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Data mining technology for machinery equipment and information networks

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Abstract: In order to predict the Rate of Penetration (ROP) during drilling, a new data mining technology for drilling ROP prediction is proposed. The weight of the ROP influencing factors determined by the Analytic Hierarchy Process (AHP) and the original data are used as the input information, after neural network training and iteration, the drilled ROP model is determined, finally, the model is used to simulate and predict the ROP to be drilled in the same area. Simulation results show that the Analytic Hierarchy Process-Back Propagation (AHP-BP) combined model established by the feedforward neural network principle can improve the iterative convergence speed and the reliability of the training results to a certain extent. Experimental results show that the predicted value of drilling speed is basically close to the actual value, the relative error is controlled within 10%, and the prediction effect is good with an accuracy of 98%.

Keywords: rate of penetration prediction; data mining; analytic hierarchy process; neural network; AHP-BP; analytic hierarchy process-back propagation; neural network.

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1 Introduction

In recent years, with the evolution of communication methods and the development of storage devices, a huge amount of information has been created and recorded in all links and stages of life and industry, from the country to the economy and everyone has gradually realised the value of information, which will become the power of the country in the future employs symbol of power and wealth. One of our activities is information generation, which is the process of finding useful information based on ‘cultural history’ through the use of good research to obtain unproven information such as historical monuments from a specific area of mining. Just as people value specific knowledge based on years of work experience, in the information age, information is an important part of acquiring, retrieving and retaining knowledge from the vast amounts of data collected every day (Fu and Zhang, 2021). As a value discovery method, data mining technology integrates and penetrates with other fields, and gradually enters the life of ordinary people, generate various effective recommendation results for users and change the way we live and produce, such as: In the field of finance, data mining is used for stock market return forecasting and risk assessment; In the field of military logistics for route planning and material delivery; In the field of military training for model evaluation, etc., the application of data mining has the following outstanding characteristics: The process uses all existing data, and deliberately creating data in order to prove the user’s unknown points of interest will lead to deviation from the target. The data is large in scale, many types, and complex in structure, so traditional statistical methods should not be used. The systems applying data mining technology often integrate functions such as data management and parameter configuration. The mining results are not absolutely correct or absolutely feasible, and may not be accurate in the actual application process, and the knowledge generated in a certain confidence space is effective. With the passage of time and the accumulation of data, the patterns or rules that have been mined may lose their use value, and the mining process needs to be repeated regularly to manage and maintain the mining results. The mining process and results are closely related and deeply integrated with application scenarios, and better mining results can be obtained by using customised data mining technology for different application scenarios (Maleki et al., 2021).

2 Literature review

Du and Zhao (2021) proposed a mathematics teaching network media fusion technology based on big data mining and information fusion, combined with the characteristics of multimedia technology and network technology in terms of openness, creativity and subjectivity, a mathematics teaching database model was constructed. The multi-thread integrated scheduling method is used to design the mathematics teaching database model, the fuzzy control method is used to control the multimedia in mathematics teaching, and the big data association rule mining method is used to realise the information fusion of mathematics teaching resources

(Du and Zhao, 2021). Zheng et al. (2020) based on DM technology, by discussing the functional structure mapping of product functional design, a product conceptual design model was proposed. Zhou et al. (2021) proposed a web-based product design system based on DM technology. In Chang et al. (2020), using DM algorithm to realise the evaluation port of construction machinery design scheme. Jiang et al. (2021) proposed the information integration theorem that multi-dimensional information contains more information than single-dimensional information, but it did not get people’s attention at that time, the full development of DF thought was in the late 1980s. Originating from the need for Command Control and Communication Integration (C³I) systems in the military field, sonar signal understanding system, Big Data Extraction and Technology Analytics (BETA), Total Control and Analytics Centre (TCAC), Intelligent Network and Component Analysis (INCA), Technology Resource Web Data Systems (TRWDS), Automated System for Analysis and Simulation (ASAS), Learning Engineering Networking Systems and Computational Exploration (LENSE), Platform As A Service (PAAS), Technology Optimisation Processing (TOP), Data Analytics for Generalised Resources (DAGR), Technology Analysis Tools for Resources (TATR), Automated Machine System Utilisation Intelligence (AMSUI), Engineering Networked Systems for Control and Security (ENSCS) and other military information fusion systems have been developed successively, indicating that DF technology has been favoured in the military field (Jiang et al., 2021).

In Wang et al. (2021), after analysing drilling fluid parameters, formation parameters, drilling process and wellbore geometry factors, an expert system (Drilling Advisor) for dealing with the frictional resistance of drilling tools and tripping blocks was developed by using SI and LISP programming languages, more than 3000 rules and dozens of drilling parameters are described in the system’s knowledge base, the expert system analyses the causes of sticking by synthesising various influencing factors, such as downhole liquid column pressure and formation pore pressure difference, wellbore filter cake, well diameter reduction, well fall and mud bag, etc., a confidence model for judging the causes of stuck is established, and corresponding solutions for stuck are given according to the judged causes of stuck. The system can provide on-site technicians with a targeted method for removing the stick after a stuck pipe accident occurs, and is a good analysis and disposal tool (Wang et al., 2021). In Mosavi et al. (2022), for the first time, mathematical analysis method was applied to the study of stuck pipe problem, and a method of multivariate statistical analysis and modelling based on various drilling parameters was proposed to predict the problem of drilling tool resistance, in the process of research, they collected a large amount of drilling history data and data, and through the analysis and summary of the data, they concluded the difference between the related drilling parameters when the stuck pipe accident occurred in the drilling and the normal operation (Mosavi et al., 2022). After years of theoretical research, Kou et al. (2021) proposed a discriminant analysis method on this basis, which summarised the parameter changes and differences in different states of drilling and applied them to the field, perfecting and improving the previous research results, after

testing and analysis, it is found that this technology can not only be used to monitor the occurrence of downhole sticking accidents, but also can continuously update the expert experience used to identify the causes of stuck pipe by monitoring the changes of drilling parameters.

The author proposes the Analytic Hierarchy Process-Neural Network Combination Model (AHP-BP), the weights of the factors affecting the ROP determined by the AHP and the original data are used as input information, after neural network training and iteration, the drilled ROP model is determined, finally, the model is used to simulate and predict the ROP to be drilled in the same area.

3 Research methods

3.1 Resource sharing system architecture

The architecture of a comprehensive resource-sharing service platform for mechanical equipment should support business process restructuring, technology collaboration and collaborative manufacturing processes across firms through effective resource sharing and optimal allocation. To facilitate resource sharing and promote inter-enterprise collaboration, the author's functional design makes use of the internet and intranet to access and arrange sharable resources across organisations. It also supports virtual enterprise application system integration by providing a standardised platform for enterprise web service registration and discovery. Three primary layers are the Basic Service Layer, the Application Service Layer and the Portal Layer which are used to arrange the platform's services (Xiang and Yamamoto, 2021).

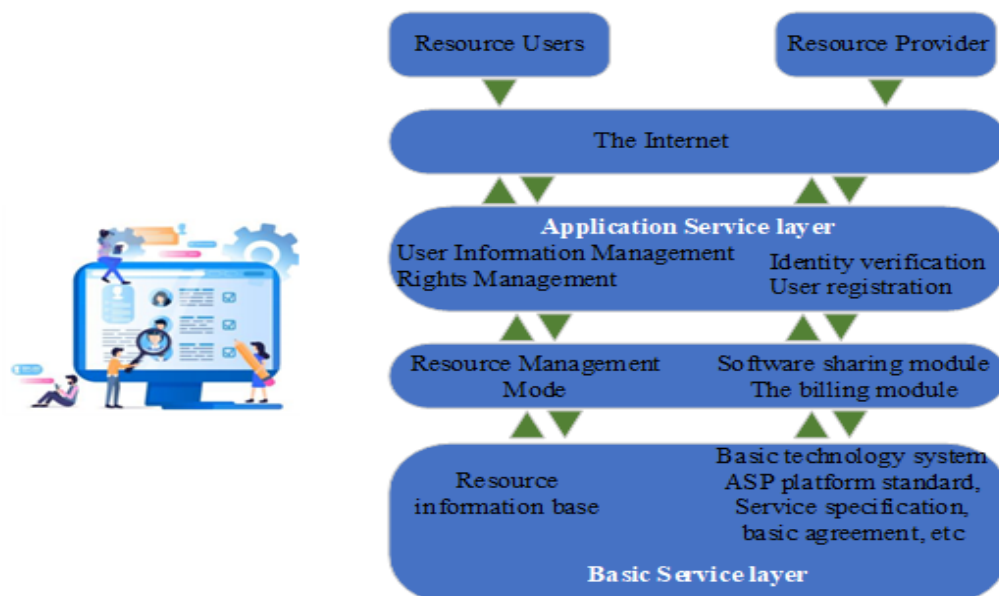
A basic technological system (architecture, standards and specifications), ASP platform standards, service specifications and protocols, system security services and the resource information database make up the Basic Service Layer. The platform's primary business logic is housed in the Application Service Layer, which, after optimisation and

combination, provides users with specific services. This layer consists of a billing module, a software sharing module for cross-platform collaborative activities, and a resource management module for platform resource information management (Liu et al., 2021). Finally, with features like user information management, authority management, identity verification and user registration, the Portal Layer offers an intuitive user interface. Resource integration and management, cooperative inter-enterprise assistance, networked manufacturing services, unified descriptions, shared resource maintenance and security control for alliance companies are all made possible by this multi-layered framework. Its functional architecture is shown in Figure 1.

3.2 Network resource data mining rule extraction and setting

In order to ensure the effective mining of network resources, it is also necessary to set data mining rules according to different network resource types, and extract the rules to connect with multiple data mining behaviour ports. In this process, set I to be an item set of m resources, and D to represent the association rule database, then each data can participate in the setting process of mining rules as a subset. If the mining rule is in the form of the former including the latter, the former can be used as a pre-condition for performing data mining behaviour, and the latter as a transaction database, that is, the comparison process of the mining data. In this way, the network resource data mining rule is set, and the confidence level of this rule is preset as $s\%$, it is considered that within the scope of $s\%$, there is some kind of regularity in the data mining and this kind of regularity can be used as a reference standard for data mining. According to preset rules, the intersection of resource subsets is performed (Farhadi et al., 2021). In this way, the setting of data mining rules for network resources and the extraction of data mining results are realised.

Figure 1 Resource sharing system architecture (see online version for colours)



3.3 Cleaning and screening of data mining results

In order to avoid abnormal data mining results, it is necessary to clean and screen the data after outputting the network resource mining subset results. In this process, the repeated resource records of the output subset results should be performed first, and the information structure should be randomly extracted in the free format by classifying the encoded fields, and the structured information should be separated. The accuracy of the data results is checked by searching for fields, if it is found that there is a field with repeated codes, the matching of repeated records can be performed and retrieve if its source is the same network address. When the identification result shows that the duplicate encoded information belongs to the same source, the redundant value can be directly deleted to clear the data entity.

The data cleaning and screening process proposed above is a relatively simple operation process, in order to meet the high-quality requirements of the front-end for network resources, after the above processing is completed, the attributes of the data set can be merged to match the data records and perform distance matching on resource information with the same duplicate records or similar data. For the values with high similarity in this process, the processing method of clearing them can be directly adopted (Dogan, 2020). To sum up, the cleaning and screening of data mining results are realised, and the design and research of network resource data mining technology based on genetic algorithm is completed.

3.4 AHP-neural network combination model

3.4.1 The principle of AHP

Analytic Hierarchy Process (AHP) was proposed by the famous operations researcher T. L. Saaty in the 1970s. This method divides various factors in complex problems into orderly levels of interrelatedness, makes them organised, and directly and effectively combines data, expert opinions and subjective and objective judgments of analysts, and has a comparative analysis of each level. Importance is given quantitatively, then use mathematical methods to determine the relative importance weights of all elements at each level, the steps are as follows:

- Determine the set of objectives and evaluation factors.
- Construct the judgment matrix.
- Calculate the importance ranking, that is, the weight distribution.
- Consistency check.

3.4.2 Artificial neural network

The most widely used artificial neural network is the feedforward network model BPNN (Back Propagation Neural Network), which consists of an input layer, a hidden layer (which can be one or more layers) and an output layer, the

learning process consists of two processes of signal forward propagation and error back propagation.

Each neuron in the input layer of the feedforward network is responsible for receiving input information from the outside world, and pass it to each neuron in the middle layer; The hidden layer (i.e., the middle layer) is the internal information processing layer, which is responsible for information transformation; After the information transmitted from the hidden layer to the neurons of the output layer is further processed, a forward propagation process of learning is completed and the information processing result is output from the output layer to the outside world. When the actual output does not match the expected output, it enters the back-propagation stage of the error. The error passes through the output layer, corrects the weights of each layer according to the method of error gradient descent, and transfers back to the hidden layer and the input layer by layer. The cycle of information forward propagation and error back propagation is the process of continuously adjusting the weights of each layer, and it is also the process of neural network learning and training, this process continues until the error of the network output is reduced to an acceptable level, or is preset up to the number of learning times (Shin et al., 2020).

3.4.3 AHP-BP combination model

The input layer in the BPNN network generally uses the pre-processed sample data directly, by default, each neuron has the same effect on the result, however, in actual engineering, different engineering parameters and geological parameters have different effects on ROP, and there are different weights. The degree of influence of various factors on the results is quantified by the AHP method, and the weight and the initial sample data are used as the input layer for network training, which not only shortens the network training time, but also improves the convergence speed and the reliability of the training results. The specific algorithm of the AHP-BP combination model is as follows:

Suppose a single group of original data is an n -dimensional array $r_i (i=1,2,\dots,n)$, and the weights obtained by AHP are assigned as $\xi_i (i=1,2,\dots,n)$. In the 3-layer perceptron, $X=(x_1, x_2, \dots, x_n)^T$ is the input vector, $Y=(y_1, y_2, \dots, y_m)^T$ is the hidden layer output vector, $O=(o_1, o_2, \dots, o_l)^T$ is the output layer output vector, $D=(d_1, d_2, \dots, d_l)^T$ is the expected output vector, the column vector v_{ij} is the weight vector between the input layer neuron i and the hidden layer neuron j , and w_{jk} is the weight matrix between the hidden layer and the output layer. There is the following equation (1) mathematical relationship between each layer (Xiao, 2020).

$$X_i = r_i \cdot \xi_i (i = 1, 2, \dots, n) \quad (1)$$

For the input layer there is the following formula (2):

$$\begin{cases} y_i = f(g_j) \\ g_j = \sum_{i=1}^n v_{ij} x_i (j = 1, 2, \dots, m) \end{cases} \quad (2)$$

For the hidden layer, there is the following formula (3):

$$\begin{cases} o_k = f(h_k) \\ h_k = \sum_{j=1}^m w_{jk} y_j \quad (k = 1, 2, \dots, l) \end{cases} \quad (3)$$

Among them, g_j and h_k , respectively represent the input value of the j -th neuron in the hidden layer and the k -th neuron in the output layer. The transformation functions $f(x)$ are all unipolar Sigmoid functions, $f(x) = \frac{1}{1 + e^{-x}}$, $f(x)$ are continuously differentiable, and $f'(x) = f(x)[1 - f(x)]$.

When the network output is not equal to the expected output, there is an output error E , which is defined as the following formula (4):

$$\begin{aligned} E &= \frac{1}{2} \sum_{k=1}^l (d_k - o_k)^2 = \frac{1}{2} \sum_{k=1}^l \left[d_k - f\left(\sum_{j=0}^m w_{jk} y_j\right) \right]^2 \\ &= \frac{1}{2} \sum_{k=1}^l \left\{ d_k - f\left[\sum_{j=0}^m w_{jk} f\left(\sum_{i=1}^n v_{ij} x_i\right)\right] \right\}^2 \end{aligned} \quad (4)$$

It can be seen from equation (4) that the error is a function of the weights w_{jk} and v_{ij} of each layer, so the error can be reduced by adjusting the weights. The BP network adopts the gradient descent algorithm, as shown in the following formulas (5) and (6):

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}}, j = 1, 2, \dots, m; k = 1, 2, \dots, l \quad (5)$$

$$\Delta v_{ij} = -\eta \frac{\partial E}{\partial v_{ij}}, i = 1, 2, \dots, n; j = 1, 2, \dots, m \quad (6)$$

where η is a constant and $\eta \in (0, 1)$ is the scaling factor, the learning rate.

Taking E into equations (5) and (6), the weight adjustment formula of the BP learning algorithm of the 3-layer perceptron can be obtained as the following equations (7) and (8):

$$\Delta w_{jk} = \eta (d_k - o_k) o_k (1 - o_k) y_j \quad (7)$$

$$\Delta v_{ij} = \eta \left[\sum_{k=1}^l (d_k - o_k) o_k (1 - o_k) \right] y_j (1 - y_j) x_i \quad (8)$$

3.5 ROP prediction model

The ROP of deep wells is affected by many factors, mainly including geological factors and engineering factors, among them, geological factors include objective factors such as horizon, lithology and rock compressive strength, engineering factors include bit type, drilling parameters and drilling fluid density and other factors that can be intervened (Gao, 2021).

3.5.1 Design of input layer and output layer

For the target horizon, select rock compressive strength, drill bit size, drill bit type, drilling parameters (pump pressure,

rotational speed) and drilling fluid density as input layer neurons, the drilling parameters and drilling fluid density are read from the logging data, the size and type of the drill bit are based on the drill bit used in actual drilling and the rock compressive strength is calculated from the logging data. The initial value of the input layer of the traditional BP network is the standardised original data, while in the AHP-BP combined model, through the analytic hierarchy process, according to the influence of different factors on the drilling speed, different initial weights are assigned to each neuron and the normalised original data is used as the input layer to participate in the network training.

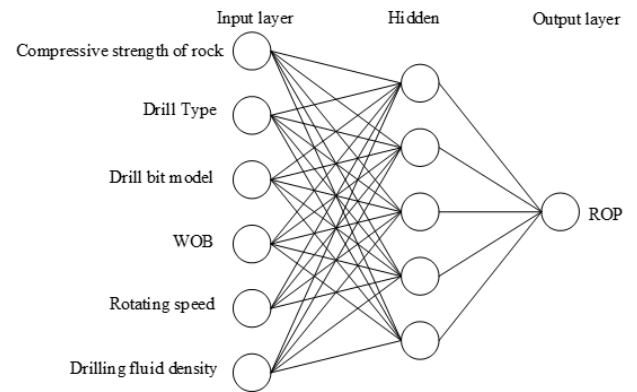
The output layer adopts a single neuron structure, and takes the actual penetration rate as the target value to iterate and optimise the weights of the feedforward neural network.

3.5.2 Hidden layer design

The 3-layer BP neural network can complete any mapping from n to m , so the author adopts a 3-layer network structure of 1 input layer, 1 output layer and 1 hidden layer to reduce the amount of calculation.

The number of neurons in the hidden layer in the neural network directly affects the convergence speed and calculation accuracy of the model, for each additional neuron, the calculation amount will increase proportionally and fewer neurons will lead to insufficient model convergence and reduced calculation accuracy. Since the initial input value of the input layer in the AHP-BP combined model has been weighted by the AHP algorithm, the iterative calculation amount of the model is reduced, and considering the previous analysis, the number of neurons in the hidden layer is selected to be 5 (Gong, 2021). Figure 2 shows the penetration rate prediction model based on neural network.

Figure 2 The penetration rate prediction model based on neural network



The Geological data about sub-surface formations and sensor data from gear, such as drill bits and mud pumps, are among the data gathered for model training from previous drilling operations. During the drilling process, this data is collected using a variety of monitoring devices, including logs and real-time measurements. The predictive model is then trained using the pre-processed data, which raises the accuracy of the ROP prediction.

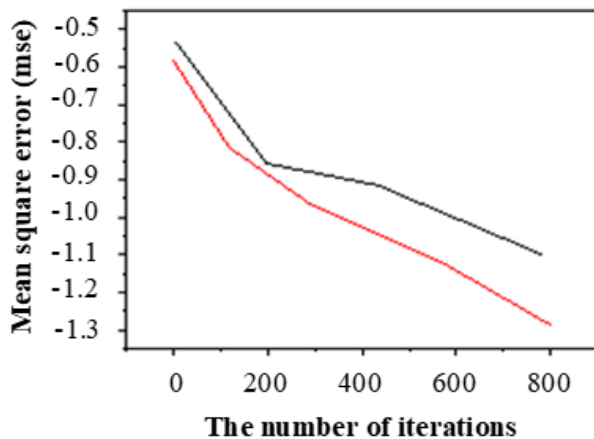
4 Analysis of results

Taking a deep well as an example, the average drilling depth of this block is 5274 m, the target layer is the Paleozoic Ordovician, the lithology is mainly limestone and the ROP is low from 5000 m to the drilling depth. When using the AHP-BP combined model to predict the ROP, the main factors affecting the ROP are used as neurons, including rock compressive strength, bit size, bit type (roller cone bit, PDC bit, TSP bit), pump pressure, rotational speed and drilling fluid density. There is a weight matrix for the neurons in the input layer, which is obtained by Analytic Hierarchy Process (AHP).

By collecting and arranging the data of offset wells, establishing a basic database, selecting typical samples and pre-processing the data, together with the weight matrix obtained by the AHP as the input layer, the ROP prediction model for this block is obtained through iterative training (He et al., 2020; Zakia et al., 2021).

The neural network training curves are shown in Figure 3. Through the comparative analysis, it can be seen that the convergence speed of the AHP-BP model is significantly improved compared with the traditional neural network model, and the problem that the minimum point cannot be converged can be avoided. Finally, the author used the data of the target well to simulate, and obtained the comparison curve between the actual ROP and the simulated ROP (see Figure 4). The red line stands for the proposed work, and the black line represents the existing work in Figures 3, 4 and 5.

Figure 3 Traditional neural network training curve (see online version for colours)



It can be seen from the figure that the predicted value of drilling speed is basically close to the actual value, the relative error is controlled within 10%, and the prediction effect is good. Through the comparison and analysis with the actual drilling data of the offset well, it is found that the ROP of this well is lower than the average value from the depth of 5080 m. By adjusting the input layer parameters and changing

the drill bit type, the ROP optimisation curve (see Figure 5) is obtained, combined with the analysis of the well history data, we can obtain: Sikai 5080–5206 m is the Ordovician limestone stratum, the PDC bit is used in the actual drilling, and the drilling time is long, mostly between 60 m and 70 m, the selection of the bit does not match the formation, resulting in too low ROP, if the roller cone bit is used, the ROP will be significantly improved. After 5206 m, the roller cone bit was used, and the ROP was increased to the normal range.

Figure 4 Comparison curve between predicted ROP and actual ROP by neural network (see online version for colours)

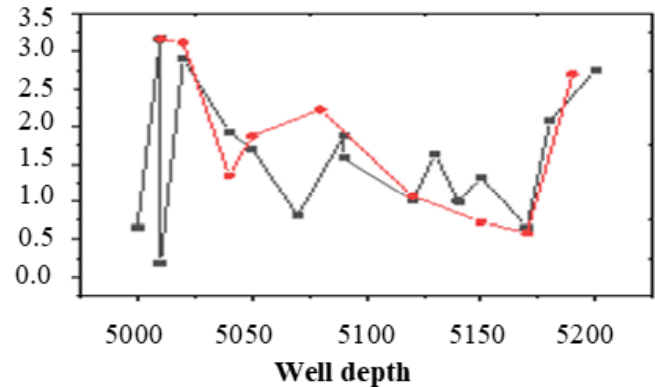
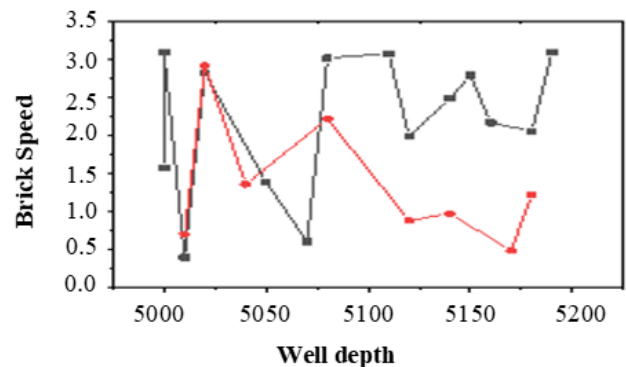


Figure 5 ROP optimisation curve based on neural network (see online version for colours)



5 Discussion

In this section, the performance of the proposed approach and the existing approach which are discussed in the literature section has been compared. Moreover, the existing models such as Network Teaching (NT) (Du and Zhao, 2021), Data Mining in Alarm Analysis (DM-AA) (Zheng et al., 2020), K-Nearest Neighbour – Dynamic Time Warping (KNN-DTW) (Zhou et al., 2021), Back-Propagation Neural Network (BPNN) (Chang et al., 2020), (Region-Convolutional Neural Network (R-CNN) (Jiang et al., 2021), Finite Control Set Model Predictive Control (FCS-MPC) (Wang et al., 2021) and Random Forest (RF) (Mosavi et al., 2022) are taken in consideration.

Table 1 The performance of the proposed approach and the existing approach

Methods	Sen	Spec	Acc	Pre	F-Measure	NPV	FPR	FNR	MCC
Proposed	0.975495	0.997804	0.987694	0.975726	0.974977	0.996246	0.018241	0.045493	0.95204
NT (Du and Zhao, 2021)	0.887807	0.968877	0.947518	0.891201	0.891131	0.970094	0.043621	0.126731	0.844722
DM-AA (Zheng et al., 2020)	0.887294	0.966339	0.947554	0.88815	0.888786	0.966251	0.043538	0.129141	0.841077
KNN-DTW (Zhou et al., 2021)	0.818424	0.949592	0.92351	0.818633	0.817541	0.949782	0.059423	0.177988	0.777131
BPNN (Chang et al., 2020)	0.766901	0.76717	0.76717	0.817541	0.818424	0.88815	0.47745	0.39120	0.82103
RCNN (Jiang et al., 2021)	0.767238	0.924057	0.882198	0.766901	0.764958	0.921433	0.08764	0.2613	0.664618
FCS-MPC (Wang et al., 2021)	0.88815	0.947554	0.947554	0.88815	0.968877	0.89153	0.693218	0.95120	0.91240
RF (Mosavi et al., 2022)	0.810067	0.812872	0.812872	0.92351	0.949592	0.882198	0.81309	0.65891	0.89214

6 Conclusion

The study concludes by showing that the suggested data mining method, which combines a Backpropagation (BP) neural network model with the Analytic Hierarchy Process (AHP), successfully improves the estimation of Rate of Penetration (ROP) in drilling operations. The method achieves faster convergence and dependable training results by using neural network training to create a predictive model and the AHP to prioritise ROP influencing factors. With an accuracy rate of 98% and simulation results that are 10% more accurate than conventional drilling techniques, this study is more sophisticated than previous research of its kind, showing that the AHP-BP combined model offers a reliable and accurate tool for ROP prediction in comparable drilling environments.

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