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Research on Intelligent Identification and Analysis Algorithm of Tunnel Engineering Geological Information

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Abstract: - When tunneling, detecting abrupt changes in geological circumstances can be difficult. In recent years, the proliferation of tunneling characteristics has been strongly related to the surrounding geology. These parameters offer significant potential for using data-driven artificial intelligence (AI) approaches to infer patterns from information without reference to known consequences. This research introduces the Simulated Fire Hawk Optimizer-based Deep Action Selection Network (SFHO-DASN) model, which uses a Simulated Fire Hawk Optimizer to anticipate the geological conditions needed for tunneling. The optimized hybrid neural network technique can anticipate geological conditions effectively, as demonstrated by a case study of the constructed model. It is especially significant for rock types, water intrusion, karst caverns, and surface subsidence, for which the predicted accuracy is greater than 95%. These findings imply that the geological circumstances behind the tunnel face could be reliably and correctly predicted by a DASN that has received the proper training. This procedure's most significant advantage is its ability to adjust every scored parameter's weighting in response to variations in geological circumstances. The accuracy performance of the proposed neural network outperforms the conventional neural network, as indicated by the area under the curve (AUC) and performance analysis. A proposed model for geology prediction can attain predictive accuracy with a small number of tunneling parameters, according to an analysis of the feature relevance of each tunneling parameter. The suggested approach ought to be more practical for proposals about tunnel support architecture in the East Asian geological region and for future tunnel building.

Keywords: Geological information, Artificial intelligence, Tunnel Engineering, Optimization, and performance analysis

1. INTRODUCTION

The rapid population growth and the consequent scarcity of living space have necessitated a significant increase in underground development, a process aimed at improving human well-being [1]. Tunnel engineering, a field that plays a crucial role in this underground expansion, involves the construction of artificial, primarily horizontal apertures in the earth that are significantly longer than their other dimensions and typically have a uniform cross-section [2]. These tunnels are vital connections in numerous railroads, urban transportation systems, and highways. They are also essential for large-scale operations such as mining, hydroelectric power production, wastewater collection and disposal, flood prevention, and urban water distribution and supply [3]. Furthermore, tunnels have a long history of military use for offensive and defensive purposes. However, the complex geological conditions and potential hazards during tunnel construction pose serious challenges that can lead to significant loss of life and property.

The geological analysis method is the most commonly used method for identifying the types and properties of rock formations and forecasting the geological conditions in front of the tunnel face. Geohazards and engineering mishaps, including collapses, flood and mud inrushes, and tunnel boring machine (TBM) jams, can happen during tunnel excavation without prompt diagnosis and prediction techniques [5-6]. Similarly, underground mining can experience rock bursts, groundwater outbursts, and coal bursts. Hence, to minimize such losses, it is crucial to enhance the precise and efficient diagnosis and forecast of unfavorable geological conditions flaws, such as faults, karst caves, and groundwater penetration. This study investigates how data-driven AI approaches are used to determine the kind of geological conditions encountered, which might lessen the likelihood of jamming and geohazard [7-8]. For this, a number of the most well-liked AI methods that have been described in the literature were taken into consideration.

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Combining covariance with a genetic algorithm (GA) for information-based construction in tunnel engineering, Kaiyun Liu and Baoguo Liu [9] introduced the Gauss process regression coupled algorithm (GA-CCGPR). This approach may be applied broadly because of its quick processing benefits, ease of usage, and high accuracy. However, there is a maximum inaccuracy for prediction. Qian Zhang et al. [10] employed the ANN, KNN, SVM, and CART algorithms to create a geological recognition classifier while considering complicated correlations. It demonstrates how the suggested ANN predictor works better than other models. However, more research is needed on using ANNs in tunnel engineering. A tunnel hazards database is constructed by Si W. et al. [12] using data mining technology to achieve the organized representation of tunnel multi-source structural security data, which is then successfully applied to the engineering field.

Wu et al. [11] have suggested a novel multi-source data integration approach that combines the use of the support vector machine (SVM), cloud model (CM), and evidence-based reasoning (ER). There is a more significant delay between decision-makers and a disaster. Li, X et al. [13] describe a unique subsea TBM tunnel intelligent construction system and utilize a case study to determine its adaptability. The system is based on automated compliance checking (ACC) optimization, fuzzy set theory integrated with Dempster-Shafer (D-S) connection theory. Using a fuzzy C-means method, Yan T. et al. [14] present a system for identifying geological features based on operational and drilling data during shield tunneling. Tunneling performance is effectively increased, and construction hazards are significantly reduced by the operational approach, which complies with the criteria of the construction code. Owing to the shortcomings of some initial models, some researchers enhance the initial neural networks using methods like genetic algorithms (GA) and particle swarm optimization (PSO) to improve prediction outcomes.

The primary objective of this research is to develop an intelligent algorithm that combines the deep belief and neuro-fuzzy algorithm-based deep learning function with metaheuristic optimization of simulated and fire hawk algorithms. This algorithm is designed to identify and analyze geological conditions in tunnel engineering. The proposed method is validated through a case study in the East Asian geological region. The features from the database are extracted and selected using the EfficientNet B7 algorithm. The performance of the proposed method is then compared with conventional methods using various metrics.

This article is structured as follows: Section 2 presents the proposed methodology, outlining the steps to develop the intelligent algorithm. Section 3 provides a detailed study of the results, including a discussion and comparative analysis of the research. Finally, Section 4 summarizes the conclusions drawn from the study and outlines potential areas for future research.

2. PROPOSED METHODOLOGY

This paper introduces a novel approach, the SFHO-DASN method, for identifying and analyzing geological information systems in tunnel engineering. This method, which we propose for the first time, is applied to the Yanjingwan tunnel in the Chinese province of Guizhou as a case study for validation. We comprehensively analyze the tunnel's geological mapping information, considering various geological factors that influence tunnel development, such as the overburden's traits and depth, the layout of the bedrock surface, the rock's characteristics, materials, and mineral composition, the structural characteristics of the rock mass, and the presence of gas, unusual rock temperatures, and ground-level water. The data on TBM and geological circumstances are sourced from the database. We begin with preprocessing using Z-score normalization to mitigate the main impacts caused by the disparity in dimensions and magnitudes between various parameters in the TBM in-situ information. Then, we employ the EfficientNet B7 method to identify the critical parameters exhibiting high sensitivity to geological variation.

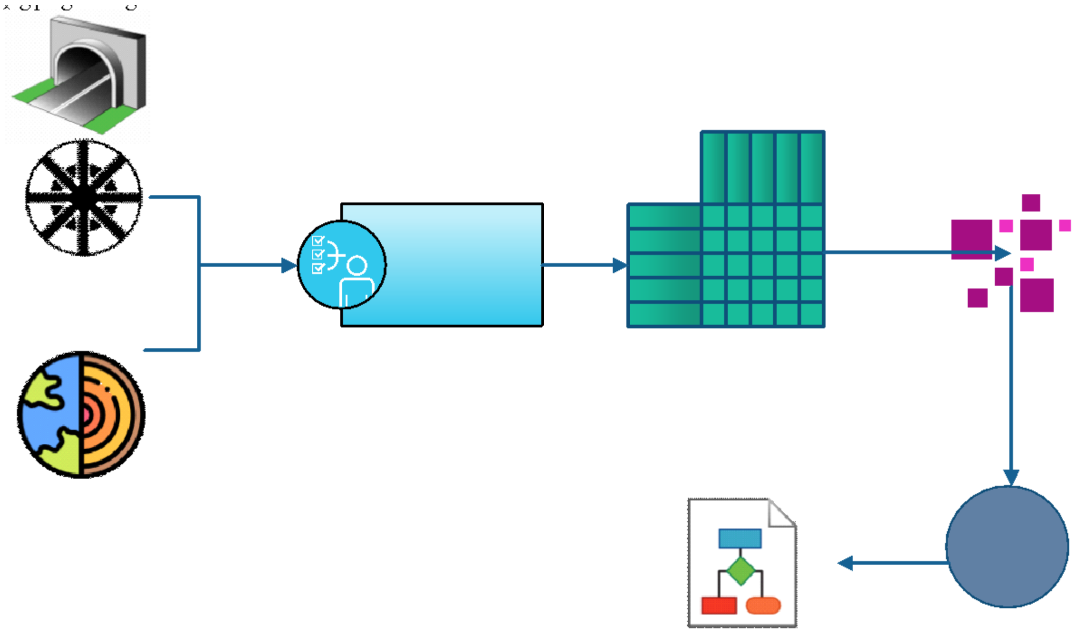

Fig.1 Proposed Methodology

Moreover, the SFHO-DASN method is not just a theoretical concept but a practical tool for executing the geological type classification in tunneling. This classification is obtained by training data sets with geological categories using our suggested method. We use the SFHO method to optimize the DASN algorithm's variables. We utilize the test set data to assess the method's efficacy and verify the correctness of the geological data system. This practical application of the SFHO-DASN method underscores its relevance and usefulness in tunnel engineering.

2.1. Data pre-processing

The shield's initial tunneling data contains many incorrect and aberrant data, which must be discarded in advance. To reduce the negative impacts produced by the varying magnitudes of the excavation variables, we employ the z-score standardization approach, which linearly changes the information to have a mean of 0 and a standard deviation of 1.

$$x' = \frac{x - \overline{M}}{\delta_M} \tag{1}$$

Where, x and x' is denoted as the raw and normalized tunnelling parameter data, δ_M and $\overline{M}$ is the standard deviation and mean value of the data, respectively.

2.2. Geological Feature Engineering

After normalizing the raw data, the feature engineering function is applied to extract and select the significant features for the identification algorithm. Here, the EfficientNet B7 algorithm is used for the feature engineering function. The network's stem is considered before any input modifying, rescaling, normalization, zero padding, conv2D, batch normalization, and activation begin. After that, each of them has seven parts. Furthermore, there are varying numbers of sub-blocks in each of these blocks. The EfficientNet B7 has a total of 813 levels. Increasing the number of channels, layers, or input image resolution can enlarge data. The MBConv does a 1 1 convolution operation to widen the channel in addition to a Depthwise convolution operation that convolutions each image channel individually. During depthwise convolution, a k-k kernel convolution approach is used for each picture layer. Each feature map in a channel used in Depthwise convolution is unique. Group normalization is done to all the layers before the RELu algorithm activates any of them. Eqn (2) provides the formal formula for RELu..

$$f(x) = \max(0, x) \tag{2}$$

A feature map that omits the Squeeze and Excitation Layer may be added to the recovered map to emphasize significant features. The 1x1 convolution method is then used to decrease the channel. When channels are limited to 1:1, confidential information is less likely to be on other channels and sensitive material is eliminated using the activation function.

Consequently, only group normalization is used. This technique concatenates the input skip-connected data with the output value that traverses many levels. The multilayer perceptron is connected to the last layer. Here, the two dense and dropout layers construct three activation functions. Additionally, softmax and ReLU activation algorithms are employed. The softmax activation function is represented by eqn. (3).

$$Soft\max(x_i) = \frac{\exp f(x_i)}{\sum_i \exp f(x_i)} \tag{3}$$

In this instance, it represents the numbers received from the neurons in the output layer. The complex function is defined by the exponential. These standardized numbers are divided by the total of the exponential values to produce probabilities. Finally, the most needed geological features are selected by the EfficientNet B7 method, such as Soil, soft rock, hard rock, internal friction angle, upper earth pressure, Groundwater, slope stability, lower earth pressure, natural severity, cohesive strength among rock mass and anchors and coefficient of lateral pressure.

2.3. SFHO-DASN based Geological Identification

The proposed SFHO-DASN algorithm combines SFHO-based metaheuristic optimization with the combination of deep neuro-fuzzy method. The DASN method combines a deep belief network with the action selection intelligent fuzzy system. The proposed SFHO algorithm tunes the hyperparameter of the DASN model. The architecture of the proposed SFHO-DASN in tunnel engineering is illustrated in Fig. 2.

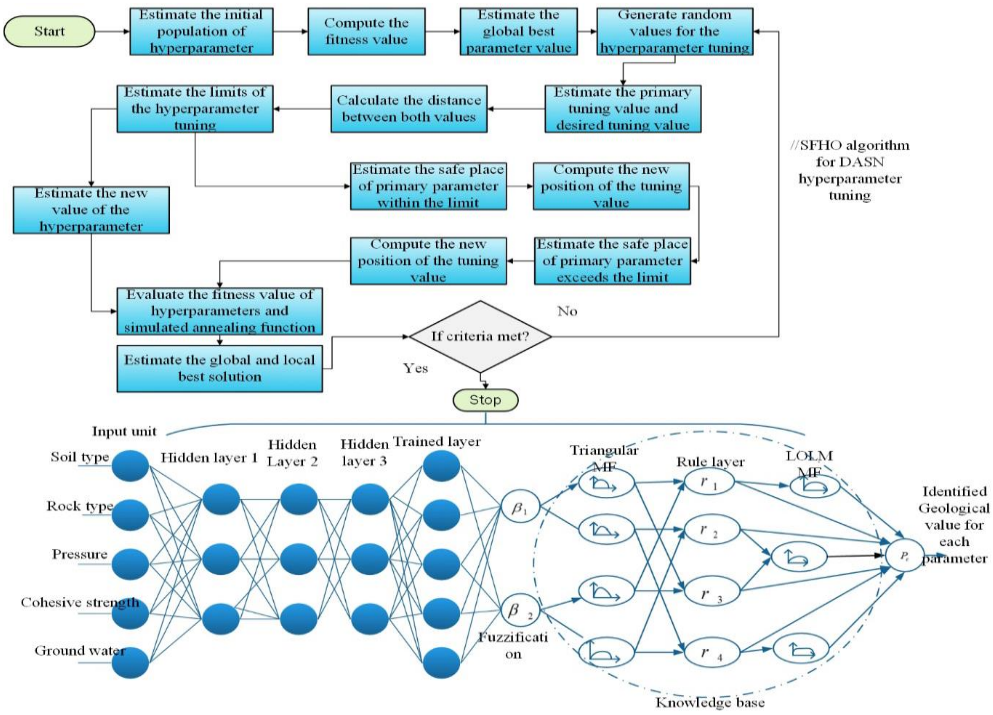

Fig.2 Architecture of proposed SFHO-DASN in tunnel engineering

a) DASN model

In DASN method, the selected features from the EfficientNet B7 output is provided as the input. For training the data, the concept of deep belief network is inbuild to the action selection intelligent algorithm. Examine the visible v_m and concealed units u_n as components of the data. Subsequently, v_m and u_n unit rates are represented as binary numbers, either 0 or 1. Eqn (4) is used to estimate the visible unit probabilities.

$$Pu_m = \frac{1}{h} \sum_{v} e^{-s(u,v)} \tag{4}$$

Where $-s(u,v)$ is the data function of visible and hidden units, and where h is the featured data function. Furthermore, the issue of producing a feasible activation function has been addressed by the establishment of a Restricted Boltzmann Machine. Eqn. (5) is used to supply the training function with the accurate units.

$$F(u,v) = -\sum_{m=1}^{M} \sum_{n=1}^{N} k_{mn} u_m v_n - \sum_{m=1}^{M} \chi_m u_m - \sum_{n=1}^{N} \delta_n v_n \tag{5}$$

In this case, the number of visible units and hidden units is shown by M and N, and the weights of the data between the visible and hidden nodes are indicated by k_{mn} and χ is the bias term. The weight of inconsistencies is the next log possibility for a training vector. Eqn (6) is utilized to determine the weights of the data in the gradient technique.

$$k_{mn}(a+1) = k_{mn}(a) + \chi \frac{\partial \log(P(u_m)}{\partial k_{mn}} \tag{6}$$

Where the mean difference between the training and tested data is used to evaluate the gradient part as $\partial \log(P(u_m) / \partial k_{mn}$. Furthermore, Boltzmann's hidden units don't offer a particular answer to help create the perfect, unbiased sample. Contrastive Divergence is the strategy commonly used to train deep belief systems. To optimize the likelihood of the training data under the model, this technique resembles the gradient of the log probability and updates the weights and biases. These Restricted Boltzmann machines are stacked in a deep network. One Restricted Boltzmann Machine's visible layer is the concealed layer of the subsequent one. Following this layer-by-layer, unsupervised training and supervised techniques such as backpropagation are used to maximize the network and minimize the discrepancy between what is expected and the actual label of the data used for training. After training, the data from the action selection intelligence system is applied for accurate identification based on the rule condition. The trained data is initially converted to fuzzified data using the fuzzification phase; the function is expressed as eqn. (7)

$$\beta_{f_a, t_{la}, t_{ra}}(d) \tag{7}$$

where f_a, d_{la}, d_{ra} indicates the label's fuzzy membership values' center, left, and right spreads, respectively, and *a* stands for a linguistic value (e.g., medium value, high value, low value, etc.). The triangular Membership function is executed in this layer. A rule in the rule base relates to a node in previous layer. One label for each observed variable is the antecedent of a de, therefore the inputs of node i in this layer are the outputs of d nodes in the preceding layer. The combination of the antecendents is the result of node i, or the firing strength of rule i. The minimal operator is the combination that is most frequently encountered. In the next layer, it receives inputs from all rules that employ this specific consequent label. The local mean-of-maximum membership function is executed using eqn. (8)

$$\beta^{-1}_{f_a,t_{la},t_{ra}}(l_r)=\left(f_a+\frac{1}{2}(t_{ra}-t_{la})\right)\left(\sum_r l_r\right)-\frac{1}{2}(t_{ra}-t_{la})\left(\sum_r l_r^2\right) \tag{8}$$

Where l_r is the degree of all rule. The outputs from the preceding layer are combined by the node in layer final to provide a single non-fuzzy controller output, which is expressed using eqn. (9),

$$P_c=\frac{\sum_{r=1} l_r\beta^{-1}(l_r)}{\sum_{r=1} l_r} \tag{9}$$

where P is created in all cases where all of the input space's dimensions are surrounded by the antecedent label functions. The only input connections with movable weights are the second and fourth layers. One remains for the remaining weights. This demonstrates that just two of the five weight layers are used by the SFHO algorithm.

a) SFHO Tuning for DASN algorithm

The SFHO method incorporates both simulated annealing and the Fire Hawk optimization function. The position update procedure in the FHO algorithm is carried out by employing the superior solution, not the global best, and the average of the solution candidates. It prevents the search process from being trapped in local optimal spots. Including a simulated annealing approach to the FHO algorithm improves these concerns, and the suggested algorithm is now known as the SFHO algorithm. First, DASN solution candidates are identified based on hawk and prey position vectors. Vectors' starting coordinates in the search space are determined via a random initialization method.

$$g_m^n(0)=g_{m,\min}^n+r.(g_{m,\max}^n-g_{m,\min}^n),\quad \begin{cases} m=1,2....a\\ n=1,2,....b\end{cases} \tag{10}$$

where b denotes the problem's size and G_m stands for the m^{th} potential solution in the search space; a is the overall amount of candidates for solutions in the field of search space; g_m^n is the m^{th} solution candidate's n^{th} selection variable; and $g_m^n(0)$ denotes the candidates' starting positions. The lowest and highest bounds of the n^{th} selection variable for the m^{th} solution candidate are represented by the numbers $g_{m,\min}^n$ and $g_{m,\max}^n$, whereas r is a random number that is evenly distributed within the interval [0,1]. The hyperparameter represents the remaining solution choices, and Fire Hawks have higher objective function values. The prey is surrounded by the fire from the chosen Fire Hawks in the search area to facilitate hunting; furthermore, the primary fire that the Fire Hawks use to disperse fire throughout the search space is the best global solution. Furthermore, the best and worst point of hyperparameter distance is estimated. The hyperparameter values are selected and tuned from the DASN algorithm using eqn. (11) in each iteration,

$$D_w^{new}=D_w+(r_1*G_b-r_2*D_{near}),\quad w=1,2....n \tag{11}$$

Where r_1 and r_2 is evenly distributed random values with the limit of (0,1), D_w^{new} is denoted as the new tuning vector of the w^{th} function, the global optimal solution is denoted as G_b and the neighbourhood tuning values are considered as D_{near}. Consequently, the safe position of the hyperparameter tuning within and exceeds the limits are expressed using eqn. (12) and (13),

$$E_s^{new} = E_s + (r_3 * D_l - r_4 * J_1), \quad \begin{cases} w = 1,2....n \\ s = 1,2....r \end{cases} \tag{12}$$

$$E_s^{new} = E_s + (r_{53} * D_{change} - r_6 * J_2), \quad \begin{cases} w = 1,2....n \\ s = 1,2....r \end{cases} \tag{13}$$

Where E_s^{new} is the new value of the s^{th} parameter enclosed with the w^{th} composition. J_1 and J_2 are the safe place of parameter value within and exceeds the w^{th} limit, r_3, r_4, r_5 and r_6 is evenly distributed random values with the limit of (0,1). This way, the global best solution is estimated, and the local best solution is analyzed using a simulated annealing function. Initialize the limit of the hyperparameter values as minimum and maximum Generate the primary solution E_s and computes its tuning function. Generate the new tuning solution E_s^{new} and find its capacity. Analyse the variation of new and old parameters values as $E_s^{new} - E_s$, if the difference is less than zero, compute the probability based on both exceptional values with a random number of intervals; otherwise, accept the new tuning solution. Moreover, if the random value is less than the probability, the latest local best solution is estimated; otherwise, the parameter value is. Once the optimal solution is achieved for both the global and best part, the criteria are stopped; otherwise, return to the next iteration.

3. RESULT AND DISCUSSION

This research presents a method for geological identification of real-world tunnel engineering. This section analyzes the effectiveness and identification performance of several intelligent algorithms. In this paper, the effect of the SFHO-DASN method is analyzed by using the tunnel project of the Yanjingwan tunnel in the Chinese province of Guizhou as an experimental project [20]. This paper uses these four indices to evaluate geological recognition results. The calculation method of each evaluation index is as follows:

$$Ac = w + x/(w + x + y + z) \tag{14}$$

$$\mathrm{Re} = w/w + z \tag{15}$$

$$\mathrm{Pr} = w/w + y \tag{16}$$

$$F1 = (2 * \mathrm{Pr} * \mathrm{Re})/(\mathrm{Pr} + \mathrm{Re}) \tag{17}$$

where a correct Geological state identification is predicted to be true positive (w), a class that is incorrectly identified to be true negative (x), A false positive (y) occurs when an incorrect class is predicted to be a positive class. and a correct identification to be false positive (z).

3.1. Performance analysis

The performance of the proposed model in tunnel engineering based on the geological data is compared with the different conventional methods such as GPR-SVM [15], ANN [16], GCN-LSTM [17], DM [18], and M-KNN [19] in terms of performance metrics. Figure 3 displays the ROC curve, which was used to evaluate the proposed model's predictive capacity compared to traditional techniques. A bigger ROC area shows a better identification, indicating the model's capacity to discriminate between 0′s and one ′s. Additionally, a high separability measure is indicated by an AUC value closer to 1, while the poorest measure of detachment is indicated by an AUC value closer to 0. With an ROC curve score of 99.73, it is evident that the suggested model outperforms the other models.

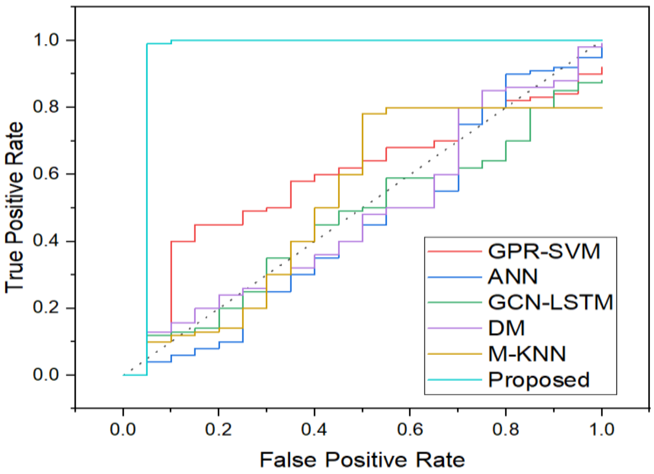

Fig.3 ROC for different Identification algorithms

Moreover, the performance of the developed model in tunnel engineering is compared with the earlier models in terms of accuracy, precision, recall, and F1-score, which is illustrated in Fig.4 (a-d). The analysis shows that the proposed model has achieved higher accuracy, precision, recall, and score than the conventional methods under varying geological features. The proposed model has achieved the highest accuracy of 99.5%, and the GCM-LSTM method attained a significantly lower accuracy of 87.9% for 11 features.

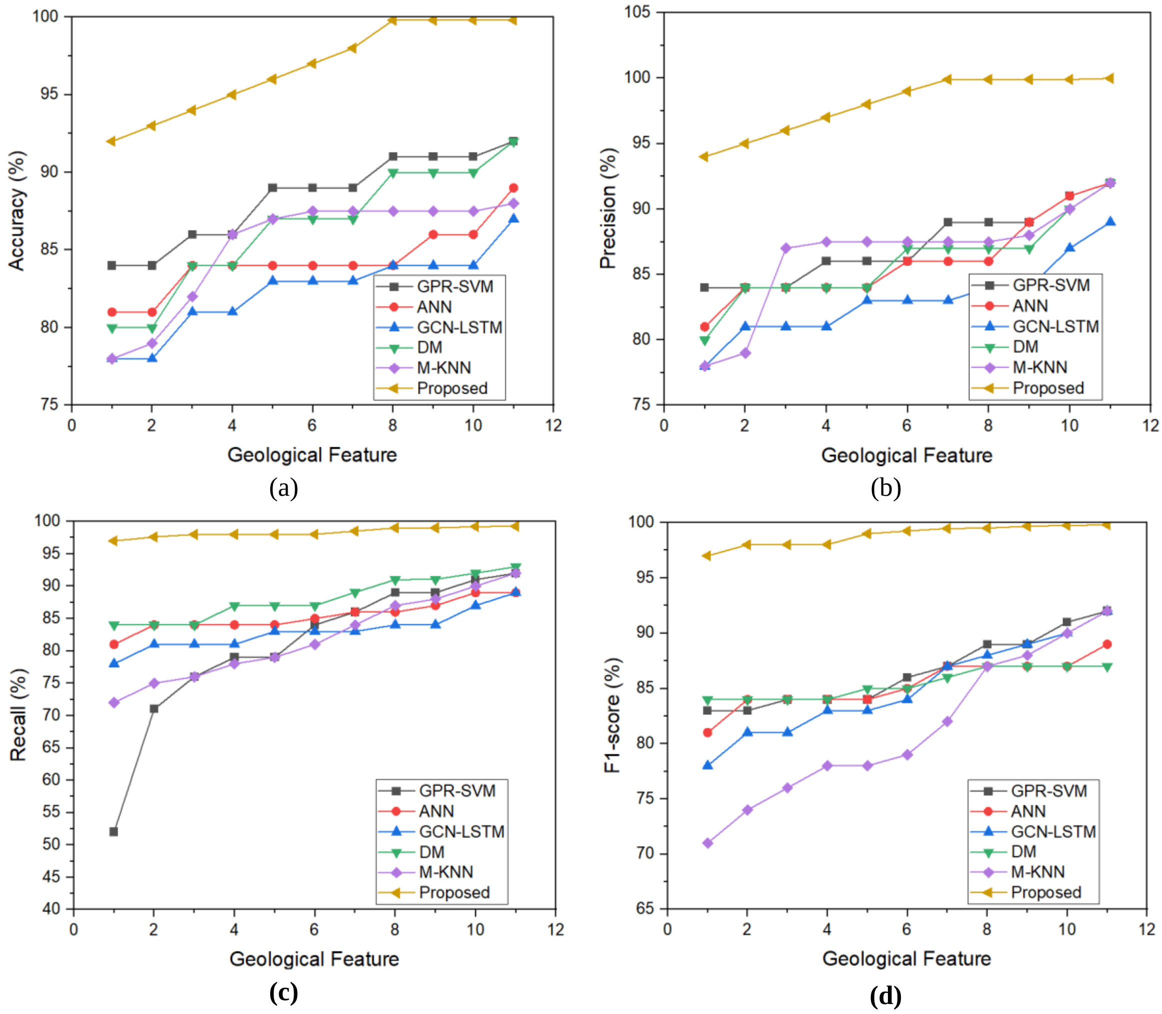

Fig.4 Performance Measures a) Accuracy, b) Precision, c) Recall and d) F1-score

The proposed model's average identification accuracy is higher than the previous models. This is probably because, unlike the EfficientNet B7, which is based on reducing dimensionality through the extraction and selection of the most significant features, the proposed framework is a sort of hybrid deep learning optimization in which the output from the previous step is provided as input to the current step. Consequently, the suggested works well while resolving geological problems related to tunnel engineering.

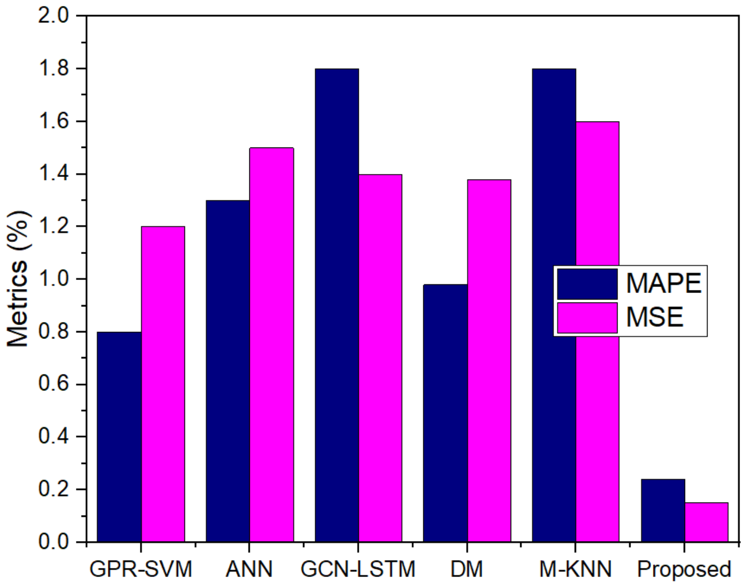

Fig.5 Comparative analysis of Error metrics MAPE and MSE

When the suggested technique identified the various geological parameters and GPR-SVM [15], ANN [16], GCN-LSTM [17], DM [18], and M-KNN [19], the indices of MSE and MAPE are presented in Fig. 5. The identification accuracy of the proposed technique was much greater than that of the standard methods when estimating different geological factors. When it came to determining the presence of rock type, soil, and water supply, the proposed approach performed better than the traditional neural network.

4. CONCLUSION

This paper proposes an incorporated deep learning method based on the geological data recorded during tunnel engineering work. The proposed method includes feature engineering, optimization, and identification of deep learning. The advanced EfficientNet B7 model is chosen for feature extraction and selection in feature engineering. The proposed method is used to identify the geology of the Yanjingwan tunnel in the Chinese province of Guizhou. The comparison of the recognition results to the measured geological types demonstrates that the suggested technique works. The degree of identification progressively rises as the input grows, finally reaching a plateau when the algorithm's accuracy exceeds 99%. Based on this, a selection approach for optimum input features is provided, as is the ideal number of input parameters for this validation instance. The accuracy, precision, recall, F1 score, Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and receiver operating characteristic (ROC) curve findings demonstrated that the new model was more resilient in learning and interpreting than the previous models. The proposed EfficentNet B7 and SFHO-DASN models can support tunnel engineering under geological variation. In the future, more regions can develop for the identification and analysis of geological data in tunnel construction functions with the same methods.

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