University Security Situation Assessment and Potential Risk Prediction Based on Spatiotemporal Graph Attention Network

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ABSTRACT With the expansion of university scale and the complexity of campus environment, campus safety has evolved into a comprehensive system involving multiple dimensions such as personnel flow, facility operation, and emergencies, including the management of laboratories, public facilities and high-density activity areas. The traditional security assessment methods for universities have limitations such as insufficient consideration of spatiotemporal correlations, weak ability to capture hidden risk patterns, and low prediction accuracy, which make it difficult to meet the needs of intelligent and proactive security management. In response to the above issues, this article proposes a university security situation assessment and risk prediction method based on Spatiotemporal Graph Attention Network (ST-GAT). Firstly, establish a multidimensional safety indicator system for universities that covers four core dimensions: personnel safety, facility safety, environmental safety, and emergency management; Secondly, establish a spatiotemporal graph structure to model the spatial correlation between campus functional areas and the temporal dynamics of safety factors; Once again, design the ST-GAT model, integrate graph attention mechanism to enhance the weights of key spatial nodes, use gate controlled cyclic units to capture longterm temporal dependencies, and achieve comprehensive evaluation of security situations and accurate prediction of potential risks. The graph representation can incorporate access-control, camera and wireless sensing nodes when campus security data are available.

INDEX TERMS university security,spatiotemporal graph attention network,risk prediction,campus management,wireless monitoring

I. INTRODUCTION

A. RESEARCH BACKGROUND

As a gathering place for a large number of teachers, students, and staff, universities have the characteristics of dense personnel, complex functional areas, and frequent personnel flow. With the deep integration of information technology and campus construction, the connotation and extension of university security continue to expand, not only involving traditional security fields such as fire protection, public security, and building safety, but also emerging security issues such as network security, public health, and laboratory hazardous material management [1,2]. According to statistics released by the Ministry of Education, the number of safety incidents in Chinese universities has shown a fluctuating upward trend in the past five years, with facility failures, crowded personnel, and sudden public health emergencies ranking among the top three. These incidents not only threaten the personal and property safety of teachers and students, but also affect the normal teaching order and the social reputation of universities[3].

B. RESEARCH SIGNIFICANCE

1) Theoretical Significance

1. Enrich the theoretical system of university security assessment, break through the limitations of traditional methods that focus on single dimensional or static assessment, construct a spatiotemporal integrated assessment framework, and provide a new theoretical perspective for the intelligent development of campus security management, especially concerning the dynamic risk assessment of specialized facilities like processing labs where safety parameters change constantly.

2. Expand the application scope of spatiotemporal graph attention networks in the field of security management, optimize the model structure and parameter settings based on the characteristics of university security data, and enhance

the adaptability of the model in handling specific security scenarios on campus.

3. Establish a multidimensional university security indicator system that integrates spatiotemporal characteristics, clarify the internal logical relationships and spatiotemporal correlation mechanisms between various security factors, and lay a theoretical foundation for the quantification and visualization of security situations[4].

2) Practical Significance

1. Provide efficient and accurate intelligent tools for the security management departments of universities, realizing the transformation of security management from "passive response" to "active prevention", reducing the occurrence of security incidents, and ensuring the personal and property safety of teachers and students.

2. Improve the efficiency of campus safety resource allocation, help management departments concentrate limited resources on key risk areas and time periods, and reduce safety management costs.

3. Provide reference for the construction of a smart and safe campus, promote the deep integration of information technology and university security management, and provide technical support for the high-quality development of higher education[5].

4. Enrich the practical cases of spatiotemporal graph neural networks in the field of public safety, providing replicable and scalable experience for safety assessment in densely populated public places such as primary and secondary schools, hospitals, and shopping malls[6].

II. RELATED THEORETICAL AND TECHNICAL FOUNDATIONS

A. DEFINITION OF CORE CONCEPTS

Potential risk prediction refers to the use of historical safety data and spatiotemporal correlation information to predict the probability and severity of potential safety events occurring in a certain period in the future through algorithm models. In the context of universities, potential risks mainly include facility failure risks (such as elevator malfunctions, fire alarm device failures), personnel safety risks (such as overcrowding, trampling, abnormal behavior), environmental safety risks (such as extreme weather, geological disasters), emergency management risks (such as insufficient emergency response capabilities), etc.

The spatiotemporal graph attention network is a deep learning model that combines spatial graph attention mechanisms with temporal modeling capabilities [7]. It models the research object as a spatiotemporal graph, where nodes represent entities with spatial attributes (such as campus functional areas), edges represent spatial relationships between entities, and node features dynamically change over time. The model assigns different weights to adjacent nodes through graph attention mechanism to enhance the influence of key nodes; By using temporal modeling modules such as GRU and LSTM to capture the dynamic changes in node features over time, the analysis and prediction of spatiotemporal data can ultimately be achieved[8]. Campus spatiotemporal map is a data structure used to model the spatiotemporal characteristics of campus safety factors [9,10]. The spatial dimension is composed of nodes and edges: nodes correspond to campus functional areas (teaching buildings, dormitories, canteens, laboratories, sports halls, etc.); The edge is determined based on the spatial adjacency and functional correlation between functional areas (such as the adjacency between teaching buildings and canteens, and the functional correlation between dormitories and access control systems). The temporal dimension is reflected through the temporal characteristics of nodes: each node corresponds to corresponding security indicator data at different time intervals (such as 1 hour, 4 hours, 1 day), forming a spatiotemporal graph sequence[11].

B. KEY TECHNICAL SUPPORT

1) Graph Attention Network (GAT) Technology

Graph attention network is a key technology for modeling spatial correlation information[12]. Its core technologies include:

1. Node feature propagation: Collect feature information of adjacent nodes for each node;

2. Attention weight calculation: The attention weight between the target node and adjacent nodes is calculated through neural networks, usually achieved through mechanisms such as additive attention or multiplicative attention;

3. Weighted feature aggregation: Aggregate the feature information of adjacent nodes based on attention weights, and update the feature representation of the target node.

The advantage of GAT lies in its ability to adaptively learn the importance of different adjacent nodes without relying on prior knowledge of graph structure, making it suitable for modeling complex spatial relationships between campus functional areas.

2) Gated Recurrent Unit (GRU) Technology

Gated Recurrent Unit (GRU) is a key technology for modeling time-series data[13]. It is an improved version of the LSTM network, which maintains good temporal dependency capture ability while having a simpler structure and fewer parameters. The core technologies include:

1. Update Gate: Controls the degree to which information from the previous moment is retained until the current moment;

2. Reset Gate: Controls the degree to which information from the previous moment is forgotten;

3. Candidate Hidden States: Generates candidate hidden states for the current time based on the reset gate and input at the current time;

4. Hidden State Update: Updates the current hidden state based on the update gate, previous hidden state, and candidate hidden states.

GRU is suitable for processing long-term data such as campus security monitoring data, and can effectively capture the temporal dynamic changes of security factors.

3) Data Preprocessing Techniques

Data preprocessing is the foundation for ensuring the effectiveness of models, and core technologies include [14]:

1. Data cleaning: Remove outliers and noise data from safety monitoring data, such as sensor failure data and manual recording errors;

2. Data normalization: Normalize the data of different indicators to eliminate the influence of dimensional differences, such as using minimum maximum normalization or Z-score normalization;

3. Missing value filling: Linear interpolation, nearest neighbor interpolation, or time series prediction methods are used to fill in missing data in the time series;

4. Spatiotemporal graph construction: Convert preprocessed data into a spatiotemporal graph sequence, including node definition, edge construction, and feature sequence organization.

III. CONSTRUCTION OF UNIVERSITY SAFETY INDICATOR SYSTEM AND SPATIOTEMPORAL GRAPH MODELING

A. CONSTRUCTION OF UNIVERSITY SAFETY INDICATOR SYSTEM

1) Principles for Constructing Indicator System

1. Principle of comprehensiveness: Covering the core dimensions and key factors of university security, ensuring that the indicator system can comprehensively reflect the campus security situation, and avoiding the omission of important security risk points.

2. Scientific principle: Clear definition of indicators, scientific calculation methods, clear logic between indicators, and the ability to objectively and accurately quantify campus safety status.

3. Principle of operability: The indicator data is easy to collect and obtain, avoiding the setting of difficult to quantify or unavailable indicators, and ensuring the practical application value of the indicator system.

4. Principle of spatiotemporal adaptability: Fully consider the spatiotemporal dynamic characteristics of indicators, select indicators that can reflect spatial differences and temporal changes, and adapt to spatiotemporal graph modeling requirements.

5. Principle of dynamism: The indicator system can be dynamically optimized based on changes in the security situation of universities and adjustments to management needs, ensuring its timeliness and adaptability[15].

2) Indicator System Framework and Content

Based on the above principles, combined with the actual situation of university safety management and expert consultation opinions[16,17], a multidimensional university safety indicator system covering 4 primary indicators, 12 secondary indicators, and 36 tertiary indicators is constructed, as follows:

3) Determination of Indicator Weights

The combination weighting method combining Analytic Hierarchy Process (AHP) and Entropy Weight Method is used to determine the weights of indicators, taking into account both subjective experience and objective data characteristics

1. Determine subjective weights using Analytic Hierarchy Process: A total of 18 experts are invited to score the relative importance of each indicator, including 6 experts from the front line of university safety management, 6 experts in the field of public safety research, and 6 experts in the field of artificial intelligence application. The selection criteria for experts include: more than 5 years of relevant research or work experience, proficiency in university safety management or spatiotemporal data analysis, and no conflict of interest with the research. The expert scoring process follows the principle of independence and objectivity, and the judgment matrix is constructed based on the 1-9 scale method. After consistency testing ($CR < 0.1$), the subjective weights are calculated[18-20].

2. Entropy weight method to determine objective weights: Based on the historical security data of three universities, calculate the information entropy of each indicator, and determine the objective weights according to the size of the information entropy. The smaller the entropy value, the higher the discrimination of the indicator and the greater the weight[21].

3. Combination weight calculation: The weighted average method is used to combine subjective and objective weights.

4) Indicator Weight Sensitivity Analysis

To verify the stability of the indicator weights determined in this study, three weight change scenarios are designed to test the impact of weight changes on the security situation assessment results:

Scenario 1: Core indicator weight adjustment ($\pm 10\%$). Core indicators include "Hazardous Material Leak Alert Count", "Emergency Response Time", "Crowd Density", etc., which are closely related to major safety incidents[22].

Scenario 2: Secondary indicator weight adjustment ($\pm 15\%$). Secondary indicators include "Lighting Equipment Integrity Rate", "Green Coverage Rate", etc., with relatively indirect impact on safety.

Scenario 3: Random adjustment of all indicator weights. Randomly adjust the weight of each indicator within the range of $\pm 20\%$ to simulate the maximum possible deviation of expert judgment.

The assessment results under different scenarios are shown in Table 2. It can be seen that in all three scenarios, the change rate of the security situation assessment score is less than 5%, and there is no substantial change in the risk level classification (high risk, medium risk, low risk). This proves that the indicator weights determined in this study

TABLE 1. University Safety Indicator System Framework

Primary Indicator	Secondary Indicator	Tertiary Indicator	Data Type	Spatiotemporal Characteristics
Personnel Safety	Personnel Density & Flow	Teaching Building Personnel Density; Dormitory Personnel Density; Canteen Personnel Density; Stadium Personnel Density; Campus Entrance/Exit Flow	Numerical	Spatiotemporal Dynamic
Personnel Safety	Personnel Behavior Compliance	Unauthorized Entry Count; Abnormal Behavior Recognition Count; Conflict Incident Count; Mental Health Alert Count	Count	Spatiotemporal Dynamic
Personnel Safety	Special Population Management	Outsider Registration Rate; Visitor Retention Duration; Minor Escort Rate	Ratio/Numerical	Spatiotemporal Dynamic
Facility Safety	Building Safety	Building Structure Integrity Rate; Fire Facility Integrity Rate; Elevator Failure Rate; Emergency Passage Unobstructed Rate	Ratio/Count	Spatially Fixed + Temporally Dynamic
Facility Safety	Equipment Safety	Monitoring Equipment Online Rate; Lighting Equipment Integrity Rate; Power Equipment Failure Rate; Network Equipment Operation Status	Ratio/Status	Spatially Fixed + Temporally Dynamic
Facility Safety	Hazardous Material Management	Lab Hazardous Material Storage Compliance Rate; Hazardous Material Usage Registration Rate; Hazardous Material Leak Alert Count	Ratio/Count	Spatially Fixed + Temporally Dynamic
Environmental Safety	Natural Environment Safety	Extreme Weather Alert Count; Geological Disaster Risk Level; Air Quality Index; Noise Decibel Value	Level/Numerical	Spatiotemporal Dynamic
Environmental Safety	Artificial Environment Safety	Road Integrity Rate; Green Coverage Rate; Manhole Cover Integrity Rate; Campus Sanitation Compliance Rate	Ratio	Spatially Fixed + Temporally Dynamic
Environmental Safety	Public Health Safety	Infectious Disease Alert Count; Drinking Water Qualification Rate; Food Hygiene Compliance Rate; Garbage Disposal Compliance Rate	Count/Ratio	Spatiotemporal Dynamic
Emergency Management	Emergency Preparedness	Emergency Plan Completeness Rate; Emergency Supplies Stock Adequacy Rate; Emergency Team Formation Rate	Ratio	Spatially Fixed + Temporally Dynamic
Emergency Management	Emergency Response	Emergency Response Time; Emergency Disposal Success Rate; Emergency Drill Count	Numerical/Ratio	Spatiotemporal Dynamic

have good stability, and the impact of weight changes on the evaluation results is controllable, which further verifies the scientific rigor of the research[23].

B. CAMPUS SPATIOTEMPORAL MAPPING MODELING

1) Node Definition and Encoding

Based on the campus functional areas as the basic nodes and the spatial layout and functional attributes of universities, the campus is divided into 18 core functional areas, including teaching buildings (3 buildings), dormitory buildings (5 buildings), canteens (2), laboratories (4), sports halls (1), libraries (1), administrative buildings (1), and campus entrances and exits (2). Each node is assigned a unique code to record its spatial coordinates (latitude and longitude) and functional attributes[24].

2) Edge Construction and Weight Calculation

The construction of edges is based on spatial adjacency relationships and functional association relationships, using binary adjacency matrices to represent the connection relationships between nodes:

1. Spatial adjacency edge: If two functional areas are physically adjacent (distance $\leq$ 50 meters), a spatial adjacency edge is constructed with an initial edge weight value of 1; Otherwise, set it to 0[25].

2. Functional association edge: If there is a functional dependency or personnel flow association between two functional areas (such as teaching buildings and canteens, dormitories and campus entrances and exits), a functional association edge is constructed, and the edge weight is calculated based on the historical personnel flow and the degree of functional dependence[26].

3) Construction of Node Feature Sequence

The node feature sequence is composed of security indicator data at each time step, and the specific steps are as follows:

1. Data sampling: Sampling safety indicator data at 1-hour intervals to form a time-series data sequence, with a time window length of 24 hours (i.e. each node feature sequence contains indicator data from 24 time steps)[27,28].

2. Feature normalization: Perform Z-score normalization on the data of each indicator to eliminate dimensional differences.

3. Abnormal signal enhancement: Before feature fusion, an "abnormal signal enhancement module" is added to avoid rare but critical emergency event signals being overwhelmed. For abnormal data that meet the criteria of "values exceeding 3 times the standard deviation" or "belonging to historical high-risk event correlation indicators", an adaptive amplification factor (range: 1.5-3.0) is used for signal enhancement. The amplification factor is dynamically adjusted according to the severity of the event: if there are non-zero records in "Hazardous Material Leak Alert Count" (rare event), the amplification factor is set to 3.0; when "Major Conflict Incident Count" occurs, the amplification factor is set to 2.5; for other abnormal data, the amplification factor is set to 1.5-2.0 according to the risk level[29,30].

4. Feature fusion: A dual-layer weighted fusion strategy of "category weight + indicator specificity weight" is adopted to fuse 36 tertiary indicator data of the same node at the same time step into a feature vector (dimension: 1 $\times$ 36). Firstly, basic weights are assigned according to the indicator categories: numerical type (0.32), counting type (0.28), proportional type (0.25), hierarchical type (0.15), which are calculated by entropy weight method.

5. Spatiotemporal graph sequence generation: Combine the feature sequences of all nodes with the adjacency matrix to form a spatiotemporal graph sequence, which is used for model training and testing.

IV. DESIGN OF A UNIVERSITY SECURITY SITUATION ASSESSMENT AND RISK PREDICTION MODEL BASED ON ST-GAT

A. OVERALL MODEL ARCHITECTURE

The overall architecture of the ST-GAT model is divided into four layers: input layer, spatiotemporal feature extraction layer, situational assessment layer, and risk prediction layer.

1. Input layer: Input the spatiotemporal map sequence of the campus, including the node feature sequence (dimension: batch_2 x time_steps x num_nodes x feature-dim) and the adjacency matrix (dimension: num_nodes x num_nodes).

2. Spatiotemporal feature extraction layer: The core layer includes spatial graph attention module and temporal GRU module, which achieve deep extraction and fusion of spatiotemporal features.

3. Situation assessment layer: Based on the fused spatiotemporal features, the security situation level and overall campus security score of each node (functional area) are output through a fully connected network and softmax function.

B. CORE MODULE DESIGN

1) Sequential GRU module

The temporal GRU module is used to capture the temporal dynamic changes and long-term dependencies of security features. The specific design is as follows:

1. Input reconstruction: concatenate the spatial feature vector (dimension: 1×1024) output by the spatial graph attention module with the original node feature vector (dimension: 1×36) to form the input feature vector (dimension: 1×1060) of the temporal module.

2. GRU layer design: Set up a two-layer GRU network, each layer containing 256 hidden units. The input of the first layer GRU is a temporal feature sequence (dimension: 24×1060), and the output is a hidden state sequence (dimension: 24×256); The second layer GRU further processes the hidden state sequence output from the first layer and outputs the final temporal feature vector (dimension: 1×256) to capture long-term temporal dependencies.

3. Temporal feature fusion: The hidden state of the last time step of the second layer GRU is used as the temporal feature vector of the node, which is concatenated with the spatial feature vector to form the fused spatiotemporal feature vector (dimension: 1×1280).

2) Risk Prediction Layer

The risk prediction layer is used to forecast potential risks in various regions within the next 24 hours

1. Risk type prediction: Input the fused spatiotemporal feature vector into a fully connected network (hidden layer dimension: $512 \rightarrow 256 \rightarrow 128$), and output the probability distribution of six risk types (facility failure, crowding, fire, infectious disease, abnormal behavior, natural disaster) through a softmax function. Take the risk type with a probability greater than 0.3 as the potential risk type.

2. Risk probability and severity prediction: Based on the predicted potential risk types, two independent fully connected networks are used to output the risk occurrence probability (range: 0-1) and severity level (1- 5 levels), respectively. The severity level is determined based on factors such as the risk impact range and loss degree.

3) Model Training Optimization

Optimizer: Adam optimizer is used, with an initial learning rate of 0.001. The learning rate decay strategy is employed, with a decay rate of 0.9 every 10 epochs;

Batch size: 32;

Training epochs: 50;

Regularization: L2 regularization (weight decay coefficient of 0.0001) and dropout (dropout rate of 0.2) are used to prevent overfitting of the model;

Early stop strategy: If the validation set loss does not decrease for 5 consecutive epochs, stop training and save the optimal model.

Based on the theoretical foundation and technical support introduced in Chapter 2, and the university safety indicator system and spatiotemporal graph modeling method constructed in Chapter 3, this study designs the ST-GAT model for university security situation assessment and potential risk prediction (detailed in Chapter

4). To verify the effectiveness and superiority of the proposed model, Chapter 5 designs comparative experiments, including data preparation, selection of comparison methods, determination of evaluation indicators, and in-depth analysis of experimental results. The experimental design aims to comprehensively test the performance of ST-GAT in security situation assessment and risk prediction tasks, and highlight its advantages by comparing with traditional machine learning methods and advanced spatiotemporal deep learning models.

V. EXPERIMENTAL DESIGN AND RESULT ANALYSIS

A. EXPERIMENTAL DATA PREPARATION

1) Data Sources

Experimental data were collected from three universities of different types (comprehensive, science and engineering, and humanities universities) located in Beijing, Shanghai and Guangdong, with the data collection period spanning from September 2024 to August 2025.

The data types include:

1. Personnel flow data: Obtain personnel density and flow volume in various functional areas through campus access control systems and video surveillance facial recognition;

2. Facility operation data: Obtain operation status and fault records of fire-fighting facilities, elevators, monitoring equipment, etc. through IoT sensors;

3. Environmental monitoring data: Obtain relevant environmental indicator data through campus meteorological stations, air quality sensors, and noise sensors;

4. Emergency management data: the completeness of emergency plans, the number of emergency drills, emergency response cases, etc. recorded by the safety management department of universities;

5. Risk event data: Historical security event records, including event type, occurrence time, occurrence area, severity, etc., used for model training and validation.

2) Data Preprocessing and Partitioning

1. Perform data cleaning, normalization, and missing value filling to construct a spatiotemporal graph sequence, resulting in a total of 8760 spatiotemporal graph samples (365 days x 24 hours).

2. Data partitioning: Divide the samples into training set (6132), validation set (876), and testing set (1752) in a ratio of 7:1:2, ensuring that the time distribution of the training set, validation set, and testing set is consistent to avoid data leakage.

B. COMPARATIVE EXPERIMENTAL DESIGN

1) Comparison Method

Select 6 representative methods as comparison objects:

1. Traditional machine learning methods: Support Vector Machine (SVM), Random Forest (RF);
2. Mainstream deep learning methods: Long Short Term Memory (LSTM), Graph Convolutional Network (GCN), Graph Attention Network (GAT, without temporal modules);
3. Improved spatiotemporal model: Spatiotemporal Graph Convolutional Network (ST-GCN).

2) Evaluation Indicators

Set two types of evaluation indicators according to the experimental task:

1. Security situation assessment indicators: Accuracy, Macro-F1, Micro-F1;
2. Risk prediction indicators: Precision, Recall, F1 Score, Root Mean Square Error (RMSE).

C. EXPERIMENTAL RESULTS AND ANALYSIS

1) Results of Security Situation Assessment

The security situation assessment results of each method are shown in Table 2:

TABLE 2. Comparison of Security Situation Assessment Results of Different Methods

Method	Assessment Accuracy (%)	Macro-F1 Score (%)	Micro-F1 Score (%)
SVM	68.3±3.2	65.7±3.5	67.2±3.3
RF	75.6±2.8	73.2±3.1	74.8±2.9
LSTM	81.5±2.5	79.3±2.7	80.6±2.6
GCN	83.2±2.3	81.5±2.4	82.8±2.3
GAT (No Temporal)	85.7±2.1	83.9±2.2	85.1±2.1
ST-GCN	88.9±1.8	87.2±1.9	88.5±1.8
ST-GAT (Ours)	94.6±1.5	93.8±1.6	94.3±1.5

From Table 2, it can be seen that:

1. The ST-GAT model proposed in this article is significantly superior to other comparative methods in all evaluation indicators, with an evaluation accuracy of 94.6%, which is 19.0 percentage points higher than traditional RF methods and 5.7 percentage points higher than ST-GCN, verifying the effectiveness of spatiotemporal feature fusion and attention mechanism;
2. Models that consider spatial correlation (GCN, GAT, ST-GCN, ST-GAT) perform better than models that do not consider spatial correlation (SVM, RF, LSTM), indicating that the spatial correlation of campus safety factors has a significant impact on the evaluation results;
3. Models that simultaneously consider spatiotemporal features (ST-GCN, ST-GAT) perform better than models that only consider a single dimension (LSTM, GAT), demonstrating that the organic fusion of spatiotemporal features can improve evaluation accuracy;
4. ST-GAT is superior to ST-GCN, indicating that graph attention mechanism can more accurately capture spatial correlations of key regions and improve feature representation ability.

2) Risk Prediction Results

The risk prediction results of each method are shown in Table 3:

TABLE 3. Comparison of Risk Prediction Results of Different Methods

Method	Precision (%)	Recall (%)	F1 Score (%)	RMSE
SVM	62.5±4.1	58.3±4.5	60.3±4.3	0.286
RF	69.8±3.7	65.7±3.9	67.7±3.8	0.243
LSTM	76.4±3.2	72.5±3.4	74.4±3.3	0.198
GCN	78.6±3.0	75.2±3.2	76.9±3.1	0.182
GAT (No Temporal)	81.3±2.8	78.6±2.9	79.9±2.8	0.165
ST-GCN	85.7±2.5	83.2±2.6	84.4±2.5	0.138
ST-GAT (Ours)	92.4±2.1	90.8±2.2	91.6±2.1	0.096

From Table 3, it can be seen that:

1. The ST-GAT model performs the best in all indicators of risk prediction, with an F1 value of 91.6%, which is 23.9 percentage points higher than the RF method and 7.2 percentage points higher than the ST-GCN method. The RMSE is only 0.096, significantly lower than other methods, proving that the model can accurately predict potential risks;
2. Recall rate is a key indicator for risk prediction (to avoid missing high-risk events). The recall rate of ST-GAT reaches 90.8%, which is 18.3 percentage points higher than LSTM and can effectively identify hidden security risks;
3. The recall rate of GAT models that only consider spatial correlations is lower than that of ST-GAT, indicating that temporal dynamic features are crucial for risk prediction and can capture the temporal evolution of risk events;
4. Traditional machine learning methods have poor predictive performance and are difficult to handle the complex spatiotemporal correlations of campus safety data, while deep learning models have improved their predictive performance through automatic feature extraction capabilities.

In risk prediction tasks, the advantage of ST-GAT over ST-GCN is mainly reflected in the capture of temporal evolution laws of risks and the integration of spatiotemporal information. ST-GCN's temporal modeling is limited to local temporal convolution, which can only capture short-term temporal dependencies, while ST-GAT's GRU module can effectively mine long-term temporal evolution characteristics of risks (e.g., seasonal infectious disease risks and periodic facility failure risks).

Experimental results show that for time-varying risks such as crowding during meal peaks and laboratory hazardous material management risks, ST-GAT's prediction F1 score is 7.2 percentage points higher than ST-GCN, and the RMSE is reduced by 0.042. This is because ST-GAT can dynamically adjust the weight of temporal features according to the change trend of risk factors, while ST-GCN's fixed temporal convolution kernel cannot adapt to the dynamic changes of risk factors.

In addition, ST-GAT's deep fusion of spatiotemporal features enables it to better capture the interaction between spatial and temporal risk factors (e.g., the impact of long-distance personnel flow between dormitories and canteens on crowding risks). ST-GCN's parallel fusion mode ignores this interaction, leading to lower prediction accuracy for complex spatiotemporal correlation risks.

3) Results of Ablation Experiment

To verify the effectiveness of each core module of ST-GAT, ablation experiments were designed, and the results are shown in Table 4:

TABLE 4. Results of Ablation Experiment

Model Configuration	Assessment Accuracy (%)	Risk Prediction F1 Score (%)	Overall Performance Score (%)
ST-GAT (Full Model)	94.6	91.6	93.1
Remove Spatial Attention Module	86.3	82.5	84.4
Remove Temporal GRU Module	85.7	81.8	83.8
Remove Multi-Head Attention Mechanism	90.2	87.3	88.8
Remove Feature Fusion Module	88.5	85.6	87.1

From Table 4, it can be seen that:

After removing the spatial attention module or temporal GRU module, the model performance significantly decreased, with evaluation accuracy decreasing by 8.3 percentage points and 8.9 percentage points respectively, and risk prediction F1 values decreasing by 9.1 percentage points and 9.8 percentage points respectively. This proves that the spatial attention module and temporal GRU module are the core of the model, and their fusion is the key to improving performance;

After removing the multi head attention mechanism, the performance of the model decreased, indicating that multi head attention can enhance the stability and comprehensiveness of spatial feature representation; After removing the feature fusion module (directly using a single spatial or temporal feature), the performance of the model decreases, proving that deep fusion of spatiotemporal features can complement each other's advantages and improve overall performance.

4) Generalization Performance Analysis of Different Universities

To verify the generalization ability of the model, its performance was evaluated on test sets from three different types of universities. The results are shown in Table 5:

TABLE 5. Generalization Performance of the Model in Different Universities

University Type	Assessment Accuracy (%)	Risk Prediction F1 Score (%)	RMSE
Comprehensive University	95.2±1.4	92.3±2.0	0.091
Science & Engineering University	93.8±1.6	90.5±2.3	0.102
Liberal Arts University	94.3±1.5	91.1±2.2	0.098

From Table 5, it can be seen that:

1. The model showed good performance on test sets from three different types of universities, with evaluation accuracy higher than 93.8%, risk prediction F1 values higher than 90.5%, and RMSE lower than 0.102, demonstrating strong generalization ability of the model;

2. The model performance of comprehensive universities is slightly better, possibly due to their more comprehensive functional areas and more balanced data distribution;

3. The RMSE of science and engineering universities is slightly higher, possibly due to the large number of laboratories and more complex safety factors such as hazardous material management. However, the model can still maintain high prediction accuracy and meet practical application needs.

5) Visualization of Feature Fusion Effect

The horizontal axis represents time steps (1 hour interval, 24 time steps in total), and the vertical axis represents the normalized signal intensity. It can be seen that after feature fusion, the effective signals of heterogeneous indicators (such as "Air Quality Index" and "Unauthorized Entry Count") are fully retained, and there is no mutual interference. For rare critical events (such as the hazardous material leak alert at time step 16), the signal intensity is significantly enhanced after passing through the abnormal signal enhancement module, which is clearly distinguishable from normal signals. Quantitative statistics show that the recognition recall rate of key events is increased by 12.7% after feature fusion and signal enhancement, verifying the effectiveness of the proposed method.

VI. CONCLUSION

This article proposes a university security situation assessment and potential risk prediction method based on spatiotemporal graph attention network (ST-GAT) to address the issues of insufficient consideration of spatiotemporal correlation and low accuracy of risk prediction in traditional university security assessment methods, a model that could be adapted for fine-grained risk monitoring in high-hazard areas like university chemical testing facilities. The main research conclusions are as follows:

1. A multidimensional university safety indicator system that integrates spatiotemporal characteristics has been constructed, covering four dimensions: personnel safety, facility safety, environmental safety, and emergency management.

The spatiotemporal characteristics and weights of each indicator have been clarified, providing a scientific basis for safety situation assessment and risk prediction.

2. A spatiotemporal graph modeling method applicable to campus safety data has been established, with campus functional areas as nodes, spatial adjacency and functional association as edges, and safety indicator time-series data as node features, effectively modeling the complex spatiotemporal structure of campus safety systems.

3. Designed the ST-GAT model, which captures spatial correlations between functional regions through spatial graph attention module and temporal GRU module captures temporal dynamic changes of security factors, achieving deep fusion of spatiotemporal features and improving the accuracy of evaluation and prediction.

4. This method provides an efficient and accurate intelligent tool for university safety management, which can promote the transformation of safety management from "passive response" to "active prevention", provide technical support for the construction of a smart and safe campus, and also provide valuable experience for safety assessment of other crowded public places.

AUTHOR CONTRIBUTIONS

Conceptualization –Haiwei Wang and Feng Xu; methodology – Haiwei Wang and Feng Xu; investigation – Haiwei Wang and Feng Xu; writing-original draft preparation – Haiwei Wang and Feng Xu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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