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Deep Learning-based Research on Intelligent Analysis of Oil and Gas Pipeline Safety Events and Optimization of Emergency Response

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Abstract This paper proposes a deep learning-based multimodal signal fusion and optimization algorithm model to solve the problem of intelligent analysis and emergency response of oil and gas pipeline safety events. The wavelet transform is used to extract the time-frequency domain features of the vibration signal, and the artificial bee colony algorithm is designed to optimize the classification parameters of the support vector machine. The SVD algorithm is selected to reduce the dimensionality to reduce the redundant features and optimize the computational efficiency. In the design of emergency response strategy, a closed-loop management mechanism including leakage detection, graded response and effect evaluation is constructed. The experimental results show that the F1 value of the SVM-ABC-WT-SVD model reaches 0.994 and mAP@0.5 reaches 99.8% in the ablation test, which is 3.6% and 2.9% higher than that of the SVM model, respectively. On-site stress test verified that the average response latency of the system in high concurrency scenarios is less than 3ms, which meets the real-time emergency response requirements.

Index Terms oil and gas pipeline safety, deep learning, artificial bee colony algorithm, support vector machine, emergency response

I. Introduction

Adequate and safe supply of energy is a prerequisite for rapid economic and social development, and oil and natural gas play an important role in the big family of energy. At present, the main way of oil and gas transportation is pipeline transportation, which was widely used in the early days due to its advantages of low cost, controllable pollution, low environmental requirements and good safety [1]-[3]. With the development of the times, a series of problems have begun to appear: on the one hand, the pipeline network is gradually complex, expanding, and increasingly difficult to maintain. On the other hand, more and more frequent construction and other activities also pose a great threat to the safety of oil and gas pipelines, resulting in frequent pipeline safety incidents and a sharp increase in maintenance costs [4]-[6]. As a major energy source in various industries, the safety of oil and gas is of great importance. Therefore, ensuring the safety of oil and gas pipelines has become an important need in the energy sector. Safety during oil and gas transportation, especially real-time online detection and identification of activities that are or will be damaging oil and gas pipelines, is a key consideration for safety production [7]. When monitoring the safety of oil and gas pipelines, destructive activities such as manual excavation and mechanical excavation are the objects that need to be emphasized, because such activities are very likely to cause pipeline breakage and oil and gas leakage [8], [9]. Once such a safety accident occurs, it will not only affect the production and life of the neighboring areas and cause huge national economic losses, but also may trigger a series of secondary disasters, such as water or air pollution, fire, or even explosion, which seriously threaten the lives and properties of the people concerned [10], [11]. The consequences of such accidents far exceed the expected maintenance costs, and there is an urgent need to find ways to avoid them.

In the traditional oil and gas pipeline safety monitoring, there are actually some obvious shortcomings, the combination of monitoring technology and manual labor, mainly the degree of manual dependence is still too high, the efficiency and correctness of the experience-driven safety monitoring and management are challenged, especially in the identification of errors and emergency warnings, the efficiency of the coordination of the relevant departments is greatly reduced, and the lag of the emergency response, which results in greater economic losses [12]-[15]. In order to reduce or even eliminate the catastrophic impacts of oil and gas pipeline damages, it is imperative to carry out digital and intelligent transformation to optimize the analysis and emergency response of their safety incidents [16].

In this paper, the normalized energy and signal duration of each frequency band are extracted based on wavelet transform, and the penalty factor and kernel function parameters of the support vector machine are optimized using artificial bee colony algorithm. The optimized support vector machine classification features are used, and the SVD algorithm is selected for feature dimensionality reduction. Integrate multi-source sensing technology and hierarchical response strategy to design a full-process management program covering leakage detection, emergency decision-making and effect evaluation. Collect data from six types of typical events and examine the reasonableness of model optimization design through ablation experiments. Evaluate the feasibility of the proposed emergency response mechanism through the field experimental system empirical test.

II. Intelligent analysis model and emergency response strategy design for oil and gas pipeline safety incidents

As the core infrastructure of national energy transportation, oil and gas pipeline safety is directly related to national economic lifelines and ecological safety. In recent years, pipeline safety incidents caused by human damage, geological disasters and aging equipment are frequent, and traditional monitoring means rely on manual inspection and single sensor technology, which has the defects of response lag, high leakage rate, and insufficient precision of event classification. With the development of deep learning and artificial intelligence technology, it is possible to build an intelligent pipeline safety event analysis and emergency response system. In this regard, this paper proposes a pipeline security threat event identification method based on optimized support vector machine.

II. A. Signal pattern recognition based on optimized support vector machine

II. A. 1) Wavelet transform based feature extraction

In pattern recognition, first of all, we need to carry out feature extraction, time-frequency analysis of vibration signals collected from various types of events, and select the relevant features that can characterize each type of event to form feature vectors. Wavelet transform is suitable for time-frequency analysis of non-stationary signals, and can accurately respond to the time-frequency characteristics of the signal, in this paper, we use the “wavelet-energy” mode to extract the features of the vibration signal. First of all, i layer wavelet decomposition of the signal is carried out to obtain $1+i$ groups of wavelet coefficients in each frequency band, and the energy of wavelet coefficients in each frequency band is calculated by the formula (1):

$$E\left[f_i(t)\right]=\frac{1}{N-1}\sum_{t=1}^{N}\left[f_i(t)\right]^2 \tag{1}$$

where $f_i(t)$ is the wavelet coefficient of the i th set of N points obtained by wavelet transform.

The wavelet coefficient energy is normalized and the normalization formula is:

$$E(k)=\frac{E\left[f_k(t)\right]}{\sum_{i=1}^{9}E\left[f_i(t)\right]} \tag{2}$$

The normalized wavelet coefficient energy is used as a frequency domain feature of the signal.

In addition, the time required for manual and mechanical excavation and vehicle passing is different, which can be used as an auxiliary feature by calculating the signal duration above a set threshold. Combining the signal duration and frequency domain energy features form the final feature vector.

II. A. 2) Principles of Artificial Bee Colony Algorithm

After feature extraction, the feature vectors are classified by a support vector machine optimized based on the artificial bee colony algorithm. The optimization process of the ABC algorithm simulates the cyclic process of honey bees of different species cooperating to find a honey source in nature. In the algorithm, a scout bee randomly selects a honey source within a specified range, and when it finds the honey source, the scout bee transforms into a nectar collecting bee, which brings back the location of the honey source and nectar amount information to the hive, and shares the information with the observer bees through a dance. Observer bees compare the information brought back by the honey picking bees with the previous nectar source information stored in the memory for preferential selection, and on the basis of the selection, conduct a secondary search of the neighborhood of the preferred nectar source to find out whether there is a nectar source with a larger nectar amount. If the nectar source information brought back by the honey-picking bee is found to be inferior to the nectar source known by the observation bee, then the honey-picking bee turns into a scout bee to search for a new random nectar source.

The ABC algorithm has the same number of honey-picking bees and observation bees, and each nectar source corresponds to a possible solution x_i of the optimization problem, and its nectar amount corresponds to the fitness function F_i of the solution. For each new solution found by the honey harvesting bees, they calculate the fitness of the new solution and bring it back to the hive to share it with the observation bees. Observer bees compare the fitness of the new solution with the fitness of the known solutions in memory, select the solution with higher fitness to replace the memorized one according to the probability associated with the fitness, and discard the solution with lower fitness, thus achieving solution optimization through this process. Through the sharing of information brought back by all the honey harvesting bees, the observation bee searches the neighborhood of the solution on the basis of the preferred solution to see if it has a better solution.

II. A. 3) Support vector machine optimized based on artificial bee colony algorithm

The support vector machine is optimized using the artificial bee colony algorithm, mainly for its penalty factor C and width parameter σ, and the relevant parameters in the algorithm are set as follows:

(1) According to the principle of the artificial bee colony algorithm, initialize its parameters, which mainly include the number of observation bees and the number of nectar sources S_N, the number of termination cycles N_{mc}, and the maximum number of nectar source cycles N.

(2) Setting the fitness function so that the artificial bee colony algorithm has a convergence criterion.The procedure of ABC algorithm converges to the global minimum.Considering that the main purpose of the optimization of the support vector machine is to obtain a high correct rate of pipeline threat event recognition, the fitness function adopted is:

$$V_{obj} = 1 - V_{acc} \tag{3}$$

where V_{acc} is the classification correctness of the support vector machine.

(3) Initialize the search range for the parameters of the support vector machine model to be searched. The variation of the penalty factor C and the width parameter σ will have a great impact on the classification performance of SVM, and determining the search range will help to get better classification results.

When the optimal parameters are obtained through the ABC algorithm, the optimized support vector machine can be used for pattern classification of vibration signals to achieve the identification of pipeline security threat events.

II. A. 4) Fiber optic sensing signal feature downscaling

In practice, if all the features are used to train the model every time, it may bring many problems, such as failing to meet the real-time requirements, and even the redundant features will affect the recognition results. In addition, the huge data volume of distributed fiber optic sensing system brings huge computing pressure, at this time, feature dimensionality reduction becomes more and more important, a good feature dimensionality reduction method can improve the performance of the algorithm model in all aspects.

Feature dimensionality reduction methods can be summarized into two types: one is the operation that does not change the original feature data, i.e., feature selection; the other is that it will change the original features, i.e., feature extraction, which is also broadly defined as feature dimensionality reduction.

There are numerous feature selection algorithms, which can be roughly categorized into three types: filtered, wrapped and embedded. As the name suggests, Filter filters out the desired features and is an application of the greedy method. Generally speaking, the method needs to score all the features, and this scoring is generally based on metrics such as relevance, distance, mutual information, maximum information coefficient, and so on. The Wrapper method takes a different approach, which first identifies algorithms that can score features, then uses search strategies (e.g., forward and backward search) to select a subset of features for input to the algorithm, and then selects the set of features based on the effect of the algorithm. In order to save overhead, the scoring algorithms are generally chosen to be generally effective and simple, such as Random Forest (RF), Support Vector Machine (SVM), Nearest Neighbor (KNN), and so on. The last Embedded method is characterized by adding a regular term to some loss function, using the idea of regularization to reduce the weight of some feature attributes or make them zero. Common regularizations are Lasso for L1 and Ridge for L2, where the L1 operator has the obvious function of feature selection.

And feature extraction is generally a feature space transformation (mapping) method, which transforms the original features with high dimensions into new features with lower dimensions. There are mainly three kinds of Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Singular Value Decomposition (SVD), as detailed below:

As the name suggests, Principal Component Analysis PCA is to identify the most dominant components in the data and replace the original data with key data. Assuming that the original sample matrix $X_{mn} = \{X_1, X_2 \cdots X_m\}$, where X_i is the row matrix, $X_i = \{X_i^1, X_i^2 \cdots X_i^n\}$, indicating that there are m samples, each with n features. Firstly, all samples X_i are decentered according to equation (4).

$$X_i = X_i - \frac{1}{m}\sum_{j=1}^{m} X_j \tag{4}$$

Based on the decentralized samples, the covariance matrix XX^T of the sample matrix is calculated, and the eigenvalue decomposition of XX^T is performed to obtain all the eigenvalues and eigenvectors. According to the determined size n' of the dimensionality after dimensionality reduction, the n' eigenvectors with the largest corresponding eigenvalues are selected, which are normalized to form the eigenvector matrix $W = \{w_1, w_2 \cdots w_{n'}\}$. Finally, each sample X_i is transformed into a new sample Z_i according to equation (5).

$$Z_i = W^T X_i \tag{5}$$

The main difference between LDA and PCA is that LDA needs to use the category information of the samples and is a supervised dimensionality reduction method. Let the original sample matrix $X_{mn} = \{X_1, X_1 \cdots X_m\}$ have the category information $y_i \in \{C_1, C_2 \cdots C_k\}$, and the set of samples belonging to the k th class is X^k. First, the intra-class divergence matrix S_w and the inter-class divergence matrix S_b are computed, taking the binary classification $\left(y_i \in \{C_1, C_2\}\right)$ as an example:

$$S_w = \sum_{x \in X^1} (x-\mu_1)(x-\mu_1)^T + \sum_{x \in X^2} (x-\mu_2)(x-\mu_2)^T \tag{6}$$

$$S_b = (\mu_1 - \mu_2)(\mu_1 - \mu_2)^T \tag{7}$$

In Eq. (6) and Eq. (7) μ_i is the mean vector of the i th class of samples. Then the matrix $S_w^{-1}S_b$ is calculated and its eigenvalues and eigenvectors are found, and the later steps are consistent with PCA.

The SVD algorithm is widely used and can be seen in many machine learning algorithms. It can be used not only for feature dimensionality reduction, but also for image compression, recommender systems, text analysis and other fields. Define the SVD of the dataset X as:

$$X = U\Sigma V^T \tag{8}$$

Where U and V are square matrices of size $m \times m$ and $n \times n$, respectively, and Σ is a matrix of size $m \times n$ with only the main diagonal values non-zero, and the non-zero elements are called singular values. The common point of U and V is that they both satisfy $UU^T = I$ and $VV^T = I$, and they are both Missy-positive matrices. Find the eigenvalues of XX^T and $X^T X$ and the left and right singular vectors respectively, and form the resulting singular vectors into matrices to obtain the matrices U and V. Notice:

$$XV = U\Sigma V^T V = U\Sigma \tag{9}$$

According to equation (9), the singular value matrix Σ can be obtained. The singular values are very similar to the eigenvalues in principal component analysis, and sorting them from largest to smallest reveals that the sum of the first k singular values already accounts for the vast majority of the total sum. Meanwhile, the computation shows that the original matrix can be approximated by the singular vectors corresponding to this fraction of singular values, i.e., it satisfies Eq. (10), and this property plays an important role in the noise reduction scenario.

$$X_{mn} = U_{mm}\Sigma_{mn}V_{nn}^T \approx U_{mk}\Sigma_{kk}V_{kn}^T \tag{10}$$

As mentioned above, there are various methods to accomplish feature dimensionality reduction. In the field of fiber optic sensing, there have been researchers trying to use Filter, Wrapper, PCA and other methods to carry out some simple feature screening on the sensing signal features, and in this paper, we take SVD algorithm to carry out feature dimensionality reduction processing.

II. B. Emergency Management Strategies for Oil and Gas Pipelines

II. B. 1) Leak detection technology

Leak detection technology in emergency management strategy is a key link in oilfield pipeline safety prevention, which can detect and locate leakage events in time and reduce potential environmental and economic losses. In practical application, leak detection technologies are used, including pressure wave detection technology, acoustic wave detection technology, infrared detection technology and so on. Pressure wave detection technology identifies leaks by monitoring pressure changes in the pipeline. When a leak occurs in the pipeline, the pressure wave will propagate along the pipeline, and by analyzing the propagation time and speed of the pressure wave, the leak can be accurately located. Acoustic wave detection technology is based on the principle that leaks will produce a specific frequency sound waves, through the acoustic wave sensors deployed along the pipeline to capture these waves, analyze the frequency and intensity to determine the existence of the leak location. The advantage of this technology is that it is also highly sensitive to small leaks and can detect leaks as small as a few tens of liters per hour. Infrared detection technology utilizes the infrared absorption properties of leaking hydrocarbon gases to identify clouds of hydrocarbon gases generated by leaks through infrared scanning in the air or on the ground. This technology can quickly cover a large area, is suitable for detecting leaks on or near the surface, and shows better application results in complex terrain or areas that are difficult to access. The comprehensive application of leakage detection technology can build a multi-level, high-efficiency pipeline leakage monitoring system to realize early detection, rapid response and accurate positioning of oilfield pipeline leakage.

II. B. 2) Emergency response plan design

Emergency response plan design is the key to facing oilfield pipeline leakage incidents, aiming to ensure that once a leak occurs, measures can be taken in a rapid and orderly manner to minimize losses. In practice, the emergency response plan includes five core aspects: leak detection, immediate response, leak control, environmental remediation, and post-evaluation. First, an effective leak detection and alarm system is established to ensure that in the event of a leak, relevant personnel can be alerted in the shortest possible time. For example, by installing leak detection sensors and networking with a central control room, 24-hour real-time monitoring is realized. Once a leak is detected, the emergency response team needs to immediately activate the pre-set contingency plan, quickly assess the leakage situation, including the location of the leakage point, the type of leaking substance and the estimated amount of leakage, etc., and immediately notify all relevant personnel and departments. Effective measures are taken to control the leak, such as closing the appropriate valves to isolate the source of the leak, using emergency repair materials to seal the leak, or starting a backup pipeline to minimize the damage. Finally, an after-action evaluation is conducted to analyze the cause of the leak, assess the effectiveness of the emergency response, adjust and optimize the emergency response plan based on the evaluation results, and improve the ability to respond to similar events in the future. For example, for one spill, the emergency response team was able to arrive at the scene within 30min, basically control the spill within 1h, and complete the preliminary environmental impact assessment and emergency repair work within 24h.

III. Empirical research on intelligent analysis of oil and gas pipeline safety events and the effectiveness of emergency response

III. A. Experimental dataset and performance metrics

III. A. 1) Experimental data sources and dataset division

Data were collected at different locations along the fiber optic cable for six types of typical events: power drill drilling, sawing and grinding of pipes, hammering of pipes, walking of people, excavation, and leakage of pipes. They were labeled as type 0, type 1, type 2, type 3, type 4, and type 5 to form a database.

(1) Drilling with electric drill: Drill holes in steel pipes with electric drill to simulate drilling for oil theft and collect data.

(2) Saw milling pipes: Saw milling with a hacksaw in steel pipes to simulate saw milling stress damage and collect number dramas.

(3) Knocking on the pipeline: The experimenter continuously knocks on the pipeline with an iron bar of 4cm in diameter at a constant frequency to simulate knocking stress damage.

(4) Walking: The experimenter walks back and forth along the pipeline at normal speed.

(5) Manual excavation: the experimenter used shovels to excavate on both sides of the pipeline to simulate the normal excavation scenario.

(6) Pipeline leakage: start the motor to continuously pressurize and inflate the pipeline, and collect data when the pressure is greater than 0.4MPa.

Sample data at a rate of 2000 data points per second according to the preset parameters of the device. For each type of perturbation to collect ten times data, each continuous sampling time is 10min, after the subsequent differential averaging and data cut-off and other preprocessing operations, a total of 9600 data matrix type data samples were generated. In order to ensure the accuracy of the experimental results, the training set and validation set are partitioned in the ratio of 7:3, and there is no direct intersection between the two datasets. The number of event data for each type is shown in Table 1.

Table 1: Division of the training set and validation set for six types of event datasets

Event type	Training set	Verification set	Label
Electric drill drilling	1120	480	0
Sawing and grinding pipes	1120	480	1
Strike the pipe	1120	480	2
People walking	1120	480	3
Excavation	1120	480	4
Pipeline leakage	1120	480	5
Total	6720	2880	-

III. A. 2) Performance indicators

The precision, recall, F1 value and average accuracy mean were used as evaluation indexes to evaluate the performance of the detection model. Precision indicates the accuracy of each model in different detection methods, that is, the proportion of samples that are predicted to be positive in the actual positive sample. The recall rate indicates the recall rate of each model detected in different detection methods, that is, the predicted result is the proportion of the actual number of positive samples in the positive sample to the positive sample in the whole sample. The F1 value is the harmonic average of precision and recall, with a maximum value of 1 and a minimum value of 0. The mean average accuracy (mAP) is the area enclosed by plotting the precision and recall as two axes, mAP@0.5 represents the average accuracy of each model in different detection methods when the intersection union ratio is 0.5, and mAP@0.5:0.95 represents the average accuracy of different intersection union ratios (from 0.5 to 0.95 with a step size of 0.05). Precision, recall, F1 value, and mean average accuracy are defined as follows. True positive (TP) refers to the amount of target data in the model's detection results that match the actual class. False positives (FPs) refer to the number of target data in the model's detection results that are inconsistent with the actual category, that is, the number of false positives. False negatives (FN) refer to the number of target data that is actually positive but detected by the model as a different class, i.e., the number of missed detections. Precision and recall represent the model's confidence in object detection and the model's ability to detect all targets, respectively. The F1 value is a synthesis of the two, which represents the harmonic average of the accuracy and recall of each model in the above method, and can comprehensively evaluate the performance of the model, and the higher the F1 value, the more robust the model. The mean average precision represents the comprehensive performance of the model under different confidence levels by the area under the curve (AUC) on the PR curve of a given target class, and the higher the mean average accuracy, the better the detection performance of the model. Therefore, the greater the accuracy, recall, F1 value, and average accuracy mean, the better.

$$\mathrm{Pr}\,ecision = \frac{TP}{TP+FP} \tag{11}$$

$$\mathrm{Re}\,call = \frac{TP}{TP+FN} \tag{12}$$

$$F_1 = 2\times\frac{\mathrm{Pr}\,ecision\times\mathrm{Re}\,call}{\mathrm{Pr}\,ecision+\mathrm{Re}\,call} \tag{13}$$

$$AP[class] = \sum_{i\in confidence} precision,[recall,class,iou] \tag{14}$$

$$mAP = \frac{1}{N}\sum AP_i \tag{15}$$

III. B. Analysis of ablation experiments

Ablation experiments are used to assess the impact of the improved method in this paper on the accuracy of the original model in recognizing events. The models are mainly classified into the following types: SVM (original model), SVM-WT (adding wavelet transform time-frequency analysis), SVM-ABC (ABC improvement), SVM-SVD (adding SVD feature downscaling), SVM-WT-ABC (ABC improvement and adding wavelet transform time-frequency analysis), SVM-SVD-ABC (ABC improvement and adding SVD feature downscaling), and SVM-ABC-WT-SVD (this paper model), SVM-ABC-WT-SVD (modeled in this paper).

The event classification results of the seven ablation experiments are shown in Table 2, and the comprehensive performance indicators of the model are analyzed by precision, recall, F1 value, mAP@0.5, mAP@0.5:0.95, and the results show that the SVM-ABC-WT-SVD model has the highest performance among all performance indicators, and the F1 value of the model reaches 0.994 and mAP@0.5 reaches 99.8%, which are 3.6 and 2.9% higher than the SVM model, respectively. It shows that the model in this paper has obvious improvement in classification and positioning.

Table 2: Detailed comparison of ablation experiment results

Model	Accuracy rate	Recall rate	F1 value	mAP@0.5	mAP@0.5:0.95
SVM	0.956	0.958	0.957	96.9%	90.1%
SVM-WT	0.967	0.969	0.968	97.5%	90.8%
SVM-ABC	0.978	0.981	0.979	98.5%	91.3%
SVM-SVD	0.973	0.974	0.973	98.2%	91.1%
SVM-WT-ABC	0.985	0.983	0.984	98.9%	92.6%
SVM-SVD-ABC	0.988	0.987	0.987	99.2%	93.2%
SVM-ABC-WT-SVD	0.995	0.994	0.994	99.8%	94.1%

The training process of the SVM-ABC-WT-SVD model is shown in Figure 1, and the precision, recall, mAP@0.5, and mAP@0.5:0.95 all showed a steep upward trend from 0 to 10 rounds, and tended to be stable after 12 rounds, with no significant oscillation.

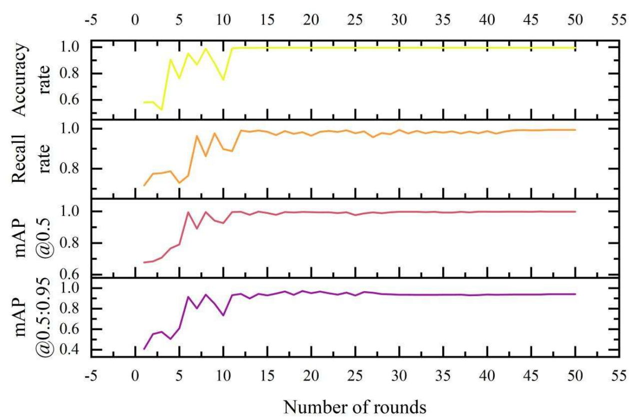

Figure 1: Model training process

The SVM-ABC-WT-SVD model confusion matrix is shown in Fig. 2, and it can be seen that for pipe excavation and pipe leakage events, which are usually recognized with low accuracy, the average accuracy of detection of this paper's model (mAP@0.5) can reach 99.68% and 99.67%, respectively.

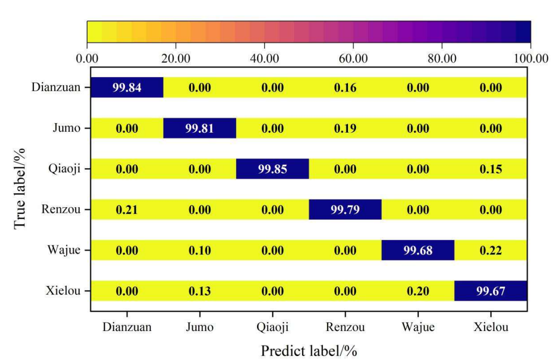

Figure 2: The confusion matrix of the SVM-ABC-WT-SVD model

III. C. Analysis of application effects

A field experiment is conducted at an oil and gas pipeline site in city A. The model proposed in this paper is used to build a field experiment system for oil and gas pipeline monitoring to explore the effect of the emergency response mechanism. The main tool used in this section is Loadrunner, which mainly tests the average response time of the model under the condition of high concurrency. The first stress test starts 5 Vusers every 5 seconds with a maximum concurrency of 200. The test results are shown in Fig. 3 and Fig. 4, where Fig. 3 demonstrates the time delay of the system under the stress test, and Fig. 4 demonstrates the load of the server.

Figure 3 shows that the average system latency is stable at around 2.82ms, indicating that the system can run smoothly under high concurrency scenarios and meet the response requirements of the oil and gas pipeline monitoring system. Figure 4 shows that the available memory is stable at about 3500MB, which does not trigger memory exhaustion, and the CPU utilization rate, physical disk time, and disk queue backlog all meet the standard values.

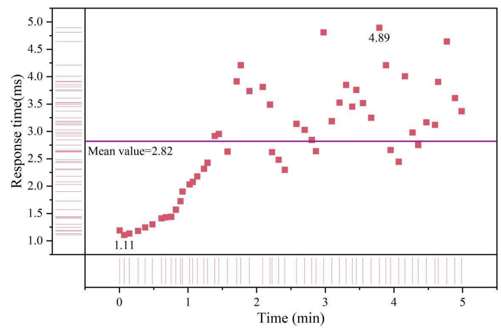

Figure 3: System time delay situation

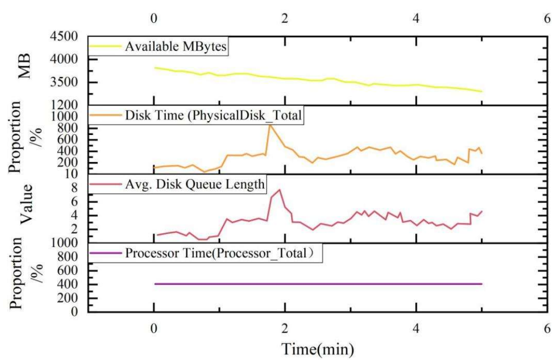

Figure 4: Load situation of the server

The second stress test starts 5 Vuser every 5 seconds, and up to 100 scripts are executed concurrently, and the result of the system resource consumption of the pressurized test is shown in Figure 5. Figure 5 shows that the available memory is stabilized above 4500MB, and the rest of the indicators reach the standard value, which verifies the effectiveness of the emergency response mechanism proposed in this paper.

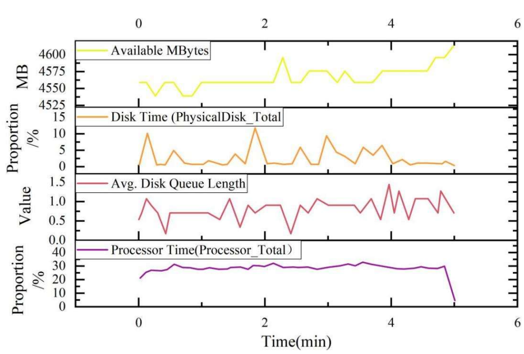

Figure 5: Results of the pressure test

IV. Conclusion

In this paper, a deep learning-based intelligent analysis and emergency response model for oil and gas pipeline safety events is designed, and the model recognition effect and emergency response capability are analyzed through experimental tests.

The SVM-ABC-WT-SVD model achieved the highest performance in all performance indexes in the ablation experiment, and the F1 value of the model reached 0.994 and mAP@0.5 reached 99.8%, which were 3.6% and 2.9% higher than those of the SVM model, respectively, indicating that the model in this paper had a significant improvement in classification and positioning. For pipeline excavation and pipeline leakage events, which usually have low recognition accuracy, the average detection accuracy (mAP@0.5) of the proposed model can reach 99.68% and 99.67%, respectively.

In the two pressure tests, the system parameters reach the standard value, and the average system delay is stable at about 2.82ms when the maximum concurrency is 200, which meets the emergency response requirements of the oil and gas pipeline monitoring system, and verifies the effectiveness of the emergency response mechanism proposed in this paper.

References

[1] Feng, L. I., Shaohua, D., Lin, C., Xiping, Z. H. U., & Zicong, H. A. N. (2023). Key safety technologies and advances in long-distance pipeline transportation of hydrogen blended natural gas. Mechanics in Engineering, 45(2), 230-244.

[2] Ameh, E. S., Ikpeseni, S. C., & Lawal, L. S. (2017). A review of field corrosion control and monitoring techniques of the upstream oil and gas pipelines. Nigerian Journal of Technological Development, 14(2), 67-73.

[3] Chen, C., Li, C., Reniers, G., & Yang, F. (2021). Safety and security of oil and gas pipeline transportation: A systematic analysis of research trends and future needs using WoS. Journal of Cleaner Production, 279, 123583.

[4] Zerouali, B., Sahraoui, Y., Nahal, M., & Chateauneuf, A. (2024). Reliability-based maintenance optimization of long-distance oil and gas transmission pipeline networks. Reliability Engineering & System Safety, 249, 110236.

[5] Belvederesi, C., & Dann, M. R. (2017). Statistical analysis of failure consequences for oil and gas pipelines. International journal of safety and security engineering, 7(2), 103-112.

[6] Kraidi, L., Shah, R., Matipa, W., & Borthwick, F. (2021). An investigation of mitigating the safety and security risks allied with oil and gas pipeline projects. Journal of Pipeline Science and Engineering, 1(3), 349-359.

[7] Sampath, S., Bhattacharya, B., Aryan, P., & Sohn, H. (2019). A real-time, non-contact method for in-line inspection of oil and gas pipelines using optical sensor array. Sensors, 19(16), 3615.

[8] Arun Sundaram, B., Kesavan, K., & Parivallal, S. (2018). Recent advances in health monitoring and assessment of in-service oil and gas buried pipelines. Journal of The Institution of Engineers (India): Series A, 99, 729-740.

[9] Guo, X., Zhang, L., Liang, W., & Haugen, S. (2018). Risk identification of third-party damage on oil and gas pipelines through the Bayesian network. Journal of Loss Prevention in the Process Industries, 54, 163-178.

[10] Kheraj, S. (2020). A history of oil spills on long-distance pipelines in Canada. Canadian Historical Review, 101(2), 161-191.

[11] Biezma, M. V., Andrés, M. A., Agudo, D., & Briz, E. (2020). Most fatal oil & gas pipeline accidents through history: A lessons learned approach. Engineering failure analysis, 110, 104446.

[12] Chen, Y., Zhang, L., Hu, J., Liu, Z., & Xu, K. (2022). Emergency response recommendation for long-distance oil and gas pipeline based on an accident case representation model. Journal of Loss Prevention in the Process Industries, 77, 104779.

[13] Chen, P., Li, R., Jia, G., Lan, H., Fu, K., & Liu, X. (2023). A decade review of the art of inspection and monitoring technologies for long-distance oil and gas pipelines in permafrost areas. Energies, 16(4), 1751.

[14] Iqbal, H., Haider, H., Waheed, B., Tesfamariam, S., & Sadiq, R. (2022). Benchmarking of oil and gas pipeline companies in British Columbia: Integrating integrity management program and safety culture using a risk-based approach. Engineering Management Journal, 34(4), 526-542.

[15] Gómez, C., & Green, D. R. (2017). Small unmanned airborne systems to support oil and gas pipeline monitoring and mapping. Arabian Journal of Geosciences, 10, 1-17.

[16] Yongsheng, Z. O. U. (2021). Intelligent construction of mountainous oil and gas pipeline and its prospect. Oil & Gas Storage and Transportation, 40(1), 1-6.