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Prediction of Emergency Response Efficiency Levels for Abnormal Events in Expressway Service Areas Based on Machine Learning Algorithms

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Abstract. Highway service areas, as key nodes in the road traffic network, undertake core functions such as passenger flow distribution and vehicle supply. During daily operation, abnormal incidents such as missing persons, abnormal vehicle stops, and facility malfunctions occur from time to time. Due to factors such as the periodic fluctuations in passenger flow density, differences in equipment deployment levels, and the variability of environmental conditions, there are significant differences in the efficiency of emergency response to abnormal events. The traditional response mode relies on manual investigation and experience-based judgment, which not only responds slowly but also fails to meet the demands of digital and intelligent operation and management. In view of the deficiencies of existing algorithms in temporal feature capture, nonlinear fitting and multi-feature association mining, this paper proposes the LSTM-KELM-Transformer classification algorithm, providing reliable technical support for the intelligent and efficient handling of abnormal events in expressway service areas. The research first conducted correlation analysis and violin graph analysis, and then carried out comparative experiments through multiple machine learning algorithms. The results showed that the proposed algorithm demonstrated significant advantages in all core evaluation indicators, with both accuracy and recall rates reaching 89.5%. It is significantly higher than the 74.8% of decision trees, 84.5% of GBDT, 81.5% of random forests, 86.6% of ExtraTrees, 84.5% of BP neural networks, 84.9% of CatBoost and 85.7% of XGBoost.

Keywords: Digital twin, Abnormal event prediction, Transformer

1. Introduction

Highway service areas, as key nodes in the road traffic network, undertake core functions such as passenger flow distribution and vehicle supply. During daily operation, abnormal incidents such as missing persons, abnormal vehicle stops, and facility malfunctions occur frequently [1]. Due to factors such as the periodic fluctuations in passenger flow density, differences in equipment deployment levels, and the variability of environmental conditions, the efficiency of emergency response to abnormal events varies greatly. The traditional response mode relies on manual investigation and experience-based judgment, which not only lags behind in response but also is

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difficult to meet the operational management requirements of digitalization and intelligence [2]. With the practical application of digital twin and intelligent perception technologies in service area scenarios, a large amount of multi-dimensional data covering equipment operation, environmental status, and event characteristics has been accumulated. How to accurately predict the efficiency level of emergency response based on these data has become the core issue for enhancing the emergency management capabilities of service areas and optimizing resource allocation. There is also an urgent need for efficient data analysis and prediction algorithms [3].

Machine learning algorithms provide key technical support for predicting the emergency response efficiency of abnormal events in service areas. Classification algorithms can mine hidden patterns from multi-dimensional feature data and establish a mapping relationship between feature variables and response efficiency levels [4]. Although traditional machine learning algorithms such as random forests and gradient boosting trees have been applied in traffic scene prediction, these algorithms are difficult to fully capture the temporal correlation of dynamic features such as passenger flow density and equipment operation status, nor can they effectively handle the complex nonlinear relationships among multi-source heterogeneous features, resulting in limited prediction accuracy and generalization ability. It is difficult to meet the requirements of real-time and accuracy for emergency response in service areas, and there is an urgent need to build a new algorithm model that is more suitable for the characteristics of the scene [5].

In view of the deficiencies of existing algorithms in temporal feature capture, nonlinear fitting and multi-feature association mining, this paper proposes the LSTM-KELM-Transformer classification algorithm. This algorithm integrates the deep extraction ability of long short-term memory networks for temporal features and effectively captures the temporal evolution laws of dynamic indicators such as passenger flow density and camera online rate. By combining the rapid learning characteristics and strong nonlinear fitting advantages of the kernel extreme learning machine, the model training efficiency and feature mapping ability can be improved. Introduce the self-attention mechanism of Transformer to accurately identify the differentiated influence weights of different feature dimensions on processing efficiency. By complementing the advantages of the three, this algorithm can fully explore the influence laws of the handling efficiency of abnormal events in service areas, improve the accuracy of classification prediction, and provide technical support for the intelligent upgrade of emergency management in service areas.

2. Data set source

The dataset used in this article contains 791 pieces of real-world scenario adaptation data, covering 10 core features and 1 target variable. This includes camera coverage, the number of concurrent video processing channels, the accuracy of pedestrian re-identification, event types, incident areas, passenger flow density, camera online rate, lighting conditions, time periods, and the number of edge computing devices. The target variable is the level of emergency response efficiency, which is classified into three categories: high efficiency, medium efficiency and low efficiency. First, conduct a correlation analysis and draw a correlation heat map, as shown in Figure 1.

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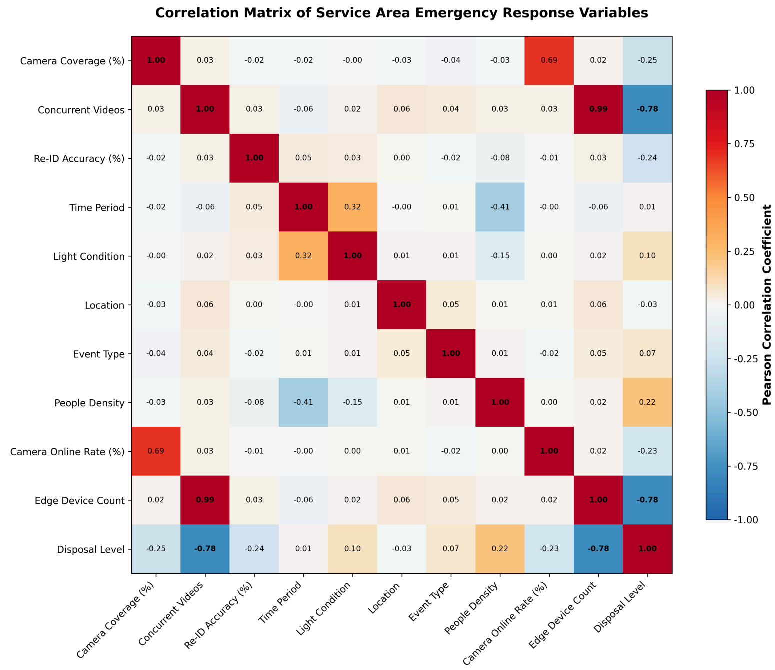
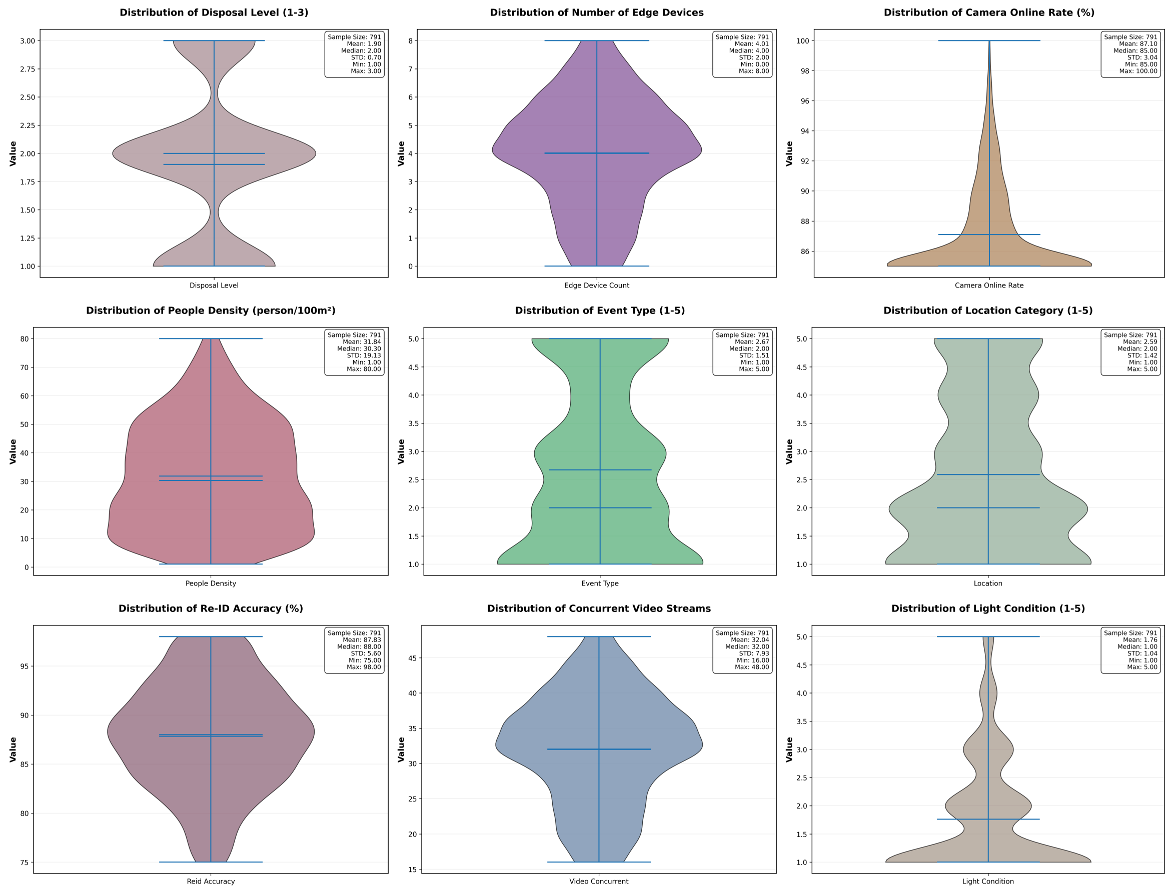


Figure 1. Correlation analysis

Draw the violin plots of each variable as shown in Figure 2.



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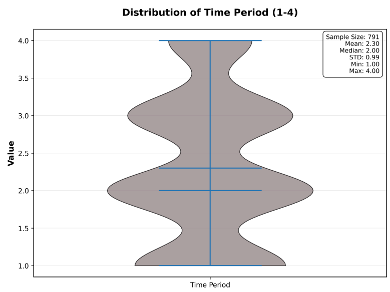

Figure 2. The violin plots of each variable

3. Method

3.1. LSTM

Long short-term memory networks are an improved version of recurrent neural networks, with the core objective of addressing the vanishing or exploding gradients that occur in traditional RNNS during long sequence processing [6]. Its key structures include the input gate, the forgetting gate, the output gate and the cell state. The cell state is similar to a conveyor belt, which can maintain the continuous flow of information during the sequence transfer process with only a small amount of linear interaction. The forgetting gate determines which information to discard from the cell state, the input gate controls the reception and storage of new information, and the output gate screens the information in the cell state and outputs it to the next layer [7]. Through the synergistic effect of the gating mechanism, LSTM can adaptively remember the key information in long sequences and ignore irrelevant details, demonstrating a powerful feature capture capability in time series data modeling. The network structure of LSTM is shown in Figure 3.

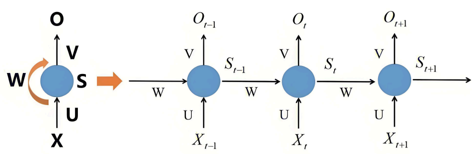

Figure 3. The network structure of LSTM

3.2. KELM

The kernel extreme learning machine is an extension of the kernel method of the extreme learning machine, based on the structural framework of a single-hidden layer feedforward neural network. Unlike traditional neural networks, KELM randomly initializes the weights and biases from the input layer to the hidden layer without the need for iterative adjustments. It only requires setting the number of nodes in the hidden layer [8]. The core idea is to use the kernel function to map the input data to a high-dimensional feature space, and in this space, directly solve the output layer weights through the least square method, avoiding the complex gradient descent optimization process. This design enables KELM to have an extremely fast training speed, while enhancing the model's nonlinear fitting ability through the flexibility of the kernel function, significantly improving computational efficiency while maintaining generalization performance.

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3.3. Transformer

Transformer is a deep learning model based on the self-attention mechanism, completely breaking away from the serialization processing dependence of the RNN series models [9]. Its core components include the multi-head self-attention mechanism and the position-WISE feedforward neural network. Through the self-attention mechanism, the dependency relationship between each position in the sequence and all other positions can be calculated in parallel, directly capturing the global feature interaction. To make up for the loss of position information caused by the absence of sequence processing, the Transformer introduces a position encoding mechanism, integrating absolute or relative position information into the input vector. Multi-head attention captures feature correlations of different dimensions through multiple parallel attention heads, and then performs feature transformation through a feedforward neural network. The network structure of the Transformer is shown in Figure 4.

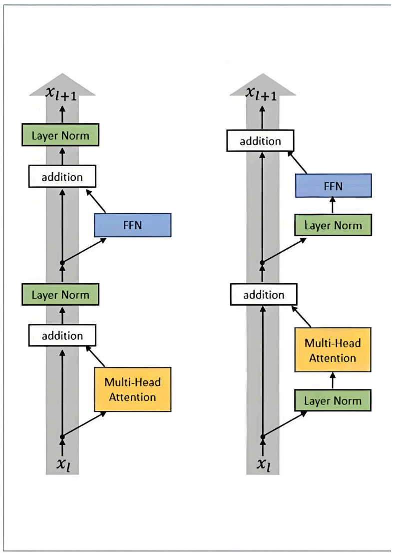

Figure 4. The network structure of the Transformer

3.4. LSTM-KELM-Transformer

The LSTM-KELM-Transformer classification algorithm is a hybrid architecture that integrates the advantages of three models and is designed for complex time series data classification tasks. This algorithm first utilizes the gating mechanism of LSTM to extract local temporal features in sequence data, capturing short-term dependencies and temporal dynamic changes [10]; Subsequently, the output of LSTM is used as the input of Transformer, and the global feature correlation is modeled through the multi-head self-attention mechanism to make up for the deficiency of LSTM in capturing global dependencies of long sequences. Finally, the high-dimensional feature vectors output by the Transformer are input into the KELM classifier, and the classification decision is completed by taking advantage of the kernel mapping capability and fast solution advantage of KELM. The synergistic effect of the three achieves an effective integration of local temporal features and global dependencies, while leveraging KELM to enhance the generalization performance and computational efficiency of the model.

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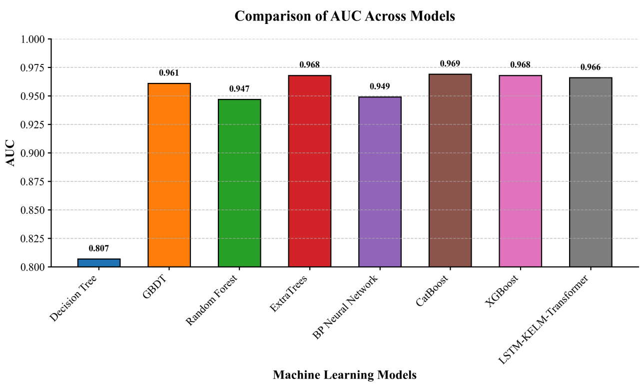
4. Result

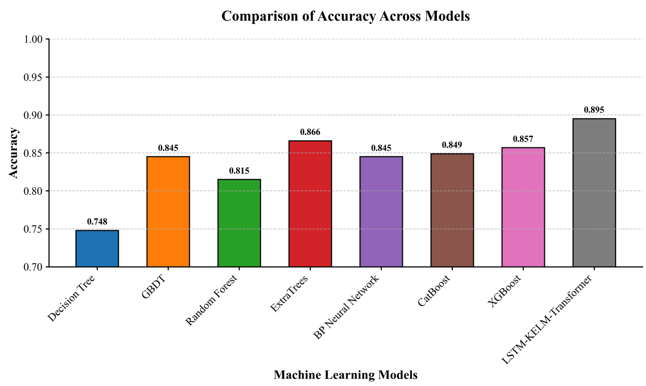
In terms of project parameter Settings, the maximum position encoding is set to 512, the number of self-attention mechanism heads is 4, the number of key channels for each head is 32, and the total number of key channels is 128. The dimension of the LSTM layer is set to 6, the relu activation function is adopted, the dropout rate of the dropout layer is 0.01, and the dimension of the fully connected layer corresponds to the number of categories. The model training uses the adam optimizer, with a maximum of 800 training rounds, a batch size of 256, an initial learning rate of 0.01, a learning rate degradation factor of 0.1, a degradation period of 650, an L2 regularization coefficient of 0.001, a gradient clipping threshold of 10, and an automatic selection of the execution environment. The regularization coefficient of the KELM module is set to 20, and the kernel parameter is 6

Output the comparison table of the results of each machine learning algorithm, as shown in Table 1, and output the comparison results of each indicator, as shown in Figure 5.

Table 1. Model evaluation parameters

Model	Accuracy	Recall	Precision	F1	AUC
Decision tree	0.748	0.748	0.749	0.746	0.807
GBDT	0.845	0.845	0.846	0.845	0.961
Random Forest	0.815	0.815	0.816	0.814	0.947
ExtraTrees	0.866	0.866	0.865	0.865	0.968
BP neural network	0.845	0.845	0.847	0.843	0.949
CatBoost	0.849	0.849	0.866	0.844	0.969
XGBoost	0.857	0.857	0.858	0.857	0.968
LSTM-KELM-Transformer	0.895	0.895	0.899	0.894	0.966





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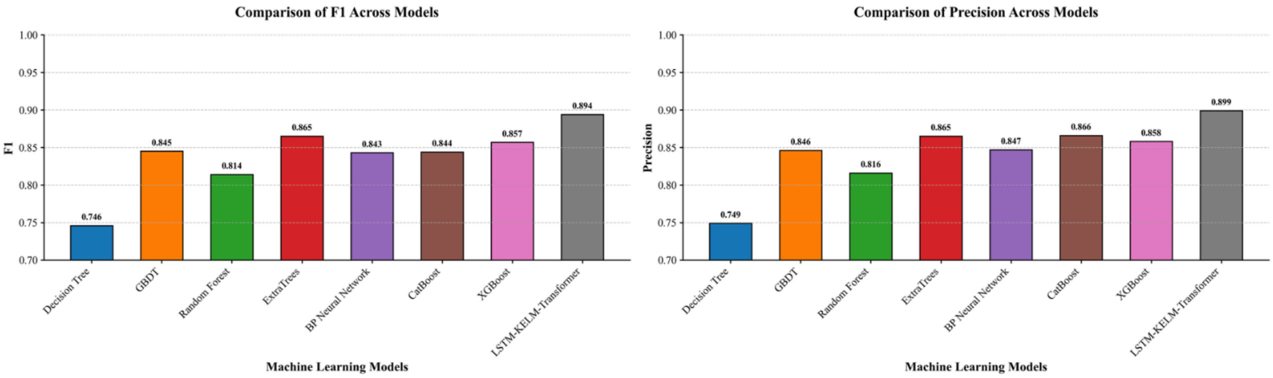

Figure 5. The comparison bar chart of each model in terms of indicators

The LSTM-KELM-Transformer algorithm proposed in this paper demonstrates significant superiority in all core evaluation indicators, with an accuracy rate of 89.5%. It is significantly higher than 74.8% of decision trees, 84.5% of GBDT, 81.5% of random forests, 86.6% of ExtraTrees, 84.5% of BP neural networks, 84.9% of CatBoost and 85.7% of XGBoost. The recall rate remains consistent with the accuracy rate at 89.5%, comprehensively surpassing other comparison algorithms as well. The accuracy rate reached 89.9%, which was higher than the 86.6% of CatBoost, the highest among all comparison algorithms. The F1 value is 89.4%, which is also better than the highest value of other algorithms, namely 86.5% of ExtraTrees. Although the algorithm's 96.6% in the AUC metric is slightly lower than CatBoost's 96.9% and ExtraTrees and XGBoost's 96.8%, it is still at the top level. Moreover, its comprehensive leading position in the four core classification metrics of accuracy, recall rate, precision rate and F1 value. It has been fully demonstrated that the LSTM-KELM-Transformer algorithm has superior comprehensive performance in feature extraction, pattern recognition and classification decision-making. Compared with traditional machine learning algorithms and single deep learning models, it can more accurately capture the complex correlations in the data, thereby achieving more reliable classification results.

5. Conclusion

Highway service areas, as key nodes in the road traffic network, undertake core responsibilities such as passenger flow guidance and vehicle supply. During daily operation, abnormal situations such as people getting lost, vehicles illegally parking, and facility malfunctions often occur. Due to factors such as the periodic fluctuations in passenger flow density, varying levels of equipment configuration, and complex and changeable environmental conditions, the efficiency of emergency response to abnormal events varies greatly. Traditional response methods rely on manual investigation and experience-based judgment, which not only respond slowly but also fail to meet the current requirements of digital and intelligent operation and management. In view of the deficiencies of the existing algorithms in capturing temporal features, fitting nonlinear relationships and mining multi-feature correlations, this paper designs the LSTM-KELM-Transformer classification algorithm. The research first conducted correlation analysis and violin graph analysis, and then carried out comparative experiments through multiple machine learning algorithms. The results showed that this algorithm demonstrated significant advantages in all core evaluation indicators, with an accuracy rate of 89.5%. The recall rate is 89.5%, far exceeding that of decision trees by 74.8%, gradient boosting decision trees by 84.5%, random forests by 81.5%, extreme

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random trees by 86.6%, backpropagation neural networks by 84.5%, category boosting trees by 84.9%, and extreme gradient boosting by 85.7%. It is comprehensively superior to other comparison algorithms. This research achievement provides reliable technical support for improving the efficiency of emergency response to abnormal events in expressway service areas and is of great significance for promoting the digital transformation of service area operation and management.

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