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An Intelligent Identification Strategy for Fault Types of Transmission Lines Through Unmanned Aerial Vehicle Inspection Based on Machine Learning Classification

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Abstract. Power transmission lines, as the core of the power system, are prone to failures due to long-term exposure to outdoor environments. Traditional manual inspection and data analysis methods are unable to meet the requirements of intelligent operation and maintenance. This paper uses 1829 sets of transmission line fault data collected by drones, covering multiple features such as electrical and environmental aspects, and classifies them into five operational states and conducts variable correlation analysis. To address the problem of insufficient feature extraction and poor generalization of a single algorithm in fault identification, a TCN-Transformer algorithm that integrates local temporal feature extraction and global attention mechanism is proposed, and an end-to-end classification prediction framework is constructed. The data set is divided in a 7:3 ratio and core parameters are set. The results show that the model has an accuracy rate of 0.823 and an AUC of 0.972. It outperforms traditional machine learning and ensemble learning models such as decision trees, random forests, and XGBoost in multiple key indicators, effectively improving the accuracy and stability of transmission line fault identification in complex scenarios, and providing a feasible technical solution for intelligent fault discrimination in drone inspections.

Keywords: Power transmission lines, transmission line faults, TCN, Transformer

1. Introduction

Power transmission line is the core component of power system, which undertakes the important task of long-distance transmission of electric energy. Its operating state directly determines the stability and safety of power supply in power grid [1]. Transmission lines are exposed to complex outdoor environments for a long time. Affected by multiple factors such as meteorological changes, environmental corrosion, external force damage and equipment aging, various faults such as insulator pollution flashover, broken wire strands, lightning strike damage and line icing are prone to occur [2]. Traditional transmission line inspection mostly relies on manual on-the-spot inspection, which has low inspection efficiency and high labor cost. Moreover, there are great potential safety

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hazards in high-risk areas, which makes it difficult to meet the large-scale, normalized and high-precision inspection needs of modern power grid. With the rapid popularization of UAV inspection technology, the electrical parameters, environmental data and state characteristics of transmission lines can be quickly collected by relying on UAV-equipped sensing equipment, which provides massive data support for line fault identification. However, massive inspection data has problems such as feature redundancy, large noise interference and complex data correlation. Traditional manual data analysis methods can't accurately and efficiently complete fault classification and identification, and intelligent technology is urgently needed to realize automatic identification of transmission line faults [3].

The popularization of machine learning algorithms provides a new technical path for intelligent identification of transmission line faults, completely breaking the technical limitations of traditional manual research and judgment. Compared with traditional threshold discrimination and manual experience analysis methods, machine learning has powerful data feature mining and autonomous learning capabilities, and can automatically mine the potential correlation law between line operation parameters and fault types based on massive inspection data, and get rid of the over-reliance on manual experience [4]. Through the training and learning of multi-dimensional inspection data such as transmission line voltage and current, environmental temperature and humidity, equipment status, etc., the machine learning model can independently complete data feature screening, feature fusion and pattern recognition, effectively avoiding the subjective error and missed judgment problems in manual judgment [5]. At the same time, the machine learning algorithm can adapt to the processing requirements of massive inspection data, greatly improve the efficiency and intelligence level of fault identification, realize the rapid classification and prediction of transmission line faults, and provide core technical support for the intelligent transformation of power grid operation and maintenance.

The existing single machine learning and deep learning algorithms still have obvious shortcomings in transmission line fault identification. Traditional time series networks are difficult to capture long-distance dependent features of inspection data, and the general feature extraction model has insufficient ability to extract subtle fault features, resulting in low fault classification accuracy and poor generalization ability in complex scenarios. In order to solve the above technical pain points, this paper combines the advantages of time-series convolutional network and Transformer algorithm, and proposes a fault classification and prediction algorithm for transmission lines based on TCN-Transformer. Relying on the powerful local time series feature extraction capability of time series convolutional network, the local detail features of UAV inspection data are accurately captured, and the long-distance correlation features of data are mined by combining the global attention mechanism of Transformer algorithm, so as to realize the deep feature fusion of multi-dimensional inspection data. This algorithm can effectively improve the identification accuracy and stability of various faults of transmission lines in complex outdoor scenes, and provide a new technical solution for intelligent identification of transmission line faults by UAV inspection.

2. Data sources

The transmission line fault data set adopted in this paper totals 1829 sets of sample data. The data are collected on the spot during the field inspection of transmission lines by UAV, covering many actual monitoring characteristics such as line operating voltage, load current, insulator surface temperature, ambient air humidity, on-site wind speed, number of discharge pulses, wire corrosion degree and wire vibration amplitude, etc., which can comprehensively reflect the daily operation state and environmental changes of transmission lines. The target labels of the data set are divided

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into five categories: normal operation, insulator pollution flashover, wire broken strand, lightning strike fault and line icing. The correlation analysis was performed on the individual variables and the correlation heat map was plotted, as shown in Figure 1.

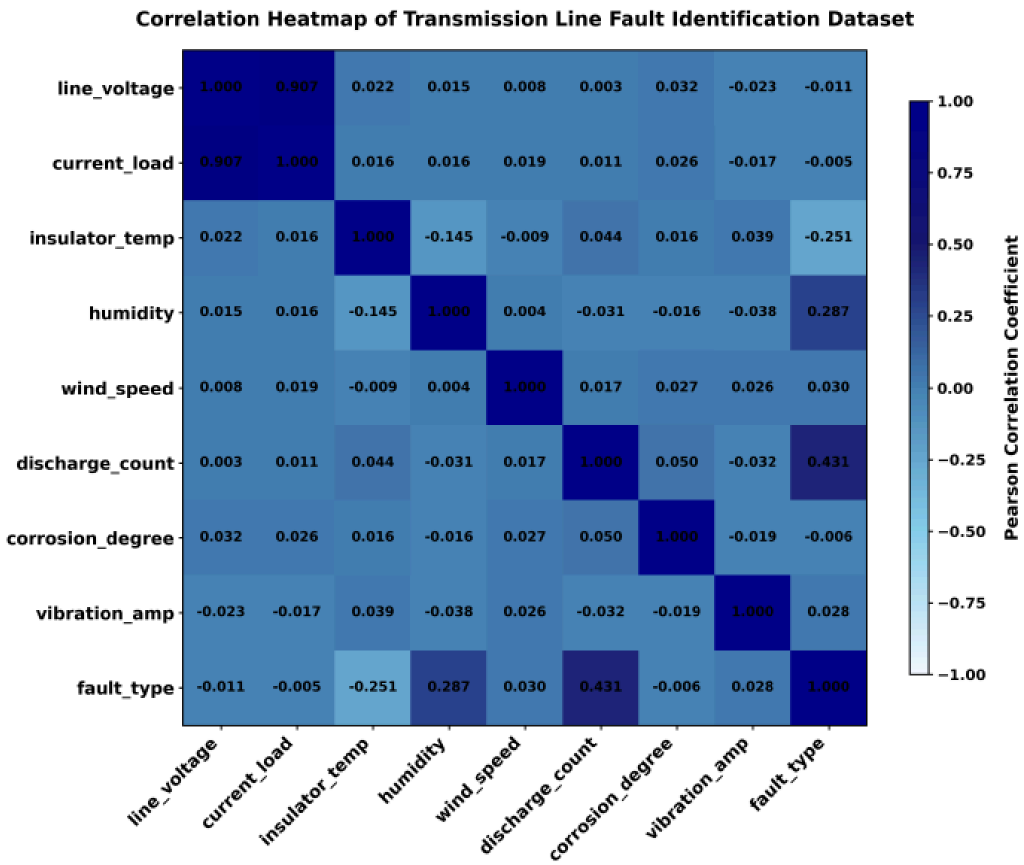

Figure 1. The correlation heat map

3. Method

3.1. TCN

TCN, or Time Series Convolutional Network, is a convolutional architecture specially designed for time series data. Its core realizes efficient sequence modeling through causal convolution, expansion convolution and residual connection. Causal convolution ensures that the output at each moment only depends on current and historical inputs through one-sided zero filling, prevents future information leakage, and strictly follows temporal causal logic [6]. Expansion convolution introduces expansion coefficients, and makes the convolution kernel sample at intervals. Without increasing parameters and network depth, the receptive field grows exponentially, and efficiently captures long-distance timing dependencies. The residual connection directly maps the input to the output, alleviates the problem of gradient disappearance in deep networks, and improves the model training stability and feature transfer ability [7]. The network structure of the TCN is shown in Figure 2.

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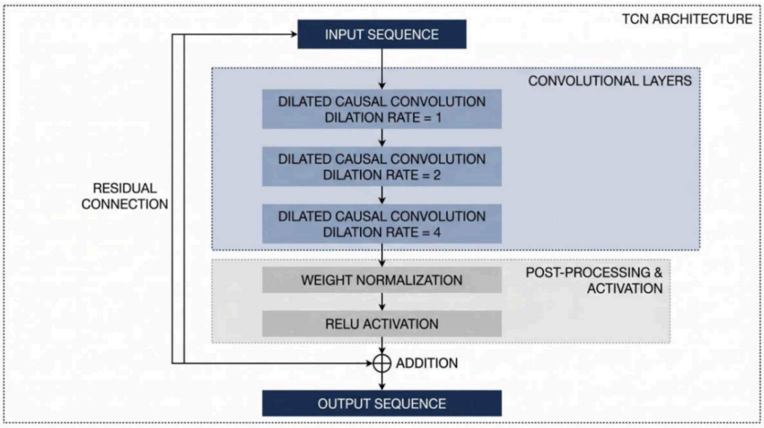

Figure 2. The network structure of the TCN

3.2. Transformer

Transformer is a sequence modeling architecture based on self-attention mechanism, which completely abandons loop and convolution structure, and relies on multi-head self-attention and position coding to realize global dependency capture. Its core is the self-attention mechanism. Through three vector matrices of query, key and value, the correlation strength between elements in the sequence is calculated, the attention weight is dynamically allocated, and the dependency relationship of elements in any position is directly established without the risk of gradient disappearance [8]. Multi-head attention maps features to multiple subspaces for parallel computation, capturing semantic and structural associations from different dimensions, and forming a more comprehensive feature representation after splicing the results. Position coding injects sequence position information through trigonometric functions or learnable parameters, which compensates for the defect that the self-attention mechanism cannot perceive the order. The network structure of Transformer is shown in Figure 3.

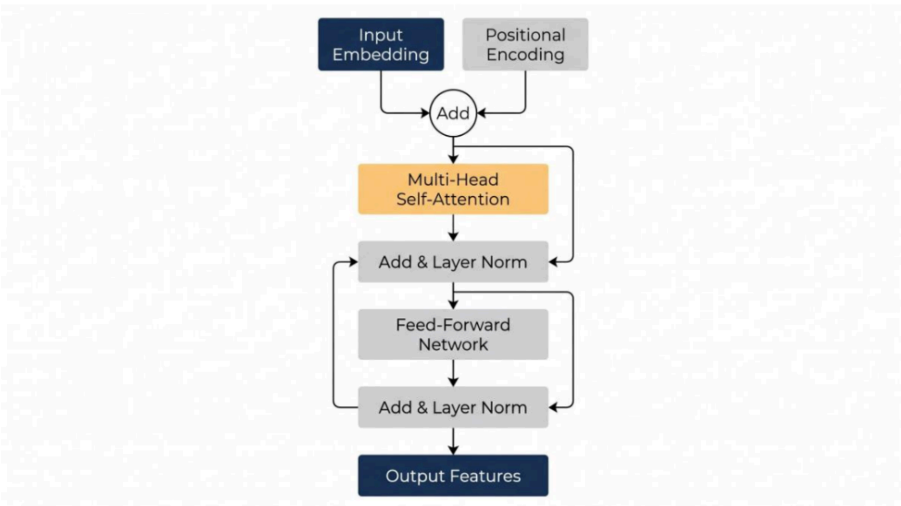

Figure 3. The network structure of Transformer

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3.3. TCN-Transformer

TCN-Transformer combines the local feature extraction ability of TCN with the global modeling advantages of Transformer to build an end-to-end classification prediction framework. The model adopts serial fusion strategy. The input time series data is processed by TCN module first, and local time series features are extracted through causal convolution. The receptive field is expanded with the help of expansion convolution, short-term and medium-term dependencies of different scales are captured, and feature sequences containing local detail information are output [9]. The TCN output feature adds position coding to make up for the sequence information lost by the convolution operation, and then inputs it into the Transformer encoder. Through the multi-head self-attention mechanism, Transformer performs global correlation modeling on the local features extracted by TCN, captures the long-distance dependency and global context information, and realizes the deep fusion of local features and global features. The fused features are mapped to the category space through the fully connected layer and activation function, and the probabilities of each category are output through Softmax normalization to complete the classification prediction [10]. The network structure of TCN-Transformer is shown in Figure 4.

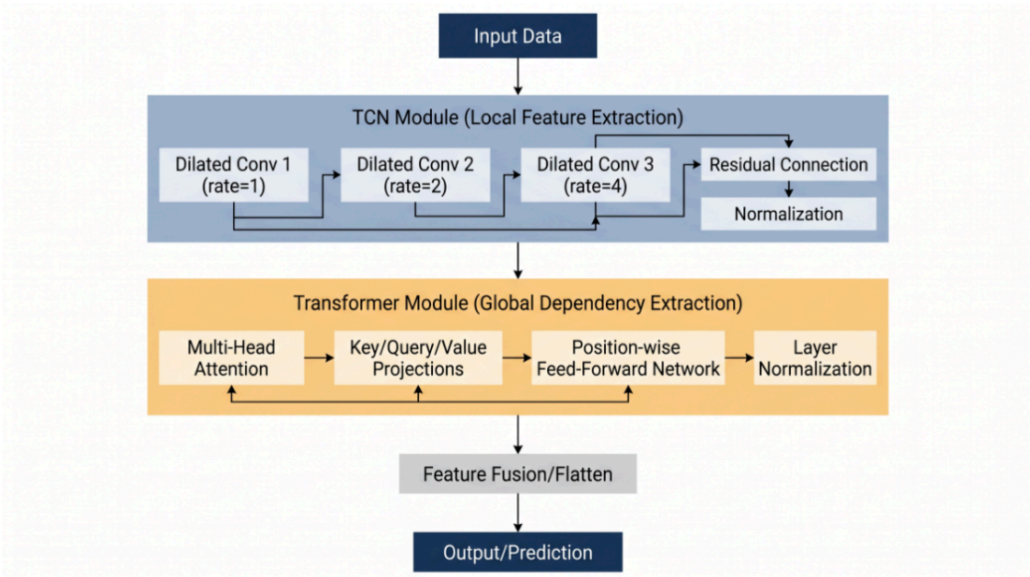

Figure 4. The network structure of TCN-Transformer

4. Result

This project is based on TCN-Transformer architecture for classification prediction. In the core parameter setting, the convolution kernel size of TCN module is set to 3 to extract local timing features, the number of multi-head attention heads of Transformer module is set to 4 to capture global dependencies, and the model training learning rate is fixed to 0.001 to ensure convergence stability. At the same time, the original data is divided into the training set and the test set according to the ratio of 7:3 for model evaluation.

Comparative experiments were performed using a variety of machine learning algorithms, and the results are shown in Table 1.

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Table 1. The results of the comparative experiment

Model	Accuracy	Recall	Precision	F1	AUC
Decision tree	0.803	0.803	0.769	0.784	0.93
AdaBoost	0.552	0.552	0.765	0.578	0.875
Random forest	0.809	0.809	0.737	0.768	0.965
BP neural network	0.617	0.617	0.381	0.471	0.754
GBDT	0.8	0.8	0.752	0.763	0.968
ExtraTrees	0.814	0.814	0.726	0.766	0.968
CatBoost	0.812	0.812	0.835	0.774	0.96
KNN	0.643	0.643	0.599	0.583	0.875
XGBoost	0.814	0.814	0.783	0.785	0.967
Logistic regression	0.772	0.772	0.737	0.74	0.957
TCN-Transformer	0.823	0.823	0.746	0.782	0.972

Plot the index comparison histogram of each machine learning algorithm, as shown in Figure 5.

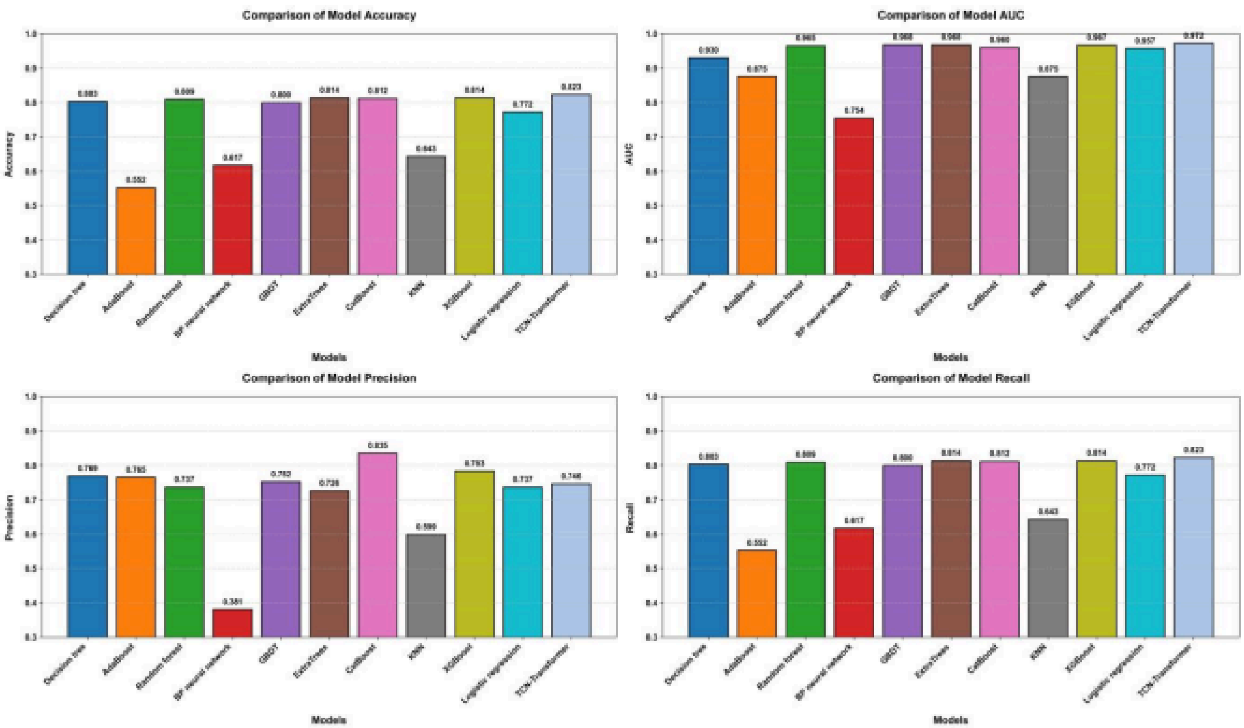

Figure 5. The index comparison histogram of each algorithm

From the values of various evaluation indexes, it can be clearly seen that the TCN-Transformer algorithm proposed in this paper has the best comprehensive performance. The accuracy recall rate and AUC value of this algorithm are higher than the traditional machine learning model, and the classification and recognition ability and generalization ability have obvious advantages. Compared

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with the tree-class ensemble learning model, the overall accuracy of TCN-Transformer surpasses the decision tree random forest GBDT extra tree and extreme gradient boosting algorithm, only the accuracy rate is slightly lower than that of some tree models, the F1 score is at the upper middle level, and the classification balance performs well. Compared with the adaptive lifting back propagation neural network and K-nearest neighbor logistic regression model, the core indexes of this algorithm are significantly different, and the model fitting effect and prediction stability are significantly ahead. Although the accuracy of the category promotion algorithm is outstanding, its overall discrimination ability is not as good as that of TCN-Transformer, which is enough to reflect that the algorithm that integrates timing and attention mechanism has stronger learning and mining ability and practical application value on the dataset.

5. Conclusion

The outdoor operation environment of transmission lines is complex, and the fault types are diverse. Traditional inspection and manual analysis have limitations such as low efficiency and large error. The massive data generated by UAV inspection urgently needs intelligent algorithms to realize automatic discrimination. This paper takes the state data of five types of transmission lines as the object, and completes the multi-dimensional feature correlation analysis, which provides the basis for the model input selection. Aiming at the shortcoming that traditional time series networks and general feature extraction models are difficult to balance local detail and global correlation, the serial fusion strategy of TCN and Transformer is adopted. First, TCN extracts local time series features, and then captures long-distance dependence and global context through Transformer to realize deep feature fusion. Comparative experiments show that TCNTransformer is optimal in core indicators such as accuracy, recall rate and AUC, and its overall performance surpasses many traditional machine learning and ensemble learning models. Only the accuracy rate is slightly lower than that of partial tree model, and its classification balance and generalization ability are outstanding. The fusion algorithm effectively solves the problem of low fault identification accuracy in complex scenarios, significantly improves the efficiency and reliability of transmission line fault classification and prediction, provides technical support for intelligent operation and maintenance of power grid and efficient utilization of UAV inspection data, and has strong engineering application and popularization value.

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