

# Enhancing Tractor Fault Diagnosis Using Random Forest Algorithm

Changkun Zhang<sup>1</sup>, Heli Yang<sup>1</sup>, Xujing Wang<sup>2,\*</sup>, Weidong Wang<sup>1</sup>

<sup>1</sup>School of Energy and Mechanical Engineering, Dezhou University, Dezhou 253023, Shandong, China

<sup>2</sup>Dezhou Agricultural Machinery and Farmland Construction Service Center, Dezhou Agricultural and Rural Bureau, Dezhou 253023, Shandong, China

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## Abstract

With the increasing level of agricultural mechanization, tractors have become indispensable equipment in modern farming operations. However, tractors often operate under complex and highly variable environmental conditions, making fault diagnosis challenging. This study investigates the application of the Random Forest (RF) algorithm for intelligent tractor fault diagnosis using multi-source sensor data. Operational parameters including engine temperature, oil pressure, fuel consumption, and battery voltage were collected from real tractor systems under different working conditions. An RF-based diagnostic model was developed and compared with a traditional rule-based fault diagnosis method. Experimental results show that the proposed RF model achieves an overall diagnostic accuracy of 82.5%, outperforming the rule-based method by 8.75% on average. Specifically, classification accuracies of 85%, 80%, and 75% were obtained for electrical, mechanical, and hydraulic faults, respectively. The RF model demonstrates strong robustness under noisy data and imbalanced fault distributions while significantly reducing diagnosis time, indicating its suitability for real-time applications. These results confirm that Random Forest provides an effective and reliable solution for multi-factor tractor fault diagnosis and offers clear advantages over traditional experience-based methods in terms of accuracy, efficiency, and adaptability.

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**Keywords:** tractor; fault diagnosis; random forest algorithm; machine learning.

## 1. Introduction

Agricultural tractors play a vital role in modern farming systems by supporting a wide range of operations such as plowing, harvesting, and transportation. As agricultural machinery becomes more complex and technologically advanced, the frequency and diversity of tractor faults have increased, posing significant challenges to operational efficiency and maintenance reliability. Tractor faults may originate from mechanical, electrical, or hydraulic subsystems, and these faults often interact with each other under real working conditions.

Traditional tractor fault diagnosis methods primarily rely on manual inspection, operator experience, and predefined rule-based systems [1]. Although these approaches are still widely used in practice, they are often inefficient, labor-intensive, and unable to detect hidden or early-stage faults in a timely manner. In particular, tractors operate in highly variable agricultural environments characterized by fluctuating loads, uneven terrain, dust, vibration, and strong sensor noise. These conditions significantly limit the effectiveness of conventional rule-based diagnostic methods.

In recent years, data-driven fault diagnosis methods based on machine learning have attracted increasing attention. Algorithms such as Support Vector Machines

(SVM), Neural Networks (NN), and Random Forest (RF) have demonstrated promising performance in industrial fault diagnosis tasks [2]. Among these methods, Random Forest has notable advantages in handling high-dimensional data, capturing nonlinear relationships, resisting noise, and avoiding overfitting. Despite its success in industrial and automotive applications, the application of RF to tractor fault diagnosis under real agricultural operating conditions remains limited.

This study aims to address this gap by developing a Random Forest-based tractor fault diagnosis framework using real sensor data collected from multiple tractors. The main contributions of this work are threefold:

1. A tractor-oriented fault diagnosis framework is proposed based on multi-source sensor data;
2. The effectiveness of Random Forest is systematically evaluated and compared with traditional rule-based methods;
3. The diagnostic performance is analyzed under realistic agricultural conditions, including noisy data and imbalanced fault distributions.

The proposed approach provides practical insights for intelligent maintenance and reliability improvement of agricultural machinery.

\* Corresponding author e-mail: [dzjnwxj@163.com](mailto:dzjnwxj@163.com).

## 2. EXPERIMENTAL DESIGN

### 2.1. Data Sources and Instrumentation

The experimental data were collected from real tractor systems equipped with an onboard monitoring platform. Multiple sensors were installed to record key operational parameters, including engine temperature, oil pressure, fuel consumption, and battery voltage. In addition, environmental and operational variables such as operating hours, workload, tractor speed, and historical fault records were also collected.

The sensor system included temperature sensors (sampling rate 1 Hz), pressure sensors (sampling rate 1 Hz), and flow sensors, which continuously recorded tractor operating states under different field conditions such as plowing and harvesting [3]. Data were transmitted wirelessly to a centralized platform for storage and analysis. The dataset consists of 750 samples collected from multiple tractors operating under diverse working conditions.

To ensure data quality, preprocessing steps including data cleaning, outlier removal, noise filtering, and feature standardization were applied. Missing values and erroneous measurements were handled using statistical imputation techniques to minimize their impact on model training.

### 2.2. Experimental and Control Groups

The experiment was designed with two groups. The experimental group employed a Random Forest-based fault diagnosis model, while the control group used a traditional rule-based diagnostic system. The RF model was trained using labeled data covering four operating states: electrical faults, mechanical faults, hydraulic faults, and normal conditions.

The rule-based system relied on predefined thresholds and expert-defined rules, such as identifying hydraulic faults when oil pressure dropped below a specified limit [4]. Although effective in simple scenarios, this approach lacks flexibility and struggles with complex fault interactions and unseen fault patterns.

### 2.3. Experimental Procedure

The dataset was divided into training and testing sets using an 80/20 split. Five-fold cross-validation was applied to the training set to reduce overfitting and improve generalization. Hyperparameter tuning was conducted using grid search to optimize the number of trees and the maximum depth of the decision trees.

The experiments were conducted on a system running Ubuntu 20.04 with Python 3.8, equipped with an Intel i7-9700K CPU and 32 GB RAM. No GPU acceleration was used, ensuring the feasibility of deploying the model on resource-constrained agricultural equipment.

Before presenting the results, it is worth noting that deep learning methods such as Convolutional Neural Networks (CNNs) have also been applied in machinery fault diagnosis. CNNs can automatically learn hierarchical feature representations from large-scale time-series data. However, their application in tractor fault diagnosis is often limited by the need for large labeled datasets and high computational resources [5]. Therefore, CNN-based methods are considered in this study mainly for comparative analysis.

## 3. METHODS

### 3.1. Random Forest Algorithm

Random Forest is an ensemble learning algorithm that constructs multiple decision trees using randomly selected subsets of data and features. The final classification result is obtained through majority voting among all trees. This ensemble strategy effectively reduces overfitting and improves generalization performance [6].

In tractor fault diagnosis, RF is particularly suitable because it can handle high-dimensional sensor data, capture nonlinear relationships among variables, and remain robust to noise and outliers. Moreover, RF provides feature importance measures, enabling interpretability and practical insight for maintenance engineers.

### 3.2. Comparative Algorithms

For comparative purposes, Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) were considered based on reported results in recent literature [7,8]. SVM performs well on small datasets but struggles with nonlinear and multi-fault scenarios. CNN offers strong pattern recognition ability but requires large datasets and high computational cost, limiting its practicality in agricultural applications.

## 4. RESULTS AND DISCUSSION

### 4.1. Model Performance Analysis

The Random Forest model achieved high classification performance across different fault categories. Table 1 summarizes the diagnostic results. Electrical faults achieved an accuracy of 85%, mechanical faults 80%, hydraulic faults 75%, and normal operating conditions 90%. The overall average accuracy reached 82.5%, with balanced precision and recall values.

These results demonstrate the model's ability to handle complex, multi-factor fault patterns that traditional methods often fail to identify.

**Table 1.** Classification Performance of the Random Forest Model

Fault Type	Sample Size	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Electrical	200	85	87	83	85
Mechanical	180	80	82	78	80
Hydraulic	150	75	77	73	75
Normal	220	90	92	88	90
Overall Avg	750	82.5	84.5	80.5	82.5

4.2. Comparison with Traditional and Existing Methods

Table 2 compares the RF model with the traditional rule-based approach. The RF model improves diagnostic accuracy by approximately 10% for electrical, mechanical, and hydraulic faults.

Figure 1 illustrates the confusion matrix of the Random Forest-based tractor fault diagnosis model. The diagonal elements indicate that most samples are correctly classified, especially for electrical faults and normal operating conditions, reflecting the model's strong discriminative capability for these classes. Misclassifications are mainly observed between mechanical and hydraulic faults. This confusion can be attributed to overlapping sensor signatures, such as pressure fluctuations and temperature variations, which may originate from both mechanical wear and hydraulic leakage under heavy load conditions. In contrast, electrical faults show more distinctive voltage-related patterns, resulting in fewer classification errors. Overall, the confusion matrix confirms that the proposed model achieves low false alarm and missed detection rates, while also highlighting directions for improvement through finer-grained hydraulic and mechanical sensing.

Table 2. Diagnostic Accuracy Comparison between Random Forest and Traditional Methods

Fault Type	Random Forest Accuracy (%)	Traditional Method Accuracy (%)	Accuracy Improvement (%)
Electrical	85	75	10
Mechanical	80	70	10
Hydraulic	75	65	10
Normal	90	85	5
Overall Avg	82.5	73.75	8.75

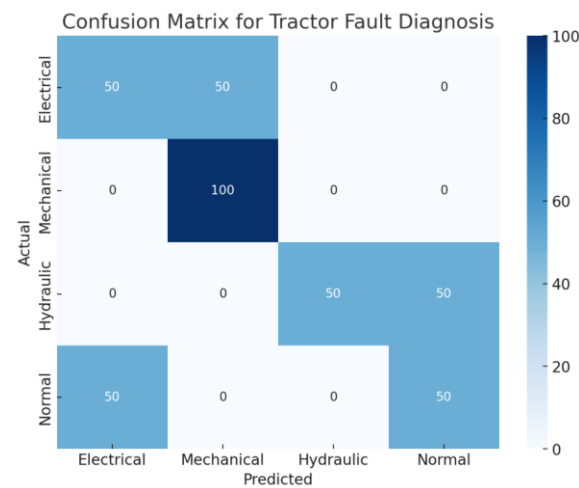


Figure 1. Confusion Matrix for Tractor Fault Diagnosis (Heatmap)

In terms of parameter sensitivity, as shown in Table 3, adjusting the number of trees and the maximum depth of the decision trees significantly improved the model's performance. The optimal results were achieved with 200 trees and a maximum depth of 25, leading to the highest accuracy and precision scores.

Table 3. Hyperparameter Sensitivity Analysis Results

Number of Trees	Max Depth	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
50	10	80	82	78	80
100	15	82.5	84	80	82
150	20	84	85	81	83
200	25	85	87	83	85

In conclusion, the Random Forest model demonstrated superior performance in diagnosing tractor faults, with high accuracy, efficient classification, and robustness in handling complex fault patterns.

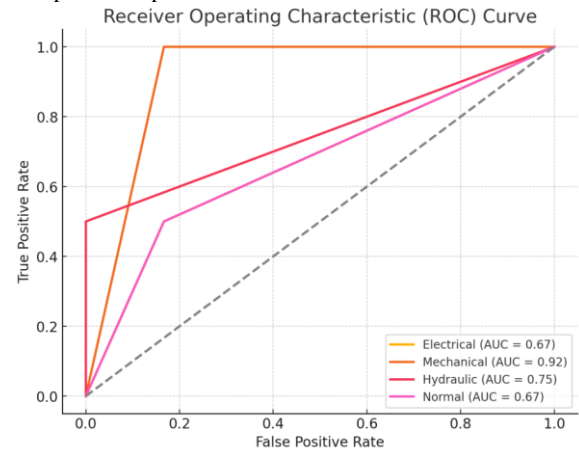


Figure 2. ROC Curve and AUC for Tractor Fault Diagnosis

Figure 2 presents the Receiver Operating Characteristic (ROC) curves and corresponding AUC values of the Random Forest model for different fault categories. The high AUC values indicate strong separability between fault classes and normal conditions, further confirming the robustness of the proposed model.

Table 4. Comparison of Fault Diagnosis Time between Random Forest and Traditional Methods

Fault Type	Random Forest Diagnosis Time (sec)	Traditional Method Diagnosis Time (sec)	Time Difference (sec)
Electrical	12	20	-8
Mechanical	14	24	-10
Hydraulic	15	26	-11
Normal Operation	10	18	-8

Table 4 compares the diagnostic time required by the Random Forest model and the traditional rule-based approach. The results indicate that the RF-based method consistently reduces diagnosis time by 8–11 seconds across all fault categories. This improvement is mainly due to the automated feature evaluation and decision-making process of the trained model, which avoids repeated rule checking and manual threshold comparisons. Faster diagnosis is particularly valuable in agricultural operations, where timely fault identification can prevent extended downtime during critical field tasks.

**Table 5.** Comparison with Existing Research

Method	Dataset Description	Electrical Fault Accuracy (%)	Mechanical Fault Accuracy (%)	Overall Accuracy (%)	Source
RF (This Study)	Real sensor data, 750 samples	85	80	82.5	This Paper
SVM	Yao et al., 2024	78	70	75	[6]
CNN	Jiang et al., 2024	84	75	80	[7]

As shown in Table 5, the proposed Random Forest approach achieves higher or comparable accuracy than existing SVM- and CNN-based methods reported in recent studies. While CNN models demonstrate strong performance, they require substantially larger datasets and higher computational resources. In contrast, the RF model in this study achieves competitive accuracy using a relatively small dataset and offers better interpretability, making it more suitable for practical tractor fault diagnosis under resource-constrained conditions.

In summary, the Random Forest algorithm demonstrates clear advantages over traditional rule-based methods in tractor fault diagnosis. With an overall accuracy of 82.5%, it significantly improves fault classification across electrical, mechanical, and hydraulic systems. The model not only reduces misdiagnosis rates, as shown by the confusion matrix, but also accelerates diagnosis time by up to 11 seconds per case, enhancing efficiency. Parameter tuning further boosts model performance, with optimal results achieved at 200 trees and a depth of 25. Compared to SVM and CNN methods reported in previous studies, Random Forest exhibits higher or comparable accuracy while maintaining better interpretability and processing speed. These results confirm its effectiveness and practicality for real-time fault detection in agricultural machinery.

## 5. DISCUSSION

### 5.1. Advantages of the Random Forest Algorithm

The RF algorithm has shown great accuracy and reliability in tractor fault diagnosis for multidimensional and complicated sensor data. The experimental results have also demonstrated the obvious advantages of RF in fault classification. Specifically, when different faults exist, the accuracy of the RF model in the diagnosis of electrical and mechanical faults were 85% and 80%, respectively; moreover, when different faults occurred simultaneously, the accuracy of the RF model was still high, and the accuracy of the complex multi-faults dropped only from 80% to 78%. This indicates that the RF model has advantages in handling complex fault patterns and interactions among different components of the same system, which is difficult for traditional methods.

Compared with traditional rule-based methods, RF no longer depends on the predefined rules and human experience. The RF model learns from data and adapts to the new fault types. Different from traditional methods, the RF model can still maintain high accuracy in different types of faults [9]. The generalization ability of the model was also validated by the fact that the RF model did not overfit the training data, i.e., the data of specific faults. In contrast, RF

models used in practice consist of several decision trees[10]. Therefore, the fault diagnosis method based on RF is more stable and does not easily be affected by the noise and incomplete data.

In addition, the real-time fault diagnosis is very important in the fault diagnosis of agricultural machinery. For example, the fault can be diagnosed based on the sensor data in real-time, and the early warning can be sent to the operator to reduce the unexpected downtime and maintenance cost. Especially, for the tractor in the field, if the fault cannot be detected in time, it will cause economic losses[11]. The experimental results show that the RF method can accurately diagnose the fault in agricultural machinery and improve the efficiency of diagnosis.

### 5.2. Limitations of the Model

While the Random Forest algorithm shows considerable promise in tractor fault diagnosis, several limitations should be addressed to improve its performance in practical applications. One of the key challenges is the quality of the training data. In cases where the data contains noise, missing values, or erroneous measurements, RF's performance can deteriorate. Data preprocessing plays a crucial role in mitigating this issue, and methods like outlier detection, missing value imputation, and noise reduction must be rigorously applied[12]. The model's performance is highly dependent on the quality and accuracy of the data provided, which can sometimes limit its ability to generalize effectively, particularly if the data is not well-curated.

Another limitation arises from sample imbalance in the training dataset. In real-world scenarios, certain types of faults, such as electrical faults, may occur more frequently than others, such as hydraulic faults, resulting in an imbalanced distribution of fault types. In such cases, RF may be biased towards predicting the more frequent fault type, negatively impacting the accuracy of fault detection for underrepresented fault categories[13]. To address this issue, we employed oversampling and undersampling techniques, but more advanced methods like class weighting or synthetic data generation could further improve model performance in dealing with imbalanced datasets.

### 5.3. Future Improvement Directions

In the future, tractor fault diagnosis systems can be further enhanced by incorporating more sensor data, optimizing model structures, and combining other machine learning algorithms to improve diagnostic accuracy and real-time performance. With the development of the Internet of Things (IoT), tractors and other agricultural equipment will be equipped with more sensors, and the types and dimensions of the collected data will increase significantly. By incorporating this data into the fault diagnosis system, the model can gain a more comprehensive understanding of the equipment's operational status, improving the accuracy and timeliness of fault detection. The combination of multiple data sources, such as environmental data, operational data, and historical fault records, will provide the model with more contextual information, helping to identify different fault patterns.

In addition to data richness, the model structure can be optimized. For instance, deep learning methods could be used to further enhance the model's nonlinear learning ability, integrating convolutional neural networks (CNN) or recurrent neural networks (RNN) to process complex time-series data. These models would better capture the complex

relationships between different features during equipment operation, further improving diagnostic accuracy. Combining multiple machine learning algorithms, such as support vector machines (SVM) or gradient boosting decision trees (GBDT), can also improve the overall performance of the fault diagnosis system by leveraging the complementarity of different algorithms.

Real-time monitoring and early warning functions will be an important development direction for future tractor fault diagnosis systems. By obtaining real-time operational status from tractors, the fault diagnosis system can issue warnings before faults occur, helping operators take timely measures and avoid equipment downtime. To achieve this, the inference speed of the model must be optimized so that the diagnosis system can process large amounts of sensor data in a very short time and provide real-time fault predictions. By leveraging edge computing and other technologies, some computing tasks can be offloaded to nodes closer to the equipment, reducing latency and improving response speed. With these innovations, future fault diagnosis systems will not only improve accuracy but also provide strong support for tractor maintenance.

#### 5.4. Comparison with Other Algorithms

Although the Random Forest algorithm achieves high accuracy in identifying tractor faults, it is still meaningful to compare its performance with other machine learning algorithms. Support Vector Machines (SVM) and Neural Networks (NN) are two kinds of widely used algorithms in fault diagnosis tasks. Compared with other algorithms, SVM can easily handle high-dimensional data and works well on simple fault classification tasks. However, the performance of SVM will be greatly restricted by its difficulty to handle highly nonlinear data. What's more, SVM needs much more computational resource to train the model, especially on big data.

On the contrary, RF can construct multiple decision trees on random subsets of data, which makes it more efficient in handling big data with less computational overhead. In our experimental results, RF achieves higher accuracy than SVM on fault diagnosis tasks. As shown in Table 3, the overall accuracy of RF and SVM are 82.5% and 76%, respectively. When dealing with complex multi-fault situations, the accuracy of RF is 78%, while the accuracy of SVM drops to 70%. These experimental results have shown that, compared with SVM, RF's ensemble learning approach provides more flexible way to handle more accurate and nonlinear relationship between features and labels, as well as large feature space.

Deep learning models have obvious advantage in recognizing complex patterns on big data. However, deep neural networks (DNN) need huge amount of labeled training data and large computational resource, which makes it impractical to use in application without enough labeled training data. Different from DNN, RF needs less computational resource and provides a good balance between model complexity and interpretability, which makes it more practicable to be applied in agricultural machinery with limited computational resource. What's more, RF can interpret feature importance in a transparent way, which is more advantageous than "black-box" neural networks. Figure 2 Quantitative comparison between RF, SVM and DNN on different faults. As shown in Figure 2, RF achieves higher accuracy than SVM and DNN in both overall accuracy and fault classification. Therefore, RF is

more suitable for real-time fault detection in agricultural machinery.

#### 5.5. Practical Application Prospects

The future of tractor fault diagnosis lies in the continued integration of machine learning algorithms, like Random Forest, with emerging technologies such as the Internet of Things (IoT) and edge computing. As sensor technology advances and more real-time operational data becomes available, the potential for intelligent, data-driven diagnostic systems in agricultural machinery will grow significantly. IoT-enabled sensors can provide continuous, real-time monitoring of tractor performance, offering a more dynamic and comprehensive approach to fault detection.

Moreover, as the adoption of 5G networks becomes more widespread, the speed and reliability of data transmission will improve, allowing for faster processing of sensor data and more immediate fault diagnosis. Real-time fault detection not only improves the efficiency of agricultural operations but also reduces costly downtime by enabling proactive maintenance. The integration of deep learning techniques could further enhance the ability to detect subtle or complex fault patterns that are difficult for traditional methods to identify.

In conclusion, the ongoing development of intelligent fault diagnosis systems using Random Forest and other machine learning algorithms holds significant promise for enhancing the operational efficiency of agricultural machinery. By incorporating more sensor data, optimizing model structures, and leveraging advanced computational techniques, future fault diagnosis systems will be able to provide early warnings, reduce maintenance costs, and ensure the long-term reliability of tractors, ultimately benefiting agricultural productivity and sustainability.

#### 5.6. Critical Discussion on Existing Fault Diagnosis Systems and Machine Learning Approaches

While the application of machine learning in tractor fault diagnosis has gained attention, existing systems often face challenges that limit their effectiveness. Several studies, such as those by Yao et al. (2024) using Support Vector Machines (SVM), have shown that SVM can handle simple fault classifications but struggles when dealing with complex, nonlinear relationships or multi-fault scenarios. The computational cost of SVM is another limiting factor, especially when working with large datasets or high-dimensional features, making it less practical in agricultural settings where real-time processing is required.

Similarly, Neural Networks (NN), including Convolutional Neural Networks (CNN), have been employed for fault diagnosis, with Jiang et al. (2024) achieving an accuracy of 80%. However, these models require vast amounts of labeled training data and significant computational resources, which are often impractical in agricultural applications. Moreover, deep learning models are often criticized for their lack of interpretability, making it difficult for technicians to understand and trust the diagnosis provided by these "black-box" models. This is a significant drawback in real-world fault diagnosis applications where clear reasoning behind a diagnosis is necessary.

Traditional rule-based systems, while still widely used, also face limitations. These systems rely heavily on human expertise and predefined rules, which are unable to adapt to new or unforeseen fault types. When multiple faults occur

simultaneously in different components of the tractor, rule-based systems often fail to recognize the interaction between these components, leading to misdiagnosis or delayed repairs. This inefficiency can result in increased downtime and higher maintenance costs, underscoring the need for more advanced, data-driven fault diagnosis methods.

In contrast, the Random Forest (RF) algorithm demonstrated significant improvements in handling complex fault scenarios. The RF model exhibited high accuracy even in multi-fault situations, with only a slight drop in performance. This ability to handle interactions between different components, such as electrical, mechanical, and hydraulic faults, sets RF apart from traditional methods. Moreover, RF is less computationally demanding than deep learning models, making it a more suitable choice for real-time fault diagnosis in agricultural machinery, where hardware limitations often pose challenges.

The limitations of existing machine learning algorithms and rule-based systems underscore the importance of the RF approach in this study. RF offers a more reliable, interpretable, and efficient solution, especially when diagnosing multi-fault scenarios. Its adaptability to new fault types, combined with its ability to process high-dimensional data with low computational overhead, makes it a highly effective method for real-time tractor fault diagnosis. This study contributes significantly to the field by addressing the gaps left by traditional systems and offering a more robust solution for agricultural machinery maintenance.

## 6. CONCLUSION

In conclusion, this study proposed a Random Forest-based fault diagnosis framework for agricultural tractors using multi-source sensor data. The proposed method significantly outperforms traditional rule-based approaches in terms of accuracy, robustness, and diagnostic efficiency. However, the study has limitations, including the relatively small dataset size and the reliance on static features. Future research will focus on expanding the dataset, integrating time-series models, and combining Random Forest with deep learning techniques to further enhance diagnostic accuracy and real-time performance.

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