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Recognition and Classification for Inter-well Nonlinear Permeability Configuration in Low Permeability Reservoirs Utilizing Machine Learning Methods

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Machine learning methods have become the leading research algorithm enjoying popularity for reservoir engineering evaluation. In this paper, one machine learning method is selected and optimized for the recognition and classification of inter-well nonlinear permeability configurations between injection and production wells in the low permeability reservoir. The above configurations are divided into four classes, i.e., homogeneous, linear increment, convexity increasing (logarithmic function), and convex downward increasing (exponential function). According to four kinds of nonlinear permeability distributions in low permeability reservoirs and the increased effect of threshold pressure gradient, the productivity formula is established. Then the decision tree, neural networks (NN) and support vector machines (SVM) are utilized for training dynamic data under the influence of the training model, i.e., the configuration in low-permeability reservoirs. The data set is formed with dynamic production data under different configuration permeability, well spacing, thickness, pressure, and production. The recognition and classification of the permeability configuration are performed using different machine learning models. The results show that compared with NN and decision tree, SVM presents better performance in the accuracy of verification, true positive rate (TPR), false-negative rate (FNR) and receiver operating characteristic (ROC). Moreover, SVM verification results are placed on the brink of the training methods. This paper provides new insights and methods for the recognition and classification of inter-well nonlinear permeability configuration in low permeability reservoirs. Additionally, the research method can also apply to solve similar theoretical problems in other unconventional reservoirs.

Keywords: classification, permeability configuration, low permeability reservoirs, machine learning methods, recognition

1 INTRODUCTION

Reservoir heterogeneity has been the main research hotspot in the area of low permeability reservoirs. They are identified in numerous heterogeneity studies in terms of typical characteristics and effective exploitation (Feng, 1986; Hao et al., 2006; Hu, 2009; Wang et al., 2013; Dou et al., 2014). Low permeability reservoirs show obvious heterogeneity, narrow throat, and poor mobility, significantly distinct from medium and high permeability reservoirs. Its fluid law also shows inconformity compared to Darcy's law. Previous research results rely on core experiments to establish empirical formulas. Among them, the threshold pressure gradient is regarded as a constant to establish an empirical formula by the experimental regression method (Deng and Liu, 2003; Han et al., 2004; Li et al., 2004; Li et al., 2008; Zhu and Liu, 2010). Existing research explores the heterogeneity characteristics however, the impact of permeability configuration distribution and threshold pressure gradient on the productivity calculation in low permeability reservoirs is still unclear.

Machine learning has become a widespread method of intelligent recognition and classification (LiuSong and Zhu, 2011; Yu et al., 2012). Numerous reports detail the use of machine learning methods for productivity prediction, connectivity evaluation, and flow characteristics analysis (Wei et al., 2017; Wang et al., 2019; Song et al., 2020; Xu et al., 2020). Normally, there are three excellent algorithms for the classifications and recognition of machine learning, i.e., decision tree, neural networks (NN) and support vector machines (SVM), by which numerous works have been conducted. The decision tree learning algorithm is one process of recursively selecting optimal features and dividing training data according to features so that each sub-data set can be optimally classified. For the data with the inconsistent number of typical samples, the information gain is biased towards those features with more values, which are easy to overfit (Li, 2009; Ahmadi and Chen, 2019; Du et al., 2020; Liu, 2020; Liu and Liu, 2021). Neural network algorithm simulates the biological neural network and is a kind of pattern matching algorithm usually used to solve classification and regression problems. The Transect Network has multiple hidden layers and can deal with non-separable linear problems. However, it needs various parameters and has no applicable method for parameter selection, easily falling into local optimum (Kurt et al., 2008; Zhong et al., 2010; Raeesi et al., 2012; Mu et al., 2016; Han and Zheng, 2020). With nonlinear mapping as the basic theory, SVM uses the inner product kernel function to replace nonlinear mapping with higher dimensional space. The SVM learning problem can be determined by a convex optimization problem, so the global minimum of the objective function can be found using known efficient algorithms. However, other classification methods (such as the rule-based classifier and NN) adopt one greedy learning strategy to search hypothesis space, which can only obtain locally optimal solutions. This is the fundamental fact that allows far-reaching generalization of the support vector machine using the method of kernels (Al-Anazi and Gates, 2010; Gholami et al., 2012; Hatampour and Razmi, 2013; Rostami and Manshad, 2014; Anifowose et al., 2015; Chang and Liu, 2015; Swietlicka et al., 2017; Zhang and She, 2017; Serfidan et al., 2020; Zhou et al., 2021). The comparison and optimization of classification calculation are carried out from the consequences of the training set and test set. Moreover, it can also be extended to solve analogous theoretical problems in other unconventional reservoirs (Cortes and Vapnik, 1995; Anifowose et al., 2014; Nwachukwu et al., 2018; Yu et al., 2020). For example, classification of lithofacies, prediction of permeability and porosity, identification of water saturation

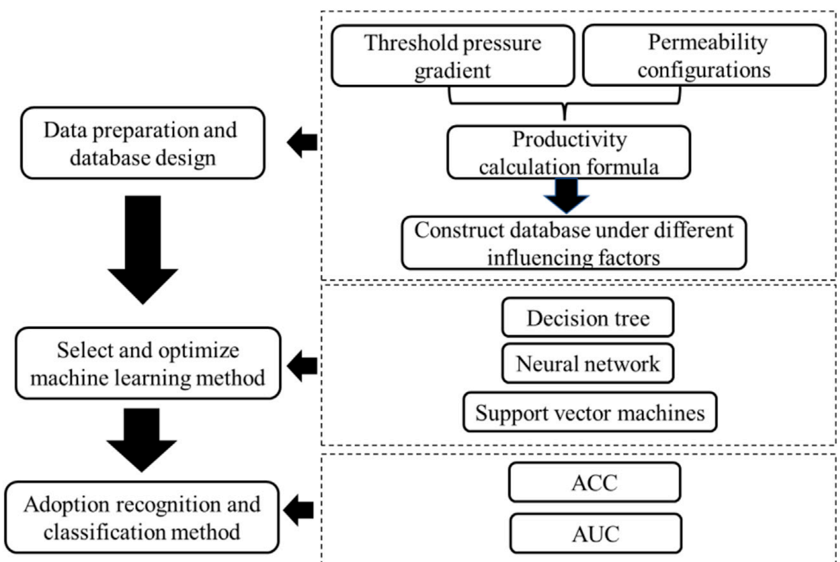

FIGURE 1 | The specific research steps.

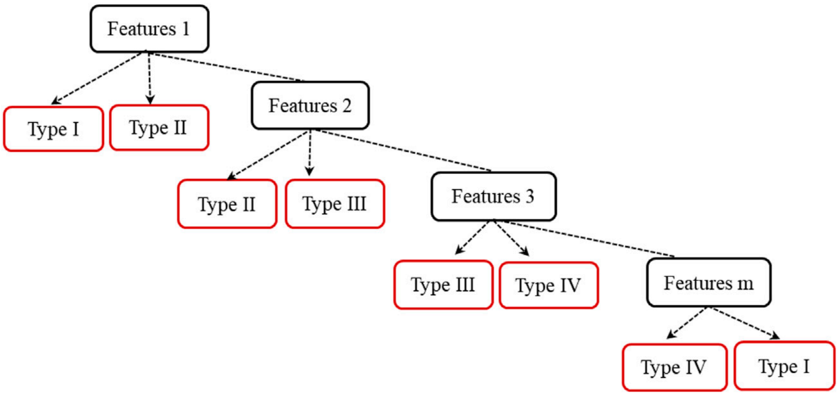

FIGURE 2 | The tree structure of the decision tree.

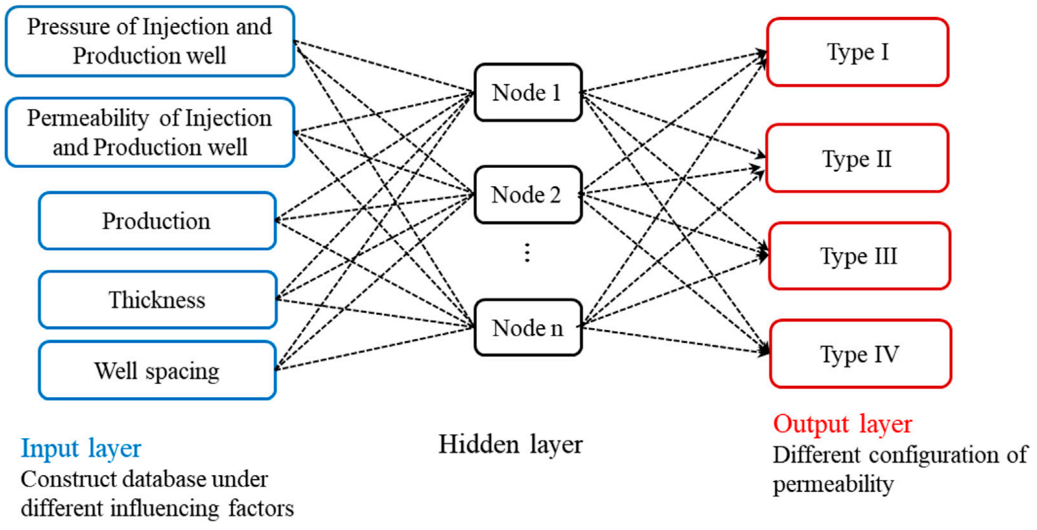

FIGURE 3 | The structure of the neural network.

using well logging data in reservoirs, and so on (Zhang et al., 2018; Wood, 2019; Zhang et al., 2020a; Tian et al., 2020; Sun et al., 2021; Zhang et al., 2021). The machine learning method is more and more being widely used in reservoir engineering (Gholami et al., 2014; Wang et al., 2014; Li et al., 2020; Silva et al., 2020).

Advantages are obvious when machine learning methods are used to recognize and classify heterogeneous permeability configurations in low permeability reservoirs. In contrast, it is challenging to judge inter-well permeability distribution by traditional methods. It has obvious theoretical significance to establish classification algorithm of dynamic basic data by machine learning method.

In this paper, a machine learning method is selected and optimized to classify inter-well nonlinear permeability configurations in low permeability reservoirs. The specific research steps are shown as follows in **Figure 1**.:

1) Four types of inter-well nonlinear permeability configurations are summarized between injection and production wells: homogeneous, linear increment, convexity increasing (logarithmic function) and convex downward increasing (exponential function); four nonlinear types as output classification data.
2) In accordance with four kinds of nonlinear permeability distributions in low permeability reservoirs and the increased effect of threshold pressure gradient, the productivity formula is established. Inter-well parameters included spacing, thickness, permeability, pressure, and production as input data.
3) Contrast to SVM, NN and decision trees are utilized to classify different permeability configurations.

The results of this paper will provide guiding significance and application prospects for oilfield development. In addition to

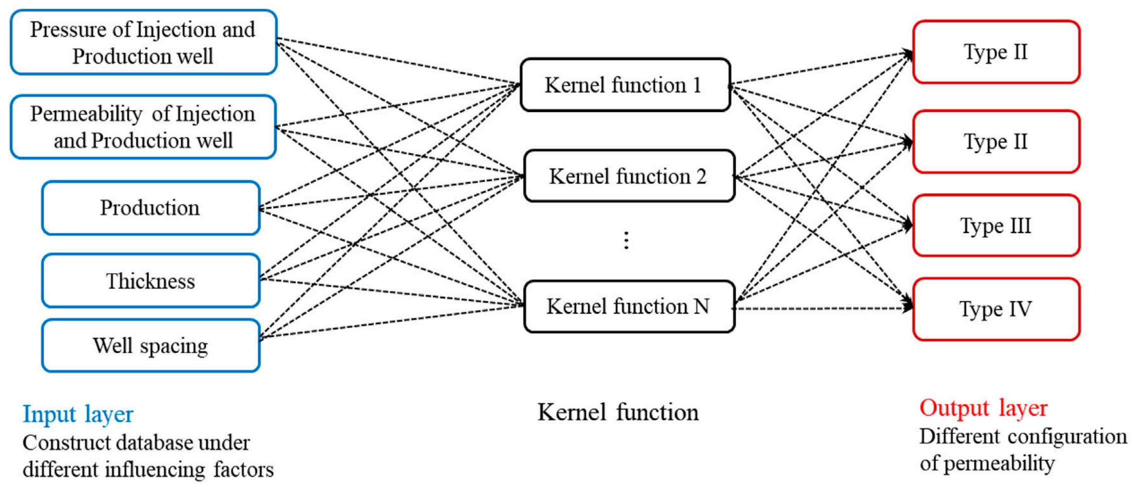

FIGURE 4 | The structure of support vector machines.

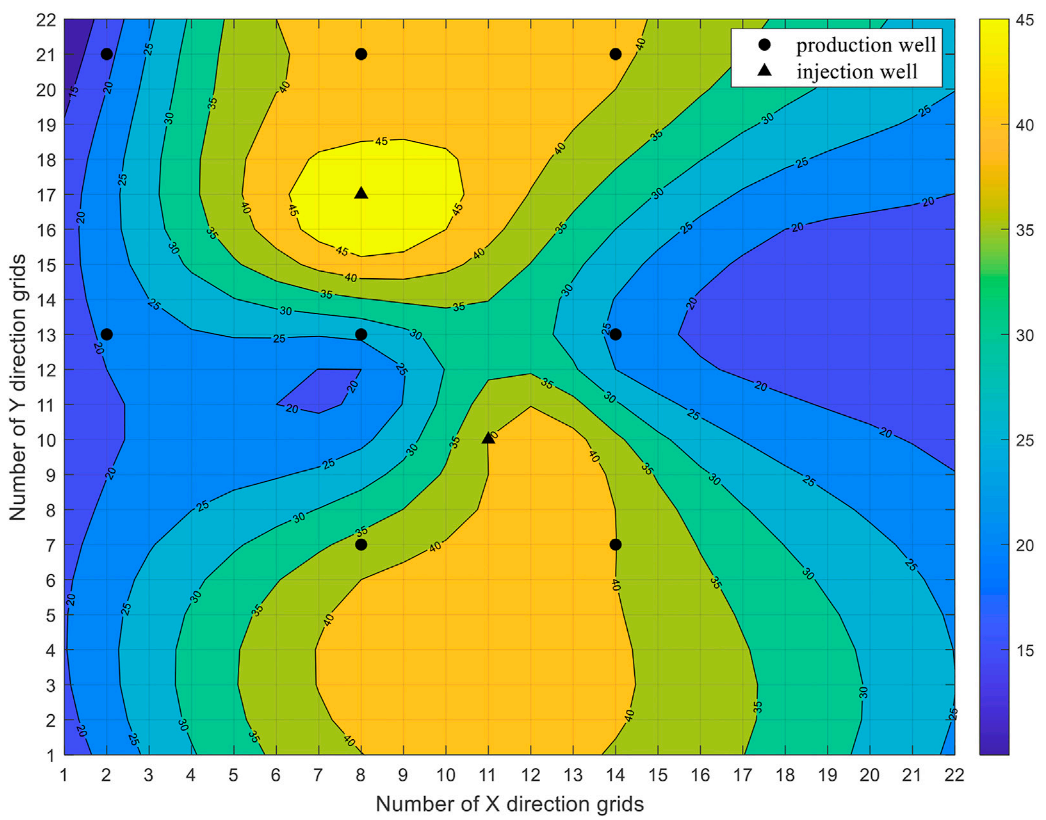

FIGURE 5 | Permeability distributing graph of reservoir numerical simulation.

classification and prediction, machine learning algorithm can also be used for numerical calculation of fluid mechanics equation in reservoirs (Zhang et al., 2020b). Machine learning algorithms plays an important role in geophysics and reservoir engineering (Sun and Zhang, 2020).

2 METHODOLOGY

2.1 Decision Trees

As a basic classification method based on features, a decision tree is frequently used with a tree structure. The learning

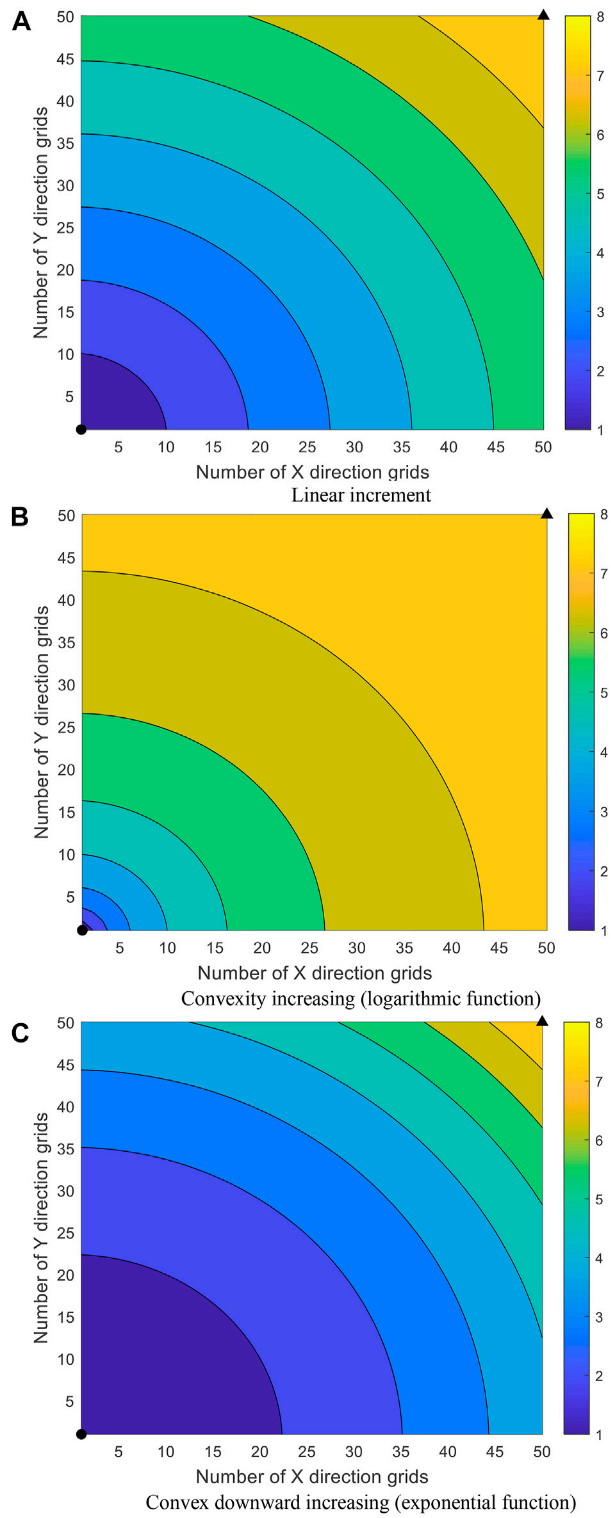

FIGURE 6 | Permeability three heterogeneous distributing graph. **(A)** Linear increment, **(B)** Convexity increasing (logarithmic function) and **(C)** Convex downward increasing (exponential function).

process usually includes three steps: feature selection, decision tree generation, and decision tree pruning, and the number of features is m, as shown in **Figure 2**. It can be viewed as sets of if-then rules or conditional probability distribution defined in feature space and class space. Its principal advantages are readability and high speed. In prediction, extra data are classified by the decision tree model, which is set up by minimizing the loss function using training data. Particularly in high-dimensional spaces, data can more easily be separated linearly and simplicity of classifiers, such as naive Bayes and linear SVMs. It could lead to better generalization than other classifiers. To solve over fitting training samples and low generalization ability, this paper chooses Bayesian as a pruning algorithm to improve the accuracy.

2.2 Neural Networks

The NN structure consists of an input layer, hidden layer, and output layer, as shown in **Figure 3**. The calculation process is mainly divided into forward and backward propagations. Forward propagation means to use the weights and thresholds in the NN to calculate the desired output variable based on the input data, while backward propagation is the process to update the weights and thresholds continuously according to the error of output variables to ensure a constant true output result. Common activation functions of NN are sigmoid, tanh and ReLU function. In NN training, increasing the number of hidden layers can reduce the error of the network and improve the accuracy, but it also increases complications and training time, or even the tendency of "over fitting". Therefore, this paper gives priority to the three-layer network through increasing the number of nodes as n and selecting the activation function to improve the accuracy.

2.3 Support Vector Machines

SVM is a binary classification model. Its rudimentary model is one linear classifier defined in feature space with the largest interval. SVM can be seen as a single hidden layer of the NN (multiple hidden layers). SVM uses a single hidden layer to perform fitting and is added kernel function, which can fit nonlinear problems (NN is fitted by a multi-layer activation function). The SVM typically uses a "kernel function" to project the sample points to high dimension space to ensure separability, as shown in **Figure 4**. Generic kernel functions include linear, polynomial, Gaussian, and sigmoid/logistic functions. In this paper, the choice of kernel function depends on the accuracy, the number of kernel functions as N. By replacing the proper objective functions, better selection of the kernel parameters can be achieved. The kernel functions are selected to optimize the parameters, and thus, are significantly a nonlinear classifier. The learning strategy of SVM is interval maximization which can be formalized as a process to solve convex quadratic programming.

TABLE 1 | Function form of different permeability configurations.

Type	configurations	Function form	correlation coefficient
I	homogeneous	$K(r) = K$	—
II	Linear increment	$K(r) = a + br$	a, b
III	convexity increasing (Logarithmic function)	$K(r) = a + b\ln r$	a, b
IV	convex downward increasing (Exponential function)	$K(r) = ae^{br}$	a, b

TABLE 2 | Basic data sets of different permeability configurations (part).

Class	constant data	Injection wells			Production wells		
	space	thickness	permeability	pressure	permeability	pressure	production
I	75	0.4	5.00	17.00	5.00	7.00	0.33
	150	0.8	15.00	22.00	15.00	7.00	2.63
	⋮			⋮	⋮	⋮	⋮
	200	1.6	30.00	17.00	30.00	7.00	6.71
II	75	0.4	10.00	17.00	1.00	7.00	0.11
	150	1.2	20.00	22.00	10.00	7.00	2.94
	⋮			⋮	⋮	⋮	⋮
	200	1.6	45.00	22.00	35.00	7.00	12.21
III	75	0.4	15.00	17.00	5.00	7.00	0.60
	150	0.8	30.00	17.00	20.00	7.00	2.88
	⋮			⋮	⋮	⋮	⋮
	200	1.6	40.00	17.00	30.00	7.00	7.78
VI	75	0.4	10.00	22.00	1.00	7.00	0.13
	150	0.8	25.00	17.00	15.00	7.00	1.88
	⋮			⋮	⋮	⋮	⋮
	200	2	45.00	17.00	35.00	7.00	10.15

2.4 Model Evaluation

The number of observations, true positive rate (TPR), false-negative rate (FNR), and false-positive rate (FPR) are utilized to verify the classification results. The formulas are as follows:

$$TPR = \frac{TP}{TP + FN} \tag{1}$$

$$FNR = \frac{FN}{TP + FN} \tag{2}$$

$$FPR = \frac{FP}{FP + TN} \tag{3}$$

where TP denotes true positive, TN means true negative, FP refers to false positives, and FN is false negative. ACC is used to describe and verify the accuracy of classification, as shown in **Eq. 4**.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \tag{4}$$

ROC (receiver operating characteristic) curve is utilized to show the TPR and FPR as a metric to evaluate classification quality. The ROC curve closer to the top left corner represents better accuracy. The AUC number is defined as the area enclosed by the ROC curve and coordinate axes. The closer it is to 1.0, the higher authenticity it will be.

3 PROCEDURE

3.1 Inter-well Nonlinear Permeability Configuration

For the permeability distribution graph of reservoir numerical simulation, the permeability heterogeneity configuration between injection-production wells has obvious heterogeneity characteristics, as shown in **Figure 5**.

In **Figure 6**, the heterogeneous configuration of permeability distribution between wells can be streamlined into the following three heterogeneous mathematical models. Therefore, there are four types of permeability distribution configurations between wells, with homogeneous as type I, linear increment as type II, convexity increasing (logarithmic function) as type III, and convex downward increasing (exponential function) as type

TABLE 3 | Comparison of different algorithm result.

Algorithm	ACC (%)	AUC
Decision tree	49.4	1.00
Neural network	88.5	1.00
Support Vector Machines	97.5	1.00

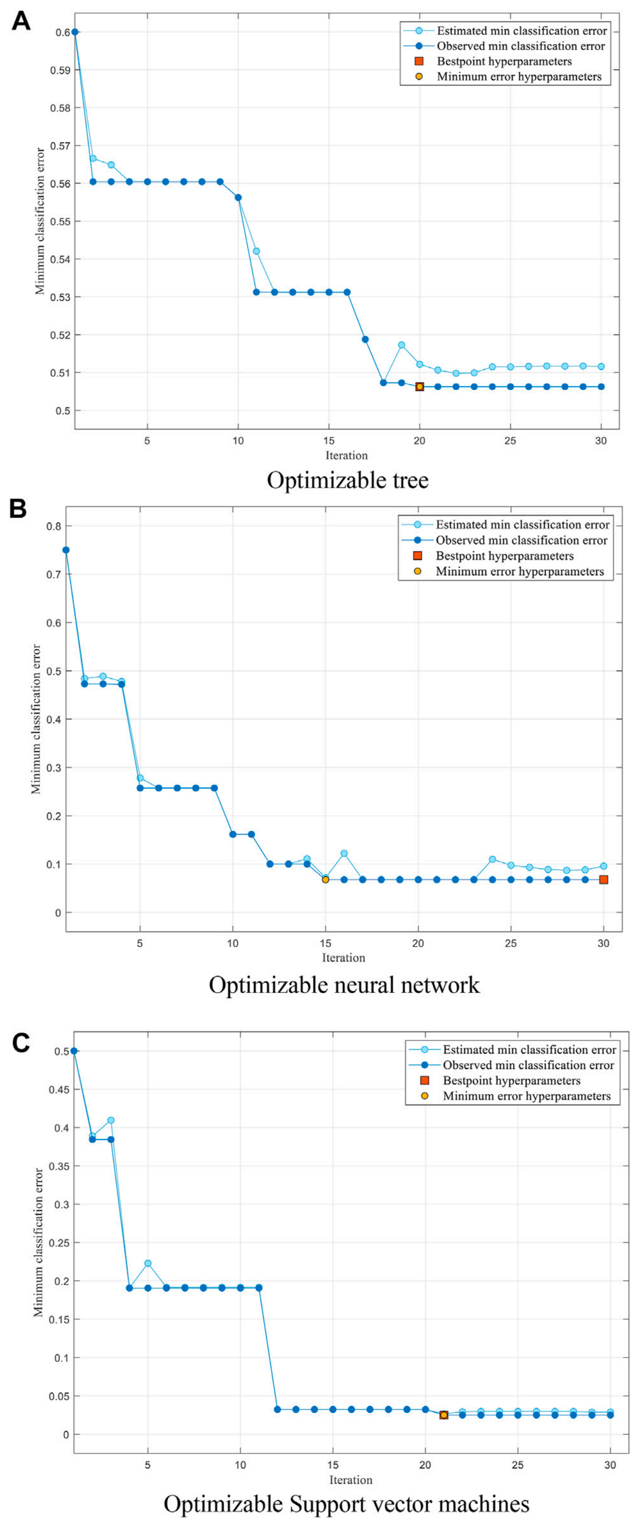

FIGURE 7 | Parameter optimization process graph. **(A)** Optimizable tree, **(B)** Optimizable neural network and **(C)** Optimizable Support vector machines.

IV. The four types have unique configurations and mathematical function forms, as shown in **Table 1**.

3.2 Single-phase Productivity Models

3.2.1 Threshold Pressure Gradient Calculation

The function form of threshold pressure gradient and permeability is obtained by the regression of experimental data in the low-permeability reservoir. The mathematical expression is as follows:

$$G = \lambda K^{n_d} \tag{5}$$

where G represents the threshold pressure gradient; λ and n_d represents the correlation coefficient.

3.2.2 Production Formula

Type I: homogeneous.

When permeability K is constant, it can be substituted into the threshold pressure gradient G. The productivity of the low-permeability reservoir can be obtained:

$$Q = K(r)\frac{2\pi rh}{\mu}\left(\frac{dp}{dr} - G(K(r), r)\right) \tag{6}$$

as

$$Q = \frac{2\pi h}{\mu}\frac{dp - G(K(r), r)dr}{\left({}^{1}/{K(r)r}\right)dr} \tag{7}$$

Where Q represents productivity, p denotes pressure, μ is viscosity, h is thickness.

$$Q = \frac{2\pi h}{\mu}\left(p\Big|_{p_w}^{p_e} - \int_{r_w}^{r_e} G(K(r), r)dr\right) \Big/ \int_{rw}^{r_e}\left({}^{1}/{K(r)r}\right)dr \tag{8}$$

Where p_e represents injection pressure, p_w denotes producing well pressure, r_e represents the wellbore radius, and r_w represents the well spacing.

Type II: linear increment.

Substituting into **Eq. 5**; **Eq. 8** can be obtained as follows.

$$Q = \frac{2\pi h}{\mu}\left(p\Big|_{p_w}^{p_e} - \frac{\lambda(a+br)^{1+n_d}}{b(1+n_d)}\Bigg|_{r_w}^{r_e}\right) \Bigg/ \frac{\ln\frac{r}{a+br}}{a}\Bigg|_{r_w}^{r_e} \tag{9}$$

Type III: logarithmic function.

Substituting $K(r) = a + b\ln r$ into **Eq. 5**; **Eq. 8** can be produced as follows.

$$Q = \frac{2\pi h}{\mu}\left(p\Big|_{p_w}^{p_e} - \lambda e^{-\frac{a}{b}}\left((-b)^{n_d}\cdot\Gamma\left(1+n_d, -\frac{a+b\ln r}{b}\right)\Bigg|_{r_w}^{r_e}\right)\right)$$
$$\Bigg/ \frac{\ln(a+b\ln r)}{\mathrm{b}}\Bigg|_{r_w}^{r_e} \tag{10}$$

Where Γ represents the Gamma function.

Type IV: Exponential function.

Substituting into **Eq. 4**; **Eq. 7** can be achieved as follows.

$$Q = \frac{2\pi h}{\mu}\left(p\Big|_{p_w}^{p_e} - \lambda\cdot\left(\frac{(ae^{br})^{n_d}}{bn_d}\Bigg|_{r_w}^{r_e}\right)\right) \Bigg/ \frac{(-\mathrm{Ei}(1, b\cdot r))}{a}\Bigg|_{r_w}^{r_e} \tag{11}$$

Where Ei represents exponential integral function.

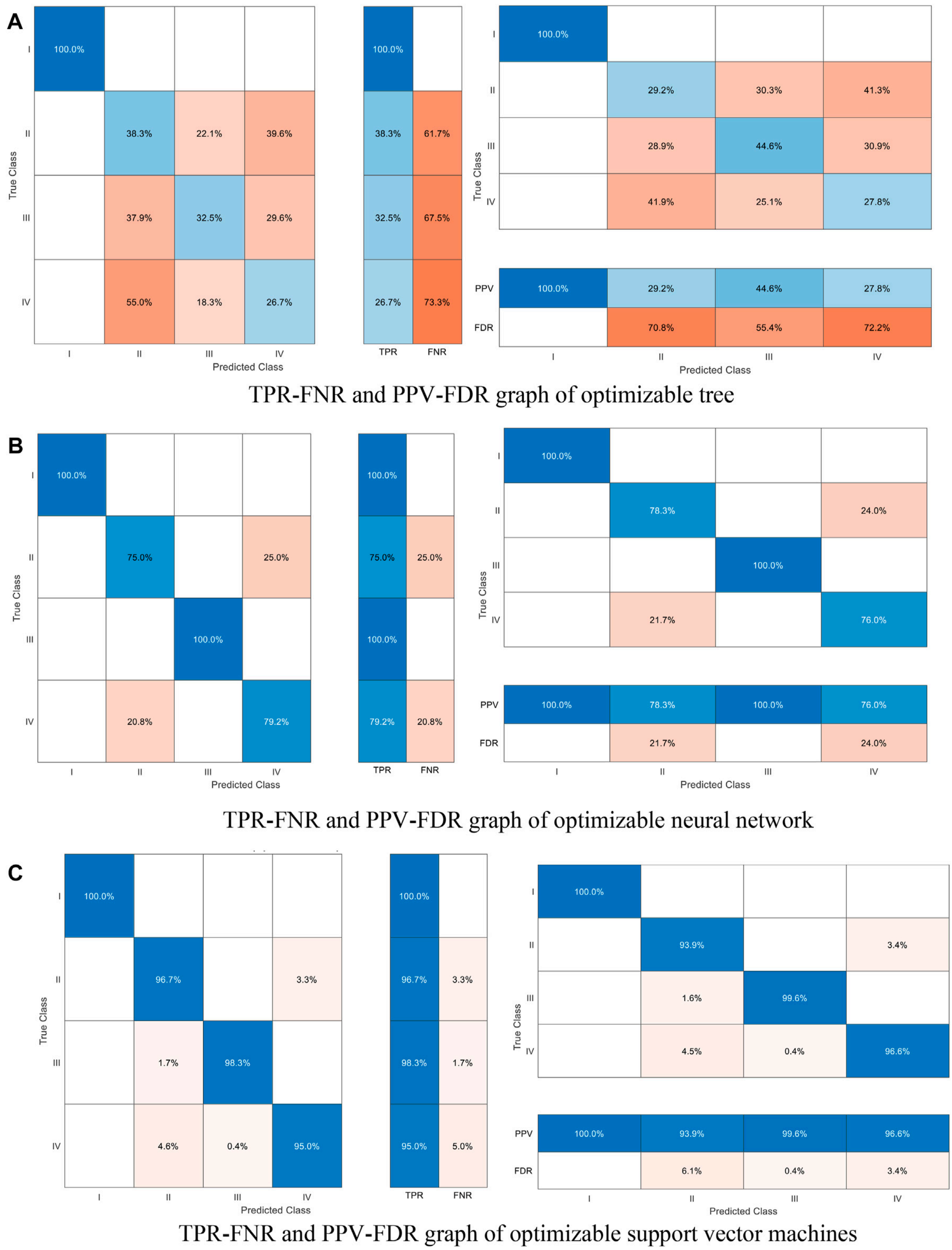

FIGURE 8 | TPR-FNR and PPV-FDR graphs of different algorithm results. **(A)** TPR-FNR and PPV-FDR graph of optimizable tree, **(B)** TPR-FNR and PPV-FDR graph of optimizable neural network and **(C)** TPR-FNR and PPV-FDR graph of optimizable support vector machines.

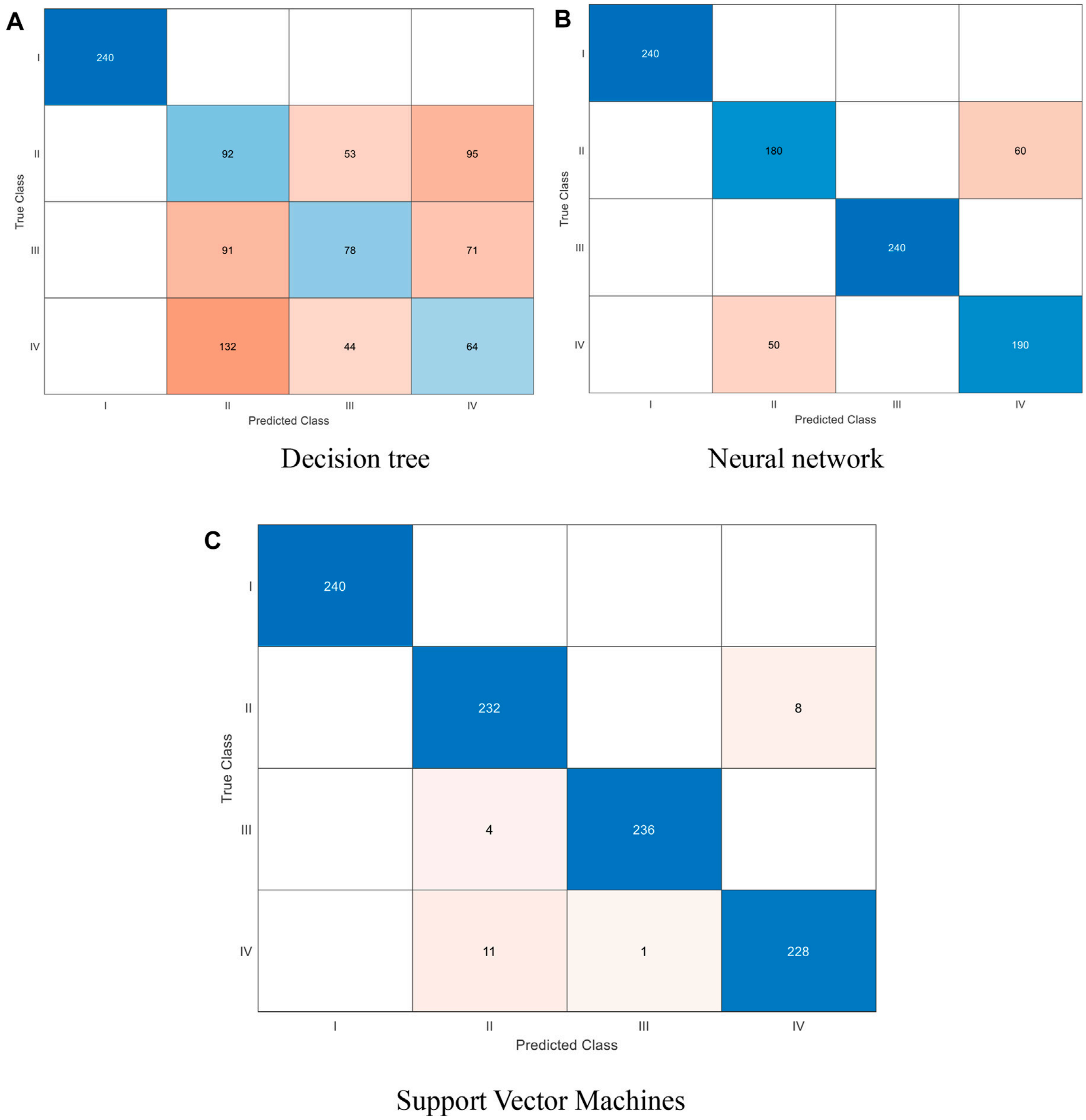

FIGURE 9 | True class and predicted class comparison diagram. **(A)** Decision tree, **(B)** Neural network and **(C)** Support Vector Machines.

In conclusion, based on altered permeability configurations and threshold pressure gradient function, the single-phase productivity calculation formula is established relevant to the low-permeability homogeneous reservoir, representing universal significance. Where, as $b = 0$ and $a = K$, it is the production formula in low-permeability homogeneous reservoir. As $\lambda = 0$, $b = 0$, and $a = K$, it is the production formula in homogeneous reservoir.

4 PROCEDURE

4.1 Dataset Collection

In this study, basic parameters of the low permeability reservoir are introduced. The porosity value is 0.25. Nonlinear permeability configuration is four classes. The permeability values of injection and production wells of the eight intervals are (1–10), (5–15), (10–20), (15–25), (20–30), (25–35), (30–40), and (35–45).

Homogeneous permeability is 5, 7.5, 15, 20, 25, 30, 35, and 40. The viscosity is 5.8. The wellbore radius of the production well is 0.1 m. The production differential pressure is 10 and 15 MPa. The well spacing is 7m, 150m, and 200 m. The reservoir thicknesses are 0.4m, 0.8m, 1.2m, 1.6m, and 2 m, respectively. Initial water saturation is 0.25. Irreducible water saturation is 0.78. Therefore, the basic data set includes 960 samples. The sets adopt 5-fold cross validation, as shown in **Table 2**.

4.2 Optimization of Algorithm Parameters

Figure 7 shows the parameter optimization process of different algorithms. The best point and minimum error hyperparameters of the decision tree exceed 0.5. The best point and minimum error hyperparameters of NN are close to 7×10^{-2}. The vest point and minimum error hyperparameters of SVM is 2.5×10^{-2}. Taken together, SVM presented the optimum performance algorithm.

4.2.1 Decision Tree

The optimal Bayesian classification is based on the decision tree algorithm. Iterations is 30.

4.2.2 Neural Network

Optimizable NN hyperparameters are as follows: there are three fully connected layers with the first, second, and third layer sizes being 22, 23, and 44, respectively; the activation function is Tanh; the regularization strength (Lambda) is Data and is standardized; the iteration limit is.

4.2.3 Support Vector Machines

Optimizable hyperparameters of SVM are as follows: the kernel function is cubic; the box constraint level is 6.79×10^2; the one-vs-one multiclass method is adopted;and standardized data are utilized.

5 RESULTS AND DISCUSSION

5.1 Model Calibration

As shown in **Figure 8**, TPR-FNR and PPV-FDR graphs of discrete algorithm results can be observed. As for Type I, three algorithms are all 100%. As for Type II, three algorithms are 38.3%, 75%, and 96.7%, respectively. As for Type III, three algorithms are 32.5%, 100%, and 98.3%, respectively. As for type IV, three algorithms are 26.7%, 79.2%, and 95.0%, respectively. From the overall evaluation, SVM shows the optimum performance algorithm.

5.2 Model Verification and Comparison

Table 3 and **Figure 9** shows the ACC and AUC of different algorithm results. The AUCs of the three algorithms are all 100%, showing that all classification algorithms are appropriate. The ACCs of the three algorithms are 49.4%, 88.5%, and 97.5%, respectively. This explains why SVM has the highest recognition accuracy of 97.5%.

6 CONCLUSION

This paper selects and determines one machine learning method to recognize and classify the nonlinear permeability configuration between injection and production wells in the low-permeability reservoir. The following conclusions can be obtained:

1) This paper abstracts and simplifies four classes of inter-well nonlinear permeability configurations between injection and production wells, i.e., homogeneous, linear increment, convexity increasing (logarithmic function), and convex downward increasing (exponential function).
2) In accordance with the four kinds of nonlinear permeability distributions in low permeability reservoirs and the increased effect of threshold pressure gradient, the productivity formula is established.

3) SVM, NN, and decision tree are used to train the dynamic data with the influence of nonlinear permeability configuration in low permeability reservoirs as the training model. The data set is trained with dynamic production data under different configuration permeability, well spacing, thickness, pressure, and production. The results show that compared with NN and Tree, SVM represents the optimum performance in the accuracy of verification, TPR, FNR and ROC. The TPR is 100%, 96.7%, 98.3%, and 95.0%. ROC is 1.0. The accuracy is 97.5%.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

JL contributed to conception and design of the study. XL organized the database. JL performed the statistical analysis. XL wrote the first draft of the manuscript. JL wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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