average, we noted that the CNN approach is better in terms of execution time than the other two approaches, with a slight decrease in the accuracy.

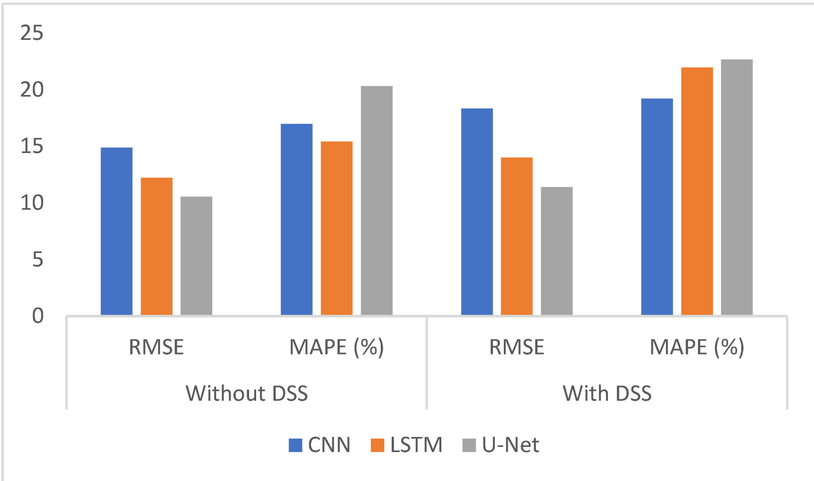

Figure 6. The accuracy of the proposed DSS system using different algorithms.

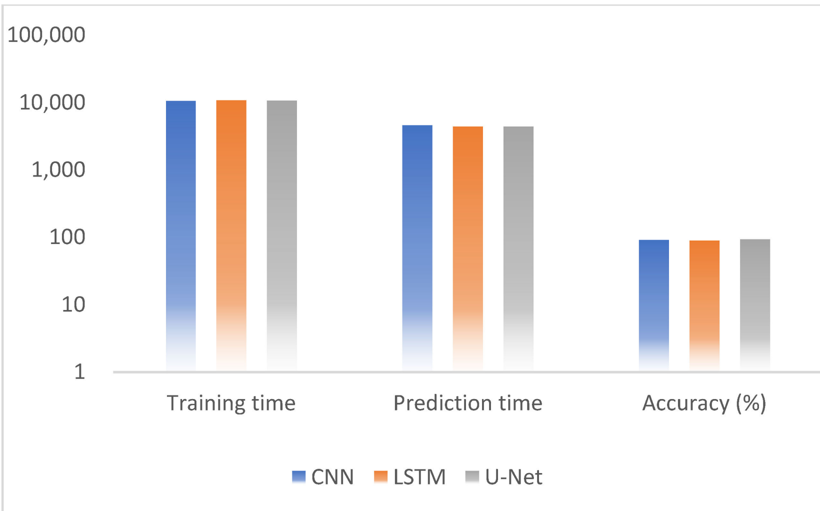

Figure 7. Model training and prediction times versus accuracy [the training and prediction times are shown in seconds].

Finally, we compared the proposed DSS and its integration with the PSO-based optimization model and the attained results are deliberated in Figure 8. We noted that the accuracy of the crack detection and prediction can be increased significantly (up to 9.57%) when the proposed DSS approach is considered. Moreover, we also noted that the accuracy of the DSS is dependent of the mechanism used in the treatment optimization modules. For example, if PSO is implemented as the optimization model, then we can see that the accuracy can be significantly improved by as much as 21.67% to no DSS approach and 11.32% to the DSS approach.

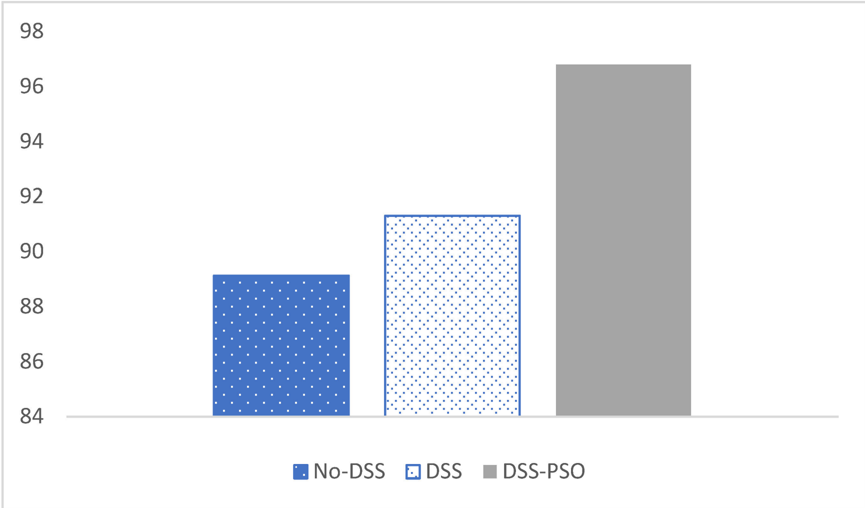

Figure 8. Overall accuracy of the proposed DSS and optimization method.

By enabling more focused, economical, and continuing crack management techniques, the combination of fracture detection, prediction, and treatment optimization models can result in more successful crack healing procedures in undisturbed loess. The integration may lead to cost reductions in terms of the supplies, labor, and crack repair tools employed. Maintenance staff may avoid using unneeded or ineffective repair materials, make repairs faster, and do so with less manpower and equipment by utilizing more focused and effective repair procedures. For instance, maintenance staff can concentrate their efforts on fixing the crack first, using the most appropriate and efficient repair method suggested by the treatment optimization module, if the system detects and forecasts that it will continue to expand. By doing this, they can steer clear of using less efficient or more expensive repair techniques that might not deal with the issue's underlying causes.

7. Conclusions and Future Work

Loess bodies with different clay grain contents have different large strength characteristics, which depend on the instability and wetting of the loess body itself; it was found that the strength, as well as the integrity of the loess bodies with less clay grain contents, were significantly improved after microbial mineralization restoration. The restoration of the loess body by microbial mineralization basically closed the loess pores and acted as the rock skeleton. Comparing the strength curves of loess bodies before and after restoration, the characteristics of both curves change from ordinary soil strength curves to hard rock strength curves, which also indicates that microbial mineralization restoration of loess bodies fundamentally closes the loess porosity and acts as a rock skeleton, which fundamentally increases the mechanical strength. In the same loess body group, the greatest growth rate ratio after soil restoration was 162.91% and 113.66% for the combination o 1 mol/L of the cementing solution, 111.57% and 59.77% for 0.5 mol/L of the cementing solution, and 153.86% and 83.88% for the combination of 1 mol/L + 2 mol/L of cementing solution. Therefore, it can be seen that medium concentration of the cementing solution is beneficial to the microbial mineralization reaction to a certain extent, and too low or too high a concentration will affect the efficiency of the cementing reaction.

The reason for this is that there are many factors to be considered in the application of loess slopes, such as temperature, humidity, pH, acidity, and alkalinity, as well as various complex microbiota in the environment. Therefore, further experiments and research are needed to explore the application of MICP technology to better and more comprehensively apply it to loess slopes and road foundation laying. In the future, we will consider other deep learning approaches to study the generalizability of our obtained results. Furthermore, the accuracy of the approach is dependent on the dataset size; therefore, we aim to propose an aggregation mechanism for the dataset than can reduce the amount of trained data in such a way that the accuracy is not affected. In addition, the PSO technique can also be modified so that the error of receiving inappropriate decisions can be improved. In the future, we will take formal approaches into consideration for the verification of AI-based solutions [29]. In the creation and validation of AI-based solutions, formal methods, which utilize mathematical models and logic to study and verify the correctness of systems, have grown in importance [30]. Researchers may make sure that their methods are dependable, resilient, and devoid of mistakes or biases by using formal approaches.

Author Contributions: Writing—original draft, Y.Y.; Supervision, Y.L. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the Shanxi Natural Science Foundation General Project ([20210302124112], Y.L.). We thank all the reviewers for their valuable comments.

Institutional Review Board Statement: Learning Technology at the National Central University for studies involving humans.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Zhang, T.C.; Li, Z.J.; Wang, S.G.; Yang, F. Analysis of the prospect of MICP technology in geotechnical engineering. *Appl. Technol. Des.* **2018**, *9*, 55–56.
2. Ramachandran, S.K.; Ramakrishnan, V.; Bang, S.S. Remedi-ation of concrete using microorganisms. *ACI Mater. J.* **2001**, *98*, 3–9.
3. Qian, C.; Wang, R.; Cheng, L.; Wang, J. Theory of microbial carbonate precipitation and its application in restoration ofcement-based materials defects. *Chin. J. Chem.* **2010**, *28*, 847–857. [CrossRef]
4. Dejong, J.T.; Fritzges, M.B.; Nusslein, K. Microbially in-duced cementation to control sand response to undrained shear. *J. Geotech. Geoenvironmental Eng.* **2006**, *132*, 1381–1392. [CrossRef]
5. Chen, J.; Lei, X.; Zhang, B. Improvement of strength of silty soils based on microbial induced calcium carbonate deposition (MICP). *Highway* **2021**, *3*, 264–269.
6. Whiffin, V.S. Microbial $CaCO_3$ Precipition for the Production of Biocement. Ph.D. Thesis, Murdoch University, Perth, Australia, 2004.
7. Harkes, M.P.; Van Paassen, L.A.; Whiffin, V.S. Immobilisation of Bacteria to a Geological Material. U.S. Patent US20090215144, 15 December 2006.
8. Harkes, M.P.; Van Paassen, L.A.; Booster, J.L.; Whiffin, V.S.; van Loosdrecht, M.C. Fixation and distribution of bacterial activity in sand to induce carbonate precipitation for ground reinforcement. *Ecol. Eng.* **2010**, *36*, 112–117. [CrossRef]
9. Wang, Y.; Konstantinou, C.; Tang, S.; Chen, H. Applications of microbial-induced carbonate precipitation: A state-of-the-art review. *Biogeotechnics* **2023**, *1*, 100008. [CrossRef]
10. Zhang, K.; Tang, C.S.; Jiang, N.J.; Pan, X.H.; Liu, B.; Wang, Y.J.; Shi, B. Microbial-induced carbonate precipitation (MICP) technology: A review on the fundamentals and engineering applications. *Environ. Earth Sci.* **2023**, *82*, 229. [CrossRef]
11. Liang, S.; Niu, J.; Dai, J.; Fang, C.; Luo, Q.; Yin, Y. Experimental study on the effect of carbon source on the effect of microbial curing of sandy soil. *Ind. Build.* **2018**, *48*, 16–21.
12. Peng, J.; Feng, Q.; Sun, Y. Study on the effect of temperature on microbial-induced calcium carbonate deposition for reinforced sandy soil. *J. Geotech. Eng.* **2018**, *40*, 1048–1055.
13. Deng, J.; Deng, H.; Zhang, Y.; Luo, Y. Experimental study on microbial-induced calcium carbonate deposition for soil reinforcement under low temperature conditions. *J. Geotech. Eng.* **2016**, *38*, 1769–1774.
14. Zhang, H.L.; Xu, P.P.; Liu, S.H.; Leng, L.-J.; Zhou, W.-G. Effect of cementation mode on microbially induced calcium carbonate deposition. *J. Biol.* **2020**, *37*, 85–89.
15. Tan, H.; Chen, F.; He, J.; Chen, J. Effect of soil particle size on the reaction rate of microbial-induced calcium carbonate deposition. *J. Harbin Eng. Univ.* **2019**, *40*, 1884–1889.
16. Wang, X.; Wang, C.; Cui, R. Study on mineralization products of microorganisms in different nutrient salt environments. *Ind. Archit.* **2019**, *49*, 208–212.
17. Pei, D.; Liu, C.; Hu, B.R.; Wu, W.J. Research progress on the mechanism and application of mineralization by *Bacillus subtilis*. *Adv. Biochem. Biophys.* **2020**, *47*, 467–482.

18. Bang, S.S.; Galinat, J.K.; Ramakrishnan, V. Calcite precipitation induced by polyurethane-immobilized *Bacillus pasteurii*. *Enzym. Microb. Technol.* **2001**, *28*, 404–409. [CrossRef]
19. Wang, Z.; Zhang, N.; Cai, G.; Jin, Y.; Ding, N.; Shen, D. Review of ground improvement using microbial induced carbonate precipitation (MICP). *Mar. Georesources Geotechnol.* **2017**, *35*, 1135–1146. [CrossRef]
20. Lian, J.J.; Gao, M.; Yan, Y.; Fu, D.; Xu, H. Research progress of self-healing concrete based on MICP technology. *South-North Water Transf. Water Conserv. Sci. Technol.* **2019**, *17*, 164–177.
21. Zhang, J.G.; Xu, S.H.; Feng, T.; Zhao, L.; Li, Z. Effect of different mineralized microorganisms on the self-healing effect of concrete cracks. *J. Tsinghua Univ. (Nat. Sci. Ed.)* **2019**, *59*, 607–613.
22. Zhou, M.; Zhang, J.; Li, Z.; Feng, T.; Zhao, L. Experimental study on the compressive strength of crack self-healing concrete based on microbial mineralization deposition. *Concrete* **2018**, *341*, 35–39.
23. Li, Z.; Feng, T.; Zhou, M.; Zhang, J.G.; Zhao, L. Experimental study on the self-healing performance of concrete cracks based on mineralized deposition of *Bacillus cereus*. *Concrete* **2017**, *332*, 5–8.
24. Chen, Y.Q. Comparison of growth measurement methods in microbial growth curves. *Light Ind. Sci. Technol.* **2020**, *36*, 7–9.
25. Kong, J.; Gao, Y.; Zhang, Y.; Lei, H.; Wang, Y.; Zhang, H. Improved attention mechanism and residual network for remote sensing image scene classification. *IEEE Access* **2021**, *9*, 134800–134808. [CrossRef]
26. Peng, J.; Huang, M.; Xie, G.; Tian, Y. Grouting method for reinforcing soil by microbially induced calcium carbonate deposition. *J. Riverhead Univ. (Nat. Sci. Ed.)* **2019**, *47*, 259–264.
27. Gray, D.H.; Alrefeai, T. Behavior of fabric versus fiber-reinforced sand. *Geotech. Geol. Eng.* **1986**, *112*, 804–820. [CrossRef]
28. Kong, J.; Zhang, Y. DU-Net-Cloud: A smart cloud-edge application with an attention mechanism and U-Net for remote sensing images and processing. *J. Cloud Comput.* **2023**, *12*, 25. [CrossRef]
29. Krichen, M.; Mihoub, A.; Alzahrani, M.Y.; Adoni, W.Y.H.; Nahhal, T. Are Formal Methods Applicable to Machine Learning and Artificial Intelligence? In Proceedings of the 2022 2nd International Conference of Smart Systems and Emerging Technologies (SMARTTECH), Riyadh, Saudi Arabia, 9–11 May 2022; IEEE: New York, NY, USA, 2022.
30. Raman, R.; Gupta, N.; Jeppu, Y. Framework for Formal Verification of Machine Learning Based Complex System-of-Systems. *Insight* **2023**, *26*, 91–102. [CrossRef]