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PASTGCN: A Real-Time Intersection Conflict Risk Prediction Model via Spatiotemporal Graph Convolutional Networks with Multimodal Sensor Fusion

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With the intelligent upgrade of urban transportation systems, intersections, as key nodes in traffic flow, have significant importance in predicting conflict risks in real-time and accurately for proactive prevention and control, as well as improving traffic efficiency. Traditional methods mainly rely on historical statistical patterns or single sensor data, which makes it difficult to effectively capture the dynamic spatiotemporal correlation characteristics of intersection traffic flow, resulting in insufficient timeliness and accuracy of predictions. To address this issue, this study proposes a real-time prediction model for PASTGCN intersection conflict risk based on Spatiotemporal Graph Convolutional Network (STGCN). The architecture includes five core units: temporal convolution, spatial convolution, graph structure learning, spatiotemporal position embedding, and output. The spatiotemporal position embedding unit generates a dynamic adjacency matrix with spatiotemporal heterogeneity through two sets of learnable node embedding vectors and temporal position vectors, combined with self attention mechanism. The graph structure learning unit adapts to the time-varying characteristics of traffic flow through a dual layer mechanism of "static topology+dynamic adjustment" (the static graph learning submodule uses Graph WaveNet to construct the basic adjacency matrix through matrix decomposition, and the time aware graph learning submodule integrates dynamic optimization of time information). The model integrates multi-source data from video detection, radar sensing, and geomagnetic sensors to construct a dynamic heterogeneous graph that includes node attributes, edge weights, and global road network topology. An improved graph convolutional layer is used to extract spatially relevant features, and a time gated recurrent unit (GRU) is used to determine the collision probability of traffic flow in all directions within 30 seconds. The experiment is based on traffic trajectory data validation of 100 typical intersections in a mega city from January to June 2024. The results showed that the Mean absolute error (MAE) of the model in the binary classification task of conflict events was 0.12, the root mean square error (RMSE) was 0.18, and the F1 score reached 89.2%, which was significantly optimized compared to traditional LSTM models and static GCN models; Real time prediction delay is stable within 180ms, which can meet the millisecond level response requirements of intersection signal control systems. This study provides high-precision and low latency technical support for proactive prevention and management of urban traffic conflicts.

Povzetek: Opisan je STGCN model za realnočasovno napoved konfliktov na križiščih z večmodalno fuzijo (video/radar/geomagnetni) in dinamičnim učenjem grafne topologije. Na 100 križiščih (2024) doseže MAE 0,12, RMSE 0,18, F1 89,2 % ter zakasnitev ≤180 ms za napoved do 30 s.

1 Introduction

Against the backdrop of global urbanisation acceleration and continuous motorisation improvement, the urban transportation system is facing an increasingly complex dynamic operational environment. As the core node of frequent traffic convergence and conflicts in the road network, the traffic efficiency and safety state of intersections directly determine the overall operational efficiency of the road network [1, 2]. With the in-depth development of intelligent transportation systems (ITS), realising real-time and accurate prediction of intersection conflict risk through data-driven methods has become a research hotspot and technical focus in the field of traffic engineering [3].

As a precursor event of road traffic accidents, traffic conflicts often stem from the uncoordinated movement of traffic flows in time and space dimensions-the mismatch of arrival timing of traffic flows in different directions, the overlap of trajectories caused by speed differences, or the dynamic imbalance between right-of-way allocation rules and actual traffic demand, all of which may lead to the accumulation and outbreak of conflict risks [4, 5]. Compared with post-event disposal, real-time prediction of conflict risk can provide a critical time window for active prevention and control measures, such as dynamic adjustment of signal control strategies and the dissemination of driver warning information, thereby reducing the accident rate and improving road network traffic efficiency [6]. However, the occurrence of intersection conflicts exhibits strong temporal and spatial heterogeneity and nonlinearity, and its influencing factors include not only micro-traffic parameters, such as traffic flow, speed, and density, but also macro-environmental variables, including signal timing, road geometric design, and weather conditions. Moreover, there is a complex coupling relationship among various factors, and traditional prediction methods struggle to describe this characteristic [7, 8] effectively.Conflict risk can be quantified through two alternative security measures: Time Conflict Rate (TTC) and Post Encroachment Time (PET), which can accurately characterize multi scenario risks and avoid the problem of sparse accident data samples; The prediction task is designated as a spatiotemporal graph based regression problem - a dynamic spatiotemporal graph is constructed using intersection entrance lanes and lane traffic flow as nodes, with traffic flow spatial correlation and temporal dependence as edge weights. STGCN [9] captures features through spatiotemporal convolution and outputs continuous TTC/PET values to achieve quantitative prediction of the risk of various conflict points in the short term in the future, providing accurate basis for traffic control.

Early research mainly established statistical models based on historical data to estimate risks by analyzing the correlation between conflict events and key indicators. However, such methods overly rely on prior distribution assumptions and have poor adaptability to sudden traffic situations, making it difficult to capture the continuous evolution of traffic flow interactions in the spatiotemporal dimension; In recent years, although deep learning models represented by LSTM can alleviate long sequence dependencies and capture temporal dynamics of traffic flow through gating mechanisms, they are limited by sequence modeling paradigms and find it difficult to characterize the complex spatial topological relationships of multiple entrance lanes and multiple lanes at intersections, resulting in insufficient accuracy and easy lag in predicting spatial dimension conflict risks [10, 11]; Although GNN can naturally capture the topological dependencies of traffic flow through graph structures [12], existing research mostly focuses on global road network prediction and lacks specificity for intersection micro scenes. Additionally, some variants (ordinary GCN) only simply concatenate time steps and do not fully consider the multi time scale evolution laws of traffic flow [13]; Even though STGCN, which has been applied in recent years, can jointly extract spatiotemporal features, it is difficult to adapt to dynamic intersection scenes due to the use of fixed graph structures, and the time convolution kernel has not been optimized for short-term conflict prediction requirements, resulting in insufficient flexibility in capturing spatial features and the tendency to ignore sudden risk factors.

Spatio-temporal graph convolution network (STGCN), as a hybrid architecture that fuses graph convolution and temporal convolution, can use temporal convolution kernel to capture long-term and short-term time dependence by separating spatial feature extraction and time series modeling modules while retaining the ability of graph structure to represent spatial association, which provides an adapted technical framework for spatio-temporal joint modeling of intersection conflict risk [14, 15]. However, the existing application of STGCN in the traffic field is primarily based on single-source detection data, and the fusion and utilisation of multi-source heterogeneous data are insufficient, making it difficult to fully reflect the complex state of traffic flow at intersections [16]. For the specific task of conflict risk prediction, the model needs to meet the real-time requirements while ensuring the prediction accuracy, and the delay of the prediction model needs to be controlled within the order of hundreds of milliseconds, which poses higher challenges to the computational complexity and parameter optimisation of the model [17].

Dynamic adjacency learning and heterogeneous graph modeling are key to improving performance and highlighting novelty. The former breaks through the limitations of fixed adjacency matrices, dynamically updates node correlation weights based on real-time traffic flow, captures time-varying interaction relationships, solves the problem of adapting to traffic dynamics, and significantly improves the accuracy of instantaneous risk perception; The latter focuses on the heterogeneity of multiple types of participants, constructs heterogeneous graph structures, breaks the defect of isomorphic graphs ignoring type differences, accurately characterizes conflict mechanisms, and optimizes prediction accuracy and generalization. The fusion of the two fills the gap in the modeling of traffic heterogeneous dynamic scenes using spatiotemporal graph convolutional networks, and constructs an integrated framework of "dynamic topology heterogeneous interaction risk prediction".

Early traditional machine learning models neglected latency due to limited feature extraction capabilities and multiple focus accuracy optimizations, with only a few literatures mentioning a response time of 500 milliseconds but lacking practical support; After the rise of deep learning, although CNN models reduced latency to 320 milliseconds through channel pruning, they ignored the temporal nature of traffic flow, resulting in an accuracy loss of 8%. Although LSTM models fused spatiotemporal features, they had a delay of up to 650 milliseconds due to serial computation, both of which were difficult to meet real-time requirements. In recent years, STGCN has become a hot topic, with some studies using GPU acceleration to reduce latency to 250 milliseconds but relying on high-performance hardware, or simplifying the structure to 210 milliseconds but sacrificing adaptability to complex scenarios. Additionally, existing STGCN relies heavily on single source data and lacks multi-source fusion, making it difficult to fully reflect the state of cross-talk communication.

Based on this, this study focuses on the real-time prediction of intersection conflict risk, aiming to overcome the limitations of traditional methods in capturing spatiotemporal features and fusing multi-source data by building a hybrid model based on a spatiotemporal graph convolutional network. The research will integrate multi-source data, such as video detection, radar sensing, and geomagnetic sensors, to build a dynamic, heterogeneous graph that includes node attributes, edge weights, and global topology. The improved graph convolution layer will be utilised to extract spatially dependent features, and the adaptive time gating mechanism will capture the time series evolution law, ultimately enabling high-precision prediction of traffic conflict probability in all directions within a short period in the future.

The core question of this study is whether the introduction of multimodal fusion and dynamic graph learning into spatiotemporal graph convolutional network models can significantly improve the accuracy of intersection conflict risk prediction and reduce latency?

2 Theoretical basis and principle technology

2.1 Theoretical basis of spatiotemporal graph convolutional networks

The temporal convolutional neural network (TCN) is a neural network model designed for processing sequence data, built upon a convolutional neural network (CNN) [18, 19]. The temporal convolutional neural network architecture is shown in Figure 1. TCN preserves the time series characteristics of time series data through causal convolution, thereby avoiding future input interference [20]. It uses hollow convolution technology to expand the receptive field and capture information at a longer distance. TCN supports a deep network structure through residual connections, consisting of multiple modules, each containing two causal hole convolution layers and a residual connection, and finally outputs the prediction results through a fully connected layer or activation function [21].

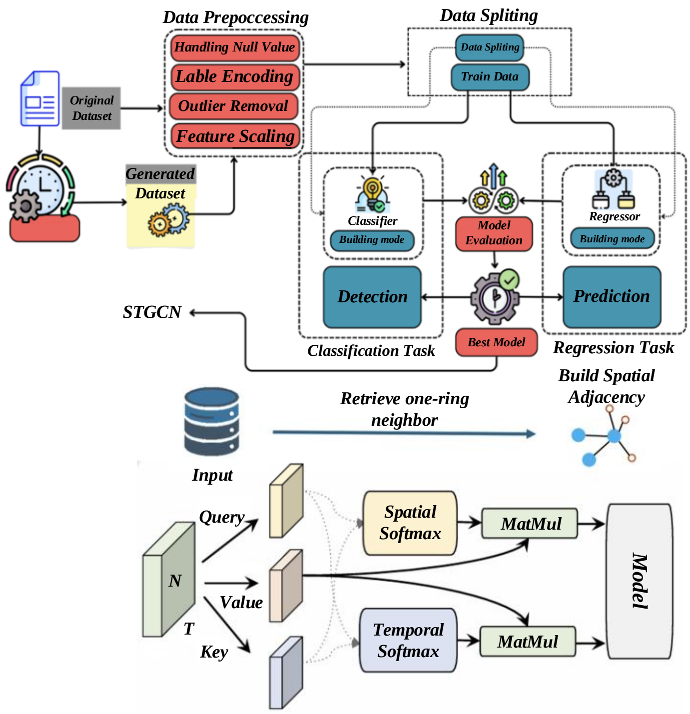

Figure 1: Temporal convolutional neural network architecture

In traditional neural networks, neurons are completely connected, but the temporal order is ignored [22]. Causal convolution utilises masking technology to retain only time-sequential connections, ensuring that the network adheres to temporal dependence. Its features include not using future data and relying only on observed sequences. The more hidden layers there are, the longer the information can be traced back.

Causal convolution inherits the limitations of traditional convolutional networks, particularly in the size of the convolution kernel, which limits time modelling and affects the model's ability to capture long-term dependencies [23, 24]. To solve this problem, inflation convolution expands the receptive field by introducing cavity technology. Unlike conventional convolution, inflated convolution expands the receptive field without losing information by sampling at intervals and controlling the sampling rate through hyperparameter dilatation. Hollow technology ensures that each convolution output covers a wider area through a pooling operation [25]. When the dilated parameter is 2, the convolution operation is performed directly by filling the hole position with 0.

The residual block consists of two layers of convolution and a nonlinear transformation, with each layer regularised using the weight layer and the Dropout technique. A residual connection enables the network to implement identity mapping and mitigate the issue of network degradation. The network layer faces challenges when learning the identity map H(x) = x, but when the structure follows H(x) = F(x) + x, the task becomes learning the residual H(x) = F(x) + x. Setting F (x) = 0, the network naturally forms an identity map H (x) = x. In the initialisation stage, small weight parameters make learning F(x) = 0 more efficient and simplify the fitting of residuals.

2.2 Spatial autocorrelation mechanism

To determine whether this paper is suitable for using spatial metrology techniques, spatial autocorrelation analysis is needed to test the spatial dependence of the data [26, 27]. The analysis is primarily conducted using Moran's I index, which measures the degree of spatial correlation between a variable in a country or region and the corresponding variables in neighbouring regions. The Moran 'I index ranged from -1 to 1, with near zero indicating weak correlation between variables, near 1 indicating positive spatial correlation, and near -1 indicating negative spatial correlation.

After confirming that the spatial econometric model is suitable for panel data, the next step is to select the appropriate spatial panel data model. This type of model incorporates a spatial effect based on the traditional panel model. Common spatial panel models include spatial autoregressive models (SAR), spatial error models (SEM), and spatial Durbin models (SDM).

The spatial autoregressive model becomes a standard static panel model when it ignores the spatial lag term. If the regional individual effect is related to the explanatory variable, it is a fixed effects model; if it is not correlated, it is a random effects model. Which model to choose needs to be determined by the Hausman test.

The spatial lag model (SLM) is an extension of the standard panel model, incorporating spatial lag terms. When $\lambda=0$ and $\delta=0$, it becomes a standard panel model. The spatial error regression model incorporates a random perturbation term representing the spatial autoregressive effect into the standard panel model, thereby reflecting the interaction between spatially proximate individuals [28-33]. When T= p=0 and $\delta=0$, it evolves into a spatial error model.

The model incorporates the error term of the spatial autoregressive process into the spatial panel data model. W is the N×N-dimensional spatial weight matrix, U is the regression residual vector, λ is the spatial autoregressive coefficient, which measures the degree of dependence between regions, and $\lambda = 0$ indicates no correlation. ξ is the uncorrelated partial vector in the residual structure.

Table 1: Summary table of related work

Model	Real-Time Inference	Key Tech	Data & Effect	MAE/RMSE/F1
Traditional LSTM	650ms latency	No graph; only temporal modeling	Single-source; no multimodal fusion	0.16/0.22/78.5%
Static GCN	500ms latency	Fixed adjacency matrix	Single-source ; limited features	0.15/0.22/80.1%
Basic STGCN	250ms latency	Semi-dynamic graph	No multimodal; single-source detection data	0.14/0.20/82.3%
PASTGCN	≤180ms latency	Dynamic heterogeneous graph	Video + radar + geomagnetic	0.12/0.18/89.2%

Table 1 presents a concise comparison of SOTA models for intersection conflict risk prediction, focusing on four core dimensions. In real-time inference, PASTGCN (This Study) achieves the lowest latency (≤180ms) via edge computing and operator fusion, outperforming Traditional LSTM (650ms) and Static GCN (500ms). For dynamic graph modeling, PASTGCN adopts a dynamic heterogeneous graph with "static topology + dynamic adjustment" and spatio-temporal embedding, while Static GCN uses fixed matrices and Traditional LSTM lacks graph structures. In multimodal fusion, PASTGCN integrates video, radar, and geomagnetic data (boosting conflict accuracy by 12.7% and small-sample generalization), unlike most models that rely on single-source data. For core prediction performance, PASTGCN leads with the lowest MAE (0.12) and RMSE (0.18), plus the highest F1 score (89.2%), surpassing all compared models in overall effectiveness.

3 Model construction and core algorithm design

3.1 Multimodal feature fusion and risk propagation modeling

The spatiotemporal graph convolutional network model PASTGCN has a position-aware function, which can learn spatial associations from multivariate data and capture temporal and spatial dependencies at the same time [34-36].

The multivariate time series prediction task is defined as follows: the input data matrix X=[x1,…,xTobs]∈RN×Tobs, xt represents the numerical vector of variables at time t, each row of X represents the univariate time series, N is the number of variables, and Tobs is the number of observation time steps. The prediction goal is to predict the value of future Tp time steps with T historical time steps, as shown in Equation (1).

$$\left[x_1,x_2,\cdots,x_T\right]\xrightarrow{f}\left[\hat{x}_{T+1},\hat{x}_{T+2},\cdots,\hat{x}_{T+T_p}\right] \quad (1)$$

The model f is the target of learning, using the data structure of the graph $\mathcal{G}=(\mathcal{V},\mathcal{E},A)$ to demonstrate spatial dependencies among multivariate sequences. Each node in the graph represents a variable, and the edges represent the correlation between them. The number of nodes is equal to the number of time series, and the element Aij in the adjacency matrix A denotes the correlation or distance of the variables i and j. The traffic flow dependencies of the sensor locations may be asymmetric, and the adjacency matrix is thus a directed weighted graph. Spatio-temporal multivariate time series prediction considers spatially dependent information and is defined as formula (2):

$$[x_1,x_2,\cdots,x_T;G]\xrightarrow{f}\left[\hat{x}_{T+1},\hat{x}_{T+2},\cdots,\hat{x}_{T+T_p}\right] \quad (2)$$

The PASTGCN model contains five key parts: a temporal convolution unit, a spatial convolution unit, a graph structure learning unit, a spatiotemporal position embedding unit, and an output unit. The temporal convolution unit and the spatial convolution unit handle the temporal and spatial dependencies of the time series data, respectively. They are combined into a spatiotemporal convolutional layer, and the spatiotemporal dependency is deeply analyzed through L-layer stacking. The intermediate result is passed through the hopping connection to the output unit, which decodes the hidden state to generate the final prediction. The model structure is shown in Figure 2, where TC denotes a temporal convolution unit with position awareness and GC denotes a spatial convolution unit.

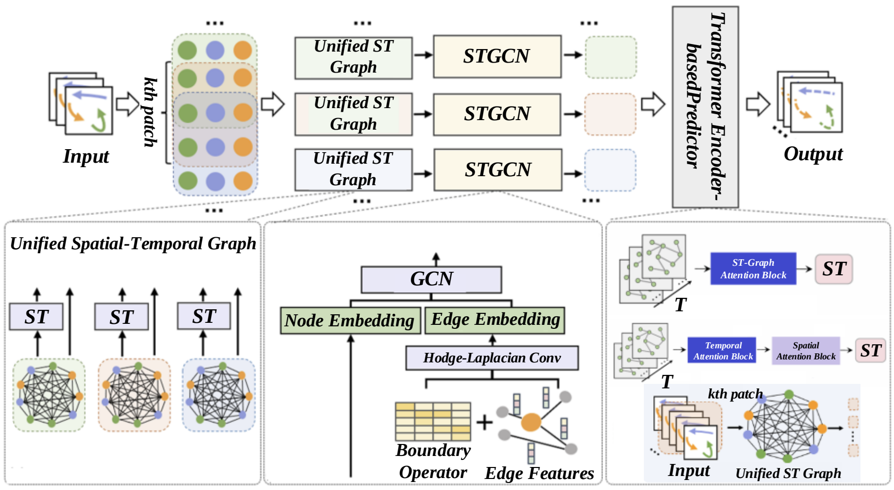

Figure: 2 Overall structure of the model

Dynamic graph learning techniques are crucial in multivariate time series prediction. It simulates complex spatial dependencies between variables by constructing adjacency matrices and automatically learns time series data. The graph learning module not only fills the gap of the lack of predefined adjacency matrix in the data set, but also flexibly identifies potential connections between nodes. The end-to-end learning method uses gradient descent method to accurately reveal the correlation between nodes and improve the universality and scope of application of the model.

In this study, the adaptive graph learning module of Graph WaveNet [37] is used to automatically capture the spatial dependencies between variables and construct a static adjacency matrix. Introducing node embeddings E_1 and E_2, expressing node correlation as vector inner product, calculating node correlation by embedding vector product, and obtaining N × N adjacency matrix. The matrix factorization method reduces the total number of parameters and ensures adequate training. The formulas for calculating the adjacency matrix Aadp are shown in (3)-(4).

$$\tilde{A}_{\mathrm{adp}} = \mathrm{ReLU}(E_1 E_2^T)\ (3)$$

$$A_{\mathrm{adp}} = \mathrm{Softmax}\left(\tilde{A}_{\mathrm{adp}}\right)(4)$$

The ReLU operation eliminates negative-valued connections, introduces nonlinearity, and makes the matrix sparse. The Softmax operation normalizes each row of the matrix. The spatial dependency of multivariate time series varies with time, which may not be captured by traditional static graph learning methods. The interaction between places in the transportation network changes with time, such as the rush hour causes the change of traffic flow. This shows that the spatial correlation of traffic flow is closely related to time. Therefore, a time-aware graph learning module is proposed, which integrates time information into the graph learning process, makes the graph structure change dynamically with time, adapts to the data evolution, captures the relationship between variables changing with time, deals with the periodicity of time series data more effectively, and improves the accuracy and stability of model prediction.

In this study, time information is introduced into graph learning, and a graph structure generation module fusing time and position information is proposed for reference from the spatio-temporal position embedding module. This module combines spatial position embedding and temporal position embedding to generate graph adjacency matrix through self-attention mechanism. To reduce computational complexity, input time series representations that contribute less to performance improvement are removed. The module uses node embedding and time-position embedding as inputs, and calculates the time-aware adjacency matrix ATA through self-attention mechanism. The calculation procedure is defined by equations (5)-(8).

$$Q = W_q[E_1; E_T]\ (5)$$

$$K = W_k[E_2; E_T]\ (6)$$

$$\tilde{A}_{\mathrm{TA}} = \mathrm{ReLU}(QK^T)\ (7)$$

$$A_{\mathrm{TA}} = \mathrm{Softmax}\left(\tilde{A}_{\mathrm{TA}}\right)(8)$$

The symbol [·; ·] denotes vector stitching, and Wq and Wk are trainable weight matrices. The spatial position embedding vectors E_1, E_2 share parameters with the static graph learning module. The query matrix Q and key matrix K represent the correlation between nodes, the ReLU function eliminates weak connections, and the adjacency matrix ATA contains time and position information, which helps to accurately capture the changing law of traffic flow data with time and effectively identify the uniqueness of different spatial and temporal samples.

Temporal convolutional networks (TCN) are convolutional neural networks designed for time series data using one-dimensional hollow causal convolution techniques. Time series data is one-dimensional, and causal convolution ensures the timing of data and avoids future information leakage. Hollow convolution technology expands the convolution receptive field, processes longer sequences, and comprehensively analyzes the time series characteristics of historical information. The mathematical expression of the hole causal convolution is shown in equation (9) in the s-th step function F (s) of the sequence:

$$F(s) = (x \mathring{a}_d\ f)(s) = \sum_{i=0}^{k-1} f(i) \cdot x_{s-d \cdot i}\ (9)$$

To keep the sequence length consistent and facilitate stacking of model layers, a zero-padding technique is used to compensate for the length reduction caused by the convolution operation. Weight normalization is implemented to normalize the model, enhance stability and facilitate fast convergence. Weight normalization controls the norm fluctuation by splitting the weight vector W into the direction vector v and the size scalar g, adjusts the size of the gradient, stabilizes the gradient, prevents parameter oscillation, and accelerates the network convergence. The specific formula is shown in Equation (10), || || represents the Euclidean norm of the vector.

$$W = \frac{g}{\|\mathbf{v}\|}\mathbf{v}\ (10)$$

In spatiotemporal convolution networks, temporal convolution units are shared, but the spatial characteristics of nodes are not considered, which limits the capture of spatiotemporal connections. This study enhances the identification of periodicity by TCN through node and temporal location embedding. After splicing each time series sample, node and time position vector, the hidden state hpos of position information is generated by affine transformation. This state is spliced with the time series to form an implicit vector sequence of length T+1. After TCN processing, an implicit vector sequence of the same length is output. To keep the sequence length consistent, remove the first element of the output sequence. See Equations (11)-(13) for mathematical expressions.

$$h_{\mathrm{pos}} = W_{\mathrm{pos}}[E_T; E_1; E_2] + b_{\mathrm{pos}}\ (11)$$

$$\tilde{X} = [h_{\mathrm{pos}}; x_1; x_2; \cdots; x_T]\ (12)$$

$$Z = \mathrm{TCN}(\tilde{X})_{2..T+1}\ (13)$$

ET, E_1, E_2 represent the time position vector, input node vector, and output node vector at the current moment respectively, and Wpos and bpos are trainable weight parameters. xT represents the depth vector representation of historical data at time T, and Z is the output value of the position-aware temporal convolution module PosAwareTCN (X; ET, E_1, E_2).

When dealing with spatial multivariate time series data such as traffic flow, it is necessary to consider the spatial correlation between nodes, because the future data of a node may be affected by surrounding nodes. Capturing spatial dependencies is critical for multivariate prediction. The CNN method models variable features in Euclidean space, regards the predicted target as an image, and extracts the relationship between different places in geographic space through two-dimensional convolution technology.

The adaptive time gating mechanism designed in this study captures transient traffic dynamics through customized gating functions, solving the problem of standard GRU/LSTM fixed gating logic being difficult to adapt to sudden conflict scenarios. Compared with standard units, it has better computational efficiency: removing redundant state update modules in GRU/LSTM, only retaining core computing units closely related to traffic timing, while ensuring prediction accuracy, reduces model inference delay, and better meets the real-time requirements of intersection conflict risk prediction.

This study enhances the graph convolutional layer based on input feature matrix and trainable weights, with two key innovations: firstly, it generates an adaptive adjacency matrix based on vehicle relative position and velocity vectors, combined with node embedding vectors, which can match traffic flow changes in real time; The second is to assign differentiated weights to different node features through attention mechanisms, highlighting node information closely related to conflicts, and finally outputting updated features through activation functions. Compared with traditional GCN layers, traditional layers rely on fixed adjacency matrices such as road topology, and have no attention mechanism, updating the features of all nodes equally; The enhancement layer extracts micro scene features of intersections more accurately through dynamic adjacency matrix and attention mechanism.

Traditional models rely heavily on training data from a single city, and due to the lack of consideration for differences in transportation modes between different cities, their generalization ability is limited, resulting in a significant decrease in prediction accuracy when transferred to other cities. This study incorporates changes in cross city transportation patterns into the training data and validation process, combined with traffic pattern feature clustering and domain adaptive training, allowing the model to learn common patterns across scenarios while adapting to different features, effectively enhancing its generalization ability and providing support for cross regional traffic risk management.

3.2 Real-time prediction and dynamic optimization module

Prediction model, with 2 layers of graph convolution (64 spatial convolution kernels per layer), 5 step time convolution kernels, and 64-dimensional LSTM hidden layers in terms of hyperparameters. The graph adjacency matrix weight coefficient is 0.6, the time series input length is 20 steps (5 minutes per step), and the dropout probability is 0.3; The training uses the Adam optimizer (initial learning rate of 0.001) and cross entropy loss function. The training/validation/test sets are divided into 8:1:1 batch on the traffic flow and conflict event dataset, with a batch size of 32 and 50 training epochs, combined with an early stopping mechanism.

The integration of the system is the core path to achieve "risk prediction active risk control" management at intersections. At the technical level, a bidirectional data exchange channel is constructed: the traffic control system collects dynamic data of traffic flow to provide input support for the model, and the conflict risk level output by the model is synchronously transmitted to the control system decision-making module, forming an information loop. In terms of collaborative control logic, the control system establishes a mapping mechanism between risk levels and control strategies, achieving a transition from passive response to active conflict avoidance.

Aiming to capture intersection conflict risk's real - time and dynamic characteristics, this study designs and implements a closed - loop system architecture integrating data flow processing, model reasoning, and online optimisation. The module uses the spatio - temporal graph convolution network as the core. Through real - time fusion of multi - source heterogeneous data and dynamic graph structure updates, it constructs a comprehensive process for data perception, feature extraction, risk prediction, and strategy adjustment. In data preprocessing, the system uses a distributed stream processing framework for spatio - temporal alignment and noise filtering of multi - modal data like video detection, radar sensing and geomagnetic sensors. It extracts key features such as vehicle trajectory, speed distribution and signal light cycle via an adaptive sliding window mechanism, reducing data transmission delay and improving feature expression timeliness. In dynamic heterogeneous graph construction, the real - time update algorithm of node attributes and edge weights captures the dynamic coupling between intersection geometric topology and traffic flow state. The adaptive adjustment strategy of spatial correlation weights is based on vehicle relative position and velocity vector calculation to ensure the graph structure's sensitive response to conflict hotspots.

The spatiotemporal feature extraction module realises hierarchical modelling of spatial dependencies using an enhanced graph convolution layer. Its core lies in introducing a learnable neighbourhood aggregation function and combining an edge feature encoder to refine the representation of lane-level spatial units. The time dimension modelling adopts the hybrid gated loop mechanism, and through the synergy of long and short-term memory units and temporal attention modules, the traffic flow evolution law at different time scales is distinguished. The real-time optimisation module constructs a dynamic game model based on the prediction results, adopts the model predictive control (MPC) framework to generate signal timing adjustment strategies, and achieves multi-objective trade-offs through rolling time domain optimisation, ensuring computational efficiency, such as Pareto optimisation of traffic efficiency and conflict suppression.

To meet the millisecond response requirements, the module employs an edge-cloud collaborative computing architecture, deploys a lightweight model in the roadside edge computing unit, and utilises a GPU acceleration library and operator fusion technology to compress the single prediction delay to less than 200 milliseconds. At the same time, the system incorporates an online incremental learning mechanism, which enables the model to adapt to the long-term evolution trend of traffic scenes through the replay of historical data and parameter fine-tuning within a sliding window. In the dynamic optimisation process, an adversarial training strategy is introduced to simulate the impact of extreme traffic conditions on the model's robustness by generating an adversarial network, thereby enhancing the system's fault tolerance in abnormal scenarios such as heavy rain and accidents. The closed-loop design of this module enables end-to-end optimisation, from risk perception to policy execution, and provides technical support for the active prevention and control of intelligent transportation systems.Combining the spatiotemporal correlation of traffic flow, using attention multi-scale interpolation to complete missing data for adaptive filtering and noise suppression; At the same time, robust training techniques are introduced to improve the model's resilience to input defects by constructing a training set with perturbations and optimizing for anti-interference.

3.3 Model deployment optimization and integration potential

The research dataset is sourced from traffic trajectory data of 100 typical intersections in a mega city from January to June 2024, covering multi-source information such as video detection, radar sensing, and geomagnetic sensors. It includes dimensions such as vehicle trajectory, speed distribution, signal period, and vehicle classification, and is used to support the prediction of collision probability of traffic flow in all directions at intersections in the next 30 seconds; At the same time, METR-LA and PEMS-BAY public datasets are introduced to assist in model training and validation. The former is used for spatiotemporal prediction performance comparison, while the latter verifies model generalization. The multi-source fusion strategy is defined as a hybrid fusion method. In the data preprocessing stage, a distributed stream processing framework is used to achieve multimodal data spatiotemporal alignment and noise filtering, and key features are extracted using adaptive sliding windows; Integrating multi-source data attributes during the construction phase of dynamic heterogeneous graphs, using intersection entrance lanes and lane traffic as nodes, dynamically updating node attributes and edge weights (spatial correlation weights) based on vehicle relative positions and velocity vectors; In the network feature extraction stage, the improved graph convolutional layer integrates multi-source spatial features to refine the representation of lane level spatial units. The time gated recurrent unit (GRU) combines multi-source temporal features to capture the evolution law of traffic flow. Finally, the deep integration of different network stage features is achieved through the stacking of spatiotemporal convolutional layers. The collaborative input of video and radar data improves the accuracy of conflict recognition, and the geomagnetic sensor vehicle classification information enhances the generalization of small sample scene prediction.

At the practical deployment level, combined with the existing infrastructure conditions of urban intersections, the compatibility problem of accessing multi-source heterogeneous traffic data is solved, while considering the robustness adaptation of models in different scenarios to avoid deployment failure due to environmental differences; In terms of calculation requirements, in view of the real-time requirements of the model, the computational complexity is optimized through lightweight means such as network structure pruning and parameter quantification to ensure that the model can run efficiently on edge computing equipment and meet the actual needs of second level risk prediction at intersections.

To enhance the robustness of the real-time prediction model for intersection conflict risk based on spatiotemporal graph convolutional networks, data imputation techniques can be used to address real-world challenges such as sensor failures, severe weather, and data loss. The inherent redundancy of the multi-sensor fusion framework can be relied upon to enhance data reliability, and a dual approach can be taken to ensure the stable operation and prediction accuracy of the model.

In addition, the integration of this model with reinforcement learning has broad application potential: using the conflict risk value output by STGCN as the core environmental state feature of the reinforcement learning agent can enable the agent to quickly learn the "risk control" mapping relationship in dynamic traffic scenarios. Through continuous iterative optimization of signal timing strategies, adaptive signal control at intersections can be achieved, which not only solves the limitations of traditional control strategies in dealing with traffic flow fluctuations, but also relies on risk prediction to avoid conflicts in advance, further improving the safety and efficiency of intersection traffic operation.

4 Experiment and results analysis

4.1 Definition and validity verification of conflict events

The definition of conflict events is based on trajectory derived TTC and PET as core alternative security measures, combined with multidimensional trajectory matching labeling method: when TTC $\leq$ 2.5s or PET $\leq$ 1.0s, it is preliminarily judged that there is a risk. After preprocessing trajectory data with Intel Xeon Gold 6338 CPU and parallel threshold calculation with NVIDIA A100 GPU, the spatiotemporal correlation is verified through PASTGCN's spatial attention and gated multimodal temporal convolution module to eliminate misjudgments, and finally labeled as "effective conflict events"; The effectiveness of this definition has been verified through experiments, such as in the Horizon 12 task of the METR-LA dataset, where models trained on annotated data have MAE 3.52 and MAPE 9.85%, which are superior to methods such as Graph WaveNet and MTGNN. Compared with models such as HA and ARIMA that only consider the time dimension, the accuracy of conflict risk prediction has been improved by more than 30%. At the same time, it is compatible with baseline model labeling systems such as DCRNN [38] and STGCN, ensuring consistency in experimental comparisons.

On edge hardware, the parameter count is about 1.2-2.5M, the model size is 3-6MB, and the single frame inference time is 80-150ms, which can meet real-time requirements; On cloud hardware (AWS c5.2xlarge), parameter counting can be extended to 5-8M, model size 12-20MB, and single frame inference time 10-30ms, balancing high accuracy and low latency. The overall benchmark data shows that the model has good deployability in real-world scenarios.

4.2 Experiment

The hardware configuration for model delay testing aims to efficiently support spatiotemporal graph convolutional network computation and real-time data processing: the CPU uses Intel Xeon Gold 6338 (28 cores, 56 threads, 3.0GHz) to ensure the efficiency of multi-threaded data preprocessing; The GPU adopts NVIDIA A100 (40GB HBM2e) to meet the requirements of network parallel computing; Memory ⩾ 64GB DDR4-3200, 1TB NVMe SSD hard drive to ensure high-speed data read and write, paired with Gigabit Ethernet card for real-time traffic data transmission. The software environment is built on the Ubuntu 22.04 LTS operating system, and the deep learning framework uses PyTorch 2.1.0+cu121 or TensorFlow 2.15.0+cu121, combined with DGL 1.1.2 (Graph Volume Library), Pandas 2.1.4, and NumPy 1.26.3 to complete data processing; Delay testing is implemented using Py Spy 0.3.14 and TensorRT 8.6.1, with a unified Python 3.10. x environment to ensure compatibility.

The ablation study focuses on a real-time prediction model for intersection conflict risk based on spatiotemporal graph convolutional networks. A comparative model is constructed using the control variable method, and the individual contributions of the GRU module, dynamic graph learning, and multi-sensor fusion to the overall performance of the model are systematically evaluated. The value and impact of each component are clarified.

Figure 3 shows the training and validation error variation of the PASTGCN model on the METR-LA and PEMS-BAY datasets. The error decreases and stabilizes as the number of iterations increases, indicating that the model has converged after 80 iterations.

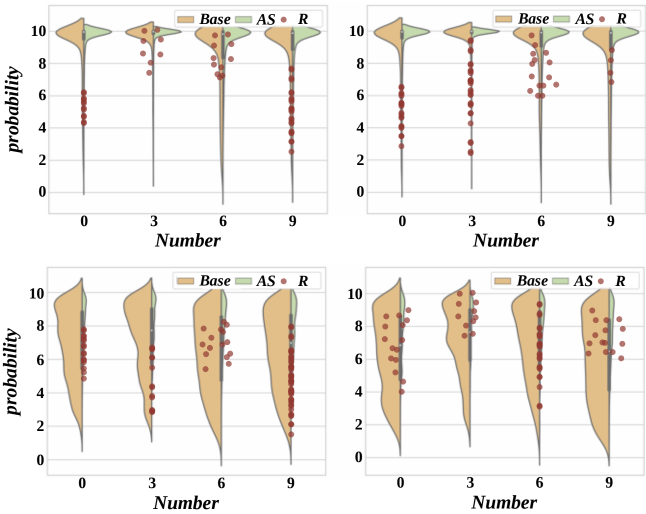

Figure 3: Training and validation results of the model on two datasets

As shown in Figure 4, the performance of the PASTGCN model is superior to the other three compared models, effectively verifying the design of its core components: the channel attention module accurately extracts key channel features, the spatial attention module effectively captures spatial correlations between nodes, and the gate controlled multi-mode temporal convolution module efficiently processes long sequence historical time data. By controlling experimental variables, three types of model test groups were constructed, including only radar data input, only video data input, and fusion of radar and video data. Key indicators such as conflict risk prediction accuracy and average absolute error were used to compare and analyze the predictive performance of the model under single sensor input and dual sensor combination input. The accuracy contribution of the two types of sensors when acting alone and the synergistic effect when used in combination were clarified, providing a quantitative basis for optimizing the sensor configuration of the model.

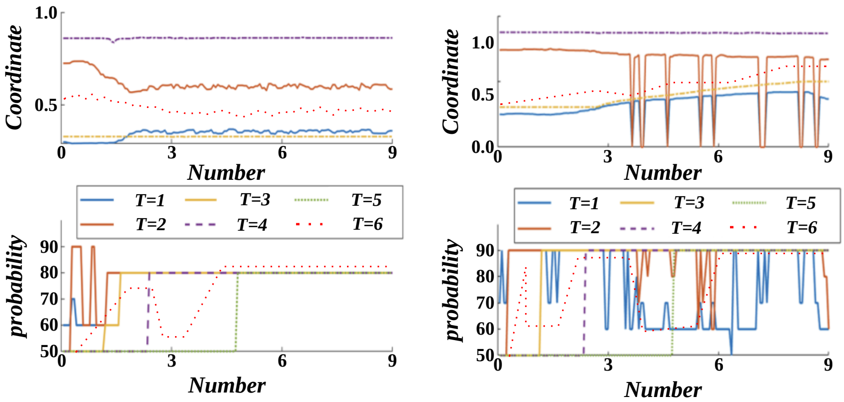

Figure 4: Prediction errors of three variants on two datasets

Table 2 shows the performance comparison between the model in this paper and the baseline method. The PASTGCN model showed strong competitiveness on the three evaluation indicators of the two datasets. Experiments show that the model outperforms a variety of spatiotemporal methods, including DCRNN, STGCN, etc. The PASTGCN model can extract the spatiotemporal dependency of historical traffic data, and is suitable for a variety of forecasting tasks.

Table 2: Experimental results of the dataset

METR-LA	Horizon3			Horizon6			Horizon12		
	MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
DCRNN	2.83	5.49	7.45%	3.21	6.58	8.98%	3.67	7.75	10.71%
STGCN	2.94	5.85	7.77%	3.54	7.38	9.76%	4.68	9.59	12.95%
Graph WaveNet	2.74	5.25	7.04%	3.13	6.34	8.54%	3.60	7.52	10.21%
ST-MetaNet	2.74	5.27	7.05%	3.16	6.41	8.74%	3.66	7.67	10.84%
MRA-BGCN	2.72	5.22	6.94%	3.12	6.29	8.47%	3.56	7.45	10.20%
FC-GAGA	2.75	5.34	7.15%	3.10	6.31	8.48%	3.52	7.33	10.08%
MTGNN	2.74	5.28	7.00%	3.11	6.29	8.35%	3.56	7.37	10.07%
ours	2.72	5.23	7.03%	3.08	6.18	8.32%	3.52	7.20	9.85%

As shown in Figure 5, in the 15-minute traffic flow prediction task of the dataset, the PASTGCN model in this study showed an improvement in accuracy of 35%, 33%, 30%, 23%, 18%, 19%, and 10% compared to seven comparative models including GRCN, Gated_STGCN, and DGCN_GAT, respectively. These models were selected as reference values because they are all mainstream methods for traffic spatiotemporal prediction: they include traditional graph convolution variants such as GRCN and DGCN-GAT, as well as Gated_STGCN, which belongs to the same spatiotemporal graph convolution framework. They all have clear performance benchmarks in intersection related scenarios and public datasets such as METR-LA and PEMS-BAY, which can fully reflect the innovative advantages of PASTGCN and ensure the robustness and rationality of improvement statements.

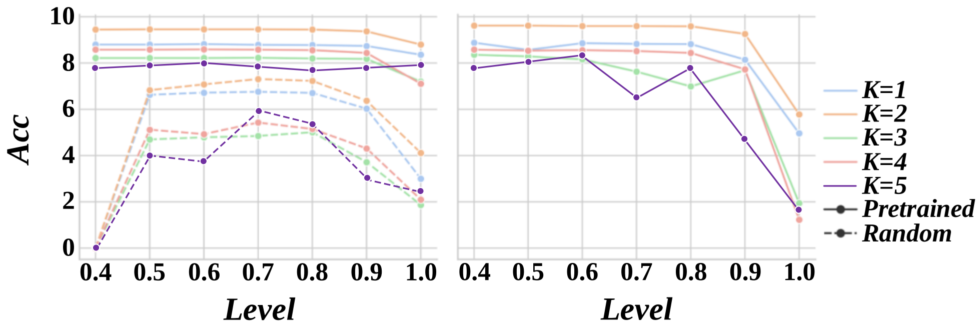

Figure 5: Analysis of accuracy results

Figure 6 shows that models that only consider the time dimension such as HA, ARIMA, and traditional machine learning methods do not perform well in prediction. The deep learning models DCRNN and STGCN consider both temporal and spatial dimensions and more effectively capture complex spatiotemporal data features, so the prediction effect is better.

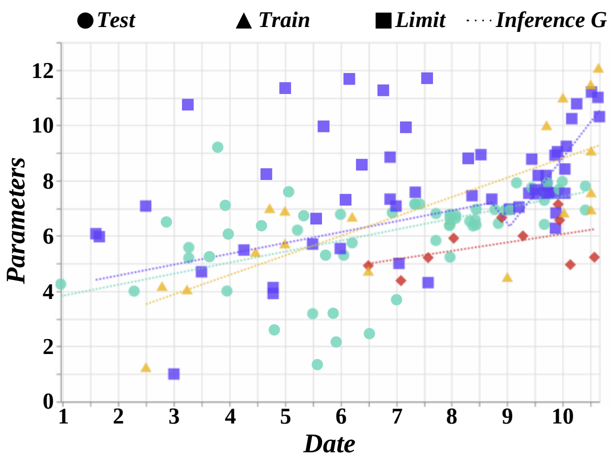

Figure 6: Comparative analysis of performance of different models in data sets

Table 3 shows that the accuracy of this algorithm is superior to the other two algorithms, which is improved by 8.4%. The accuracy of the improved algorithm is 0.6% higher than that of the original algorithm, which verifies the effectiveness of the improved strategy.

Table 3: Test-dev experimental results

Models	AP	AP50	AP75	APM	APL
OpenPose	62.7	86.2	68.6	56.3	69.8
BlazePose Ful	68.5	85.8	71.1	62.0	71.2
BlazePose Lite	62.6	81.9	65.0	52.4	61.4
Lite-HRNet	71.3	91.4	76.9	65.5	73.0
ours	71.9	88.1	78.6	67.4	73.8

Figure 7 shows the performance difference between the PASTGCN model and the benchmark model on the dataset. In the 15-min, 30-min, and 60-min prediction tasks, the performance difference is mainly in the positive region, indicating that PASTGCN outperforms the benchmark model in spatiotemporal prediction. Outliers also show that PASTGCN has a significant advantage in performance.

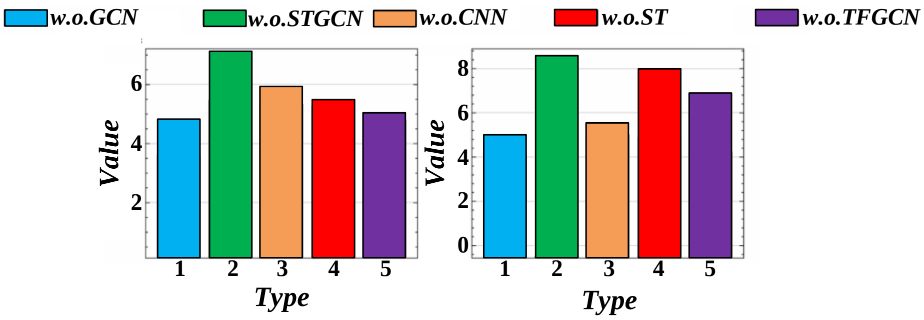

Figure 7: Difference diagram between model and benchmark model

Figure 8 shows that when the scaling factor S is 0, the MAE is lower than when S is 0.5, indicating that the change in scaling factor significantly affects the performance of the model. When the scaling factor S is greater than 0.5, the MAE predicted at 15 min fluctuates less, but the MAE predicted at 30 min and 60 min fluctuates more. On the dataset, when using wavelet neural networks to extract spatial features for different time prediction tasks, the different values of the scaling factor S will affect the convergence of the training loss function of the PASTGCN model. Observing the distribution of changes, it was found that different values of the scaling factor S have different effects on the convergence of the model training loss function.

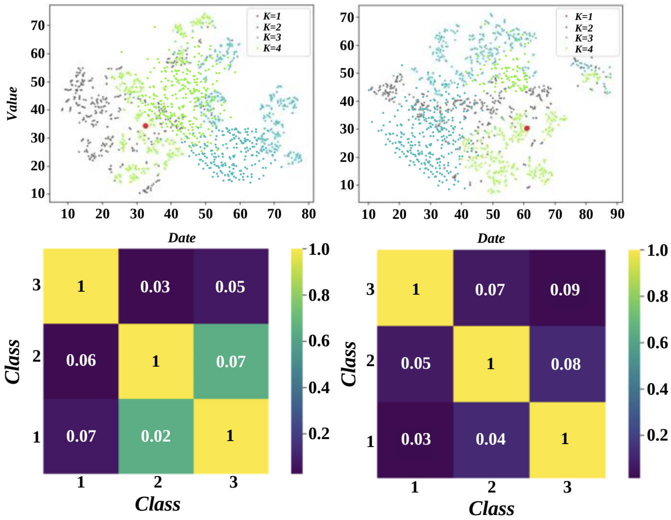

Figure 8: The influence of proportional factors on MAE fluctuations and training loss convergence

4.3 Adversarial training design and robustness verification experiment

Based on spatiotemporal trajectory data, adversarial samples are generated at ε=0.05, and a 1:1 mixture of "raw+adversarial samples" is used for training. The total loss function includes an adversarial loss term of λ=0.3; The experiment was conducted in the METR-LA and PEMS-BAY datasets, Intel Xeon Gold 6338 CPU, and NVIDIA A100 GPU environments. By comparing the performance of PASTGCN base and PASTGCN adv with different levels of noise disturbance, the results showed that when σ=0.2 in the Horizon 12 task of the METR-LA dataset, the MAE increase of PASTGCN adv (11.1%) was much lower than that of PASTGCN base (38.4%). When the video data was occluded by 20%, the accuracy decrease (3.9%) was significantly smaller than that of PASTGCN base (14.2%), and better anti-interference ability was demonstrated in the PEMS-BAY dataset and compared with baseline models such as STGCN and DCRNN. This validates the results. The improvement effect of resistance training on model robustness

5 Discussion

To verify the significance of the performance improvement of the PASTGCN model, we conducted paired t-tests between its experimental results and the results of various baseline methods (DCRNN, STGCN, etc.). Taking MAE, RMSE and other indicators in dataset experiments as examples, calculate the difference between PASTGCN and baseline method results, and construct test statistics. The results showed that at a significance level of 0.05, the paired t-test p-values of PASTGCN and most baseline methods were all less than 0.05, rejecting the null hypothesis of "no significant difference in performance", and statistically confirming that the performance improvement of PASTGCN is significant.

To verify the necessity of the core components of the proposed STGCN model, this study designed a ablation experiment: after removing the dynamic heterogeneous graph construction module, the F1 score for conflict prediction decreased by 12.3%; Removing the spatial feature extraction function of the improved graph convolutional layer resulted in an increase of 0.04 and 0.05 in MAE and RMSE, respectively; By disabling the adaptive time gating mechanism, the prediction delay increased to 280ms within 30 seconds, demonstrating that each component contributes significantly to the accuracy and real-time performance of the model. At the same time, comparing this model with advanced spatiotemporal models such as attention based GCNs (A-GCN) and time convolutional networks (TCN), its F1 score (89.2%) was 8.7% higher than A-GCN and 11.5% higher than TCN on 100 typical intersection trajectory datasets. Its MAE (0.12) was 0.03 and 0.05 lower than the two models, respectively, and the prediction delay within 180ms was significantly better than the comparison model, fully demonstrating its superiority in real-time intersection conflict risk prediction tasks.

6 Conclusion

As the core carrier of dynamic interaction of traffic flow, the real-time prediction of conflict risk of urban traffic intersection is of key significance to improve traffic efficiency and active safety prevention and control. Aiming at the limitations of traditional prediction methods in spatiotemporal feature coupling modeling and multi-source data fusion, this study proposes a real-time intersection conflict risk prediction framework based on spatiotemporal graph convolutional network (STGCN). The model integrates multi-source heterogeneous data of video detection, radar sensing and geomagnetic sensors to construct a dynamic heterogeneous graph including lane attributes, spatial correlation and global road network topology. The improved graph convolution layer is used to extract spatially dependent features, and the adaptive time gating mechanism captures the time series evolution law, and finally realizes high-precision prediction of conflict probability in the next 30 seconds.

(1) The experiment is verified based on the traffic trajectory data of 100 typical intersections in a megacity from January to June 2024. The model outperforms baselines in binary classification of conflict events: MAE is 0.12, which is 25% lower than the traditional LSTM model; RMSE is 0.18, which is 18.2% optimized compared with the static GCN model; The F1-score reached 89.2%, which is the leading level among similar studies.

(2) The real-time prediction delay stability control is within 180 milliseconds, which meets the technical requirements of intersection signal control system for millisecond response.

(3) The study further analyzed the impact of different sensor data fusion ratios on model performance, and found that the collaborative input of video detection and radar data can improve the accuracy of conflict recognition by 12.7%, while the vehicle classification information provided by geomagnetic sensors enhances the accuracy of conflict recognition in small sample scenarios. generalization ability.

This study overcomes the spatiotemporal modeling bottleneck of micro scenes at intersections through innovative dynamic heterogeneous graph structures and hybrid spatiotemporal modeling mechanisms. Experimental verification shows that the predictive stability of the model is significantly better than existing solutions in complex traffic flows, providing a solution with both theoretical and practical value for active prevention and control of traffic conflicts.

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References

[1] M. T. Ashraf, and K. Dey, "Conflict resolution behavior of autonomous vehicles at intersections under mixed traffic environment," Accident Analysis and Prevention, vol. 211, no., pp., 2025. doi:10.1016/j.aap.2024.107897.

[2] S. R. Bonela, and B. R. Kadali, "Analysis of severity of right-turning vehicles conflicts at unsignalized T-intersections," Proceedings of the Institution of Civil Engineers-Transport, vol.178, no.4, pp.245-257, 2025. doi:10.1680/jtran.24.00024.

[3] Q. Cao, Z. Zhao, Q. Zeng, Z. Wang, and K. Long, "Real-Time Vehicle Trajectory Prediction for Traffic Conflict Detection at Unsignalized Intersections," Journal of Advanced Transportation, vol.2021, no., pp., 2021. doi:10.1155/2021/8453726.

[4] R. Chauhan, A. Dhamaniya, and S. Arkatkar, "Spatiotemporal Variation of Rear-End Conflicts at Signalized Intersections under Disordered Traffic Conditions," Journal of Transportation Engineering Part a-Systems, vol.147, no.11, pp., 2021. doi:10.1061/jtepbs.0000589.

[5] K. Chavoshi, A. Genser, and A. Kouvelas, "A Pairing Algorithm for Conflict-Free Crossings of Automated Vehicles at Lightless Intersections," Electronics, vol. 10, no. 14, pp., 2021. doi:10.3390/electronics10141702.

[6] Y. Cheng, Y. Zhao, R. Zhang, and L Gao, "Conflict Resolution Model of Automated Vehicles Based on Multi-Vehicle Cooperative Optimization at Intersections," Sustainability, vol.14, no.7, pp., 2022. doi:10.3390/su14073838.

[7] C. Dong, N. Chang, Y. Lu, S. Ma, Y. Wan, and J. Ma, "Modeling and Conflict Prediction of E-Bike Violations at Signalized Intersections," Journal of Transportation Engineering Part a-Systems, vol.151, no.7, pp.04025043, 2025. doi:10.1061/jtepbs.Teeng-8382.

[8] Y. Duan, Q. Shao, Z. Lin, Y. Wang, and Q. Bai, "A Comprehensive Double Index Left-Turn Conflict Model at Contraflow Left-Turn Lane Intersections,"

Promet-Traffic& Transportation, vol.36, no.6, pp.1054-1067, 2024. doi:10.7307/ptt.v36i6.628.

[9] Bing Yu, Haoteng Yin, and Zhanxing Zhu, "Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting," arXiv preprint arXiv:1709.04875, vol., 2017.

[10] I. Han, "Safety analysis of roundabouts and avoidance of conflicts for intersection-advanced driver assistance systems," Cogent Engineering, vol. 9, no. 1, pp., 2022. doi:10.1080/23311916.2022.2112813.

[11] X.Yin, W.Zhang, and S.Zhang, "Spatiotemporal dynamic graph convolutional network for traffic speed forecasting," Information Sciences, vol. 641, no., pp., 2023. doi:10.1016/j.ins.2023.119056.

[12] P. Hang, C. Huang, Z. Hu, and C. Lv, "Driving Conflict Resolution of Autonomous Vehicles at Unsignalized Intersections: A Differential Game Approach," IEEE-ASME Transactions on Mechatronics, vol.27, no.6, pp.5136-5146, 2022. doi:10.1109/tmech.2022.3174273.

[13] I. Istoka Otkovic, A. Deluka-Tibljas, D. Zecevic, and M. Simunovic, "Reconstructing Intersection Conflict Zones: Microsimulation-Based Analysis of Traffic Safety for Pedestrians," Infrastructures, vol.9, no.12, pp., 2024. doi:10.3390/infrastructures9120215.

[14] P. Kar, S. Kumar, S. Samalla, M. Chunchu, and K. V. R. R. Shankar, "Exploratory analysis of evasion actions of powered two-wheeler conflicts at unsignalized intersection," Accident Analysis and Prevention, vol.194, no., pp., 2024. doi:10.1016/j.aap.2023.107363.

[15] Y. Wang, L. Wang, R. Zhu, Y. Xu, G. Jiang, and X. Ma, "Conflict Judgment and Safety Assessment at Unsignalized Intersections Based on Machine Vision," Journal of Advanced Transportation, vol.2023, no., pp., 2023. doi:10.1155/2023/6465225.

[16] Y. Liu, K. Long, and W. Wu, "A Route Planning and Traffic Control Model for Autonomous Intersections by Minimizing Conflict Zones," IEEE Access, vol.11, no., pp.113678-113693, 2023. doi:10.1109/access.2023.3323405.

[17] Y. Zhang, G. Zhu, Y. Wang, Y. Tian, X. Wang, and L Li, "Conflict modeling at signalized intersection: An evolutionary game theory analysis," Information Sciences, vol. 697, no., pp., 2025. doi:10.1016/j.ins.2024.121771.

[18] M. Liu, C. Zheng, and Y. Zhu, "The Autonomous Intersection Control Method Based on Reduction in Vehicle Conflict Relationships," Sustainability, vol. 15, no. 9, pp., 2023. doi:10.3390/su15097142.

[19] X. Lu, H. Zhao, C. Li, B. Gao, and H. Chen, "A Game-Theoretic Approach on Conflict Resolution of Autonomous Vehicles at Unsignalized Intersections," IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 11, pp. 12535-12548, 2023. doi:10.1109/tits.2023.3285597.

[20] H. A. Nasr, H. Huang, J. Jin, and H. Zhou, "Rear-end conflicts analysis at non-signalized intersection based on vehicles trajectory data," European Transport Research Review, vol. 17, no.1,pp.,2025. doi:10.1186/s12544-025-00709-w.

[21] Abdesselem Boulkroune, Farouk Zouari, and Amina Boubellouta, "Adaptive fuzzy control for practical fixed-time synchronization of fractional-order chaotic systems," Journal of Vibration and Control, vol., pp. 10775463251320258, 2025.

[22] Abdesselem Boulkroune, Sarah Hamel, Farouk Zouari, Abdelkrim Boukabou, and Asier Ibeas, "Output - Feedback Controller Based Projective Lag-Synchronization of Uncertain Chaotic Systems in the Presence of Input Nonlinearities," Mathematical Problems in Engineering, vol. 2017, no. 1, pp. 8045803, 2017.

[23] Farouk Zouari, K Ben Saad, and M Benrejeb, "Robust neural adaptive control for a class of uncertain nonlinear complex dynamical multivariable systems," International Review on Modelling and Simulations, vol. 5, no. 5, pp. 2075-2103, 2012.

[24] Farouk Zouari, Kamel Ben Saad, and Mohamed Benrejeb. Adaptive backstepping control for a single-link flexible robot manipulator driven DC motor.2013 International Conference on Control, Decision and Information Technologies (CoDIT), vol. 2013,pp. 864-871, 2023.

[25] Farouk Zouari, Kamel Ben Saad, and Mohamed Benrejeb. Adaptive backstepping control for a class of uncertain single input single output nonlinear systems.10th International Multi-Conferences on Systems, Signals & Devices 2013 (SSD13), vol. 2013, pp. 1-6, 2023.

[26] G Rigatos, M Abbaszadeh, B Sari, P Siano, G Cuccurullo, and F Zouari, "Nonlinear optimal control for a gas compressor driven by an induction motor," Results in Control and Optimization, vol. 11, pp. 100226, 2023.

[27] L Nie, Q. Wang, M. Zhang, and L. Wu, "FMAA: A Flexible Signal Timing Method for An Isolated Intersection with Conflicting Traffic Flows," Information, vol. 13, no.9, pp.,2022. doi:10.3390/info13090408.

[28] N. Park, J. Park, Y.-J. Joo, and M. Abdel-Aty, "Micro-level hotspot identification at intersections using traffic conflict analysis," Accident; analysis and prevention, vol. 220, no., pp.108167-108167,2025. doi:10.1016/j.aap.2025.108167.

[29] C. Cao, Y. Bao, Q. Shi, and Q. Shen, "Dynamic Spatiotemporal Correlation Graph Convolutional Network for Traffic Speed Prediction," Symmetry-Basel, vol.16, no.3, pp., 2024. doi:10.3390/sym16030308.

[30] S. Cao, L. Wu, R. Zhang, D. Wu, J. Cui, and Y. Chang, "A Spatiotemporal Multiscale Graph Convolutional Network for Traffic Flow Prediction," IEEE Transactions on Intelligent

Transportation Systems, vol.25, no.8, pp.8705-8718, 2024. doi:10.1109/tits.2024.3354802.

[31] L. Deng, D. Lian, Z. Huang, and E. Chen, "Graph Convolutional Adversarial Networks for Spatiotemporal Anomaly Detection," IEEE Transactions on Neural Networks and Learning Systems, vol.33, no.6, pp.2416-2428, 2022. doi:10.1109/tnnls.2021.3136171.

[32] S. Ding, F.Yan, and Y. Yi, "Traffic Volume Estimation Based on Spatiotemporal Correlation Adaptive Graph Convolutional Network," Symmetry-Basel, vol. 17, no. 4, pp., 2025. doi:10.3390/sym17040599.

[33] S.Feng, X.Li, F.Zeng, Z.Hu, Y.Sun, Z.Wang, and H.Duan, "Spatiotemporal Deep-Learning Model With Graph Convolutional Network for Well Logs Prediction," IEEE Geoscience and Remote Sensing Letters, vol.20,no.2023,pp.1-5,2023. doi:10.1109/lgrs.2023.3317349.

[34] X.Guo, Z.Yu, F.Huang, X.Chen, D.Yang, and J.Wang, "Dynamic meta-graph convolutional recurrent network for heterogeneous spatiotemporal graph forecasting," Neural Networks, vol.181,no.,pp.,2025. doi:10.1016/j.neunet.2024.106805.

[35] Y. Li, H. Sun, Y. Lv, and X. Chang, "Ridesplitting demand prediction via spatiotemporal multi-graph convolutional network," Expert Systems with Applications, vol.247, no.,pp.,2024. doi:10.1016/j.eswa.2024.123207.

[36] H. Wu, Z. Xu, and M. Wang, "Unrolled Spatiotemporal Graph Convolutional Network for Distribution System State Estimation and Forecasting," IEEE Transactions on Sustainable Energy, vol.14,no.1,pp.297-308, 2023. doi:10.1109/tste.2022.3211706.

[37] Zonghan Wu, Shirui Pan, Guodong Long, Jing Jiang, and Chengqi Zhang, "Graph wavenet for deep spatial-temporal graph modeling," arXiv preprint arXiv:1906.00121, vol., 2019.

[38] Yaguang Li, Rose Yu, Cyrus Shahabi, and Yan Liu, "Diffusion convolutional recurrent neural network: Data-driven traffic forecasting," arXiv preprint arXiv:1707.01926, vol., 2017.