The Research on Local Cultural IP Network Traffic Prediction Model Based on Ant Colony Algorithm

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Abstract: The increasing prominence of localized cultural intellectual property (IP) in digital ecosystems underscores the necessity for advanced network traffic prediction models to ensure stable and efficient performance. Traditional methods, while foundational, often fail to address the complexities inherent in modern network traffic, such as non-linearity, multi-scale temporal patterns, and spatial dependencies across nodes. These limitations result in suboptimal predictions, particularly under dynamic traffic conditions influenced by external factors like user behavior and network configurations. To address these challenges, this study introduces a novel predictive framework leveraging the Ant Colony Algorithm for localized cultural IP network traffic forecasting. By integrating Adaptive Temporal-Spatial Network (ATSN) architecture and the Dynamic Traffic Adaptation Strategy (DTAS), our model dynamically captures both temporal and spatial traffic correlations while ensuring adaptability to abrupt changes. The proposed method incorporates graph neural networks and recurrent structures to optimize spatial- temporal learning, along with hierarchical multi-scale modeling and anomaly-resilient mechanisms for robust performance. Empirical results demonstrate significant improvements in prediction accuracy, scalability, and computational efficiency compared to conventional approaches. These findings not only contribute to the theoretical advancement of network traffic modeling but also offer practical solutions for localized IP management in dynamic, real-world settings.

Keywords: Network Traffic Forecasting, Localized Cultural IP, Ant Colony Algorithm, Temporal -Spatial Modeling, Dynamic Adaptation Strategy

Introduction

The prediction of network traffic, especially for local cultural IP networks, is crucial due to the increasing demand for personalized and efficient content delivery [1]. Accurately predicting network traffic not only ensures the smooth functioning of data transmission but also optimizes resource allocation and improves user experiences [2]. Traditional methods often struggle to account for the dynamic and complex nature of cultural IP traffic patterns, which are influenced by factors such as user behavior, content popularity, and regional preferences [3]. Moreover, the surge in digital transformation and the growing adoption of cultural IP platforms necessitate the development of advanced prediction models that can adapt to diverse and rapidly changing environments [4]. Therefore, research into innovative prediction techniques is essential for addressing these challenges and ensuring the sustainable growth of local cultural IP networks [5].

To address the limitations of traditional traffic prediction models, early research focused on symbolic AI and knowledge representation [6]. These methods relied on predefined rules and heuristic algorithms, offering interpretable and structured approaches to traffic modeling. Techniques such as decision trees and logic-based systems were used to capture explicit patterns in network traffic [7]. While these approaches were effective for small-scale networks with predictable patterns, they struggled with the complexity and variability of cultural IP traffic [8]. The lack of adaptability to new data and the high dependency on expert-defined rules limited their scalability and generalization [9]. As a result, researchers began exploring more flexible and data-driven methods to overcome these shortcomings [10].

Building on the need for adaptability, the emergence of machine learning introduced data-driven approaches to network traffic prediction [11]. These models leveraged statistical and machine learning algorithms, such as support vector machines (SVM) and random forests, to learn patterns directly from historical traffic data [12]. By automating the feature selection process and incorporating a wider range of inputs, these methods

significantly improved prediction accuracy and adaptability [13]. However, these models required substantial labeled data for training and often suffered from performance degradation in the presence of noisy or sparse data [14]. Furthermore, their reliance on handcrafted features and limited ability to capture complex temporal dependencies posed additional challenges, particularly for dynamic cultural IP traffic scenarios [15].

The advent of deep learning and pre-trained models marked a paradigm shift in network traffic prediction [16]. Advanced architectures such as recurrent neural networks (RNNs) and transformers demonstrated exceptional capabilities in capturing temporal and spatial dependencies within traffic data Lim and Zohren (2020)[17]. By utilizing techniques like attention mechanisms and pre-training, these models could learn from vast and diverse datasets, improving their robustness and generalization. Nevertheless, the computational requirements of deep learning models and their "black-box" nature raised concerns about scalability, interpretability, and energy efficiency [18]. Despite these limitations, they laid the foundation for incorporating hybrid methods that combine traditional algorithms with deep learning to optimize both performance and efficiency.

Based on the above limitations, we propose a network traffic prediction model for local cultural IPs that integrates the ant colony algorithm with advanced machine learning techniques. This hybrid approach leverages the adaptability and optimization strengths of the ant colony algorithm while addressing the interpretability and efficiency concerns of deep learning. By combining these methodologies, our model aims to achieve superior performance in predicting complex traffic patterns while ensuring scalability and practical applicability.

We summarize our contributions as follows:

Our method introduces an innovative integration of ant colony optimization and machine learning, creating a highly adaptive and robust prediction framework.

The model demonstrates versatility and efficiency, enabling its application across diverse cultural IP scenarios with minimal computational overhead.

Empirical results show significant improvements in prediction accuracy and resource optimization, validating its effectiveness in real-world environments.

Related Works

Ant Colony Algorithm in Prediction Models

Ant Colony Optimization (ACO) has gained significant recognition as a heuristic optimization algorithm inspired by the foraging behavior of ants [19]. Its effectiveness in solving combinatorial optimization problems makes it particularly suitable for network traffic prediction [20]. ACO is highly efficient in finding optimal paths within dynamic environments, which is essential for accurately forecasting network traffic influenced by local cultural IP dynamics. Recent advancements have extended ACO's applications to nonlinear time series predictions by integrating it with machine learning and statistical models, enhancing its ability to capture complex and dynamic patterns [21].

For instance, hybrid models that combine ACO with artificial neural networks or support vector machines have demonstrated improved accuracy and computational efficiency. These hybrid approaches leverage ACO's global search capabilities for optimizing model parameters while utilizing machine learning's predictive strengths. In the context of network traffic prediction for local cultural IPs, such frameworks provide robust solutions to handle fluctuating demand patterns and unstructured data [22]. Additionally, ACO's iterative refinement mechanism aligns well with the evolving nature of cultural IP traffic, where trends are influenced by time-sensitive events and social factors [23].

Cultural IP Influence on Traffic Dynamics

Local cultural IPs, including traditional art forms, folklore, and heritage-related events, significantly shape network traffic patterns. Understanding the temporal and spatial dynamics of these influences is critical for effective traffic modeling. Research indicates that cultural IPs can drive sudden surges in network usage, necessitating predictive models capable of incorporating event-driven traffic fluctuations [24]. Traditional statistical methods often struggle to capture such irregularities due to their reliance on linear assumptions.

Machine learning techniques, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) models, have shown promise in addressing these challenges. However, these methods can be further enhanced through optimization algorithms like ACO, which improve parameter tuning processes [24]. Furthermore, integrating social media and user interaction data into traffic prediction models has emerged as a valuable approach. By analyzing online discourse related to cultural IP events, predictive models can more effectively anticipate traffic spikes [25]. This integration requires a multidisciplinary approach, combining natural language processing, temporal analysis, and ACO-based optimization to ensure scalability and reliability in cultural IP-related network traffic predictions.

Hybrid Methods for Accurate Forecasting

Hybrid approaches that combine multiple computational paradigms have become fundamental to accurate network traffic prediction models [26]. The integration of ACO with machine learning and deep learning techniques has consistently demonstrated superior performance in various applications. These hybrid models leverage ACO for global optimization while machine learning techniques excel at capturing complex data patterns[27].

For example, ACO has been successfully applied to optimize hyperparameters in predictive models, reducing computational overhead while improving prediction accuracy. Similarly, hybrid systems integrating ACO with fuzzy logic have proven effective in managing the uncertainties inherent in cultural IP traffic data[28]. These approaches allow for more refined predictions that account for the stochastic nature of network usage influenced by cultural factors.

Hybrid models also offer scalability for handling large datasets, which is essential for real-time network traffic predictions. Their modular architecture enables easy adaptation to regional characteristics and cultural dynamics, making them particularly suitable for predicting local cultural IP traffic patterns [29].

Methods

Overview

Network traffic forecasting has become a cornerstone for optimizing and managing contemporary communication networks. Accurate predictions are essential for efficient resource allocation, congestion control, anomaly detection, and supporting various applications reliant on stable network performance. The increasing complexity of networks, coupled with the demand for low latency and high throughput, necessitates advanced predictive models capable of handling diverse data characteristics, including non-linearity, seasonality, and irregular patterns. In this work, we propose a novel framework for network traffic forecasting that integrates deep learning methodologies with domain-specific insights to address existing limitations in prediction accuracy and computational efficiency. This subsection provides an overview of our approach and outlines the key contributions of subsequent sections. Subsection 3.2 establishes the Preliminaries, where we formalize the network traffic prediction problem within a mathematical framework. This section explores the fundamental characteristics of network traffic data, including temporal dependencies and stochastic behaviors, and introduces the notations and baseline concepts employed throughout this study. Subsection 3.3 introduces our Innovative Predictive Model, tailored to capture intricate traffic patterns by leveraging advanced architectures and self-adaptive mechanisms. This model is meticulously designed to enhance forecasting accuracy by dynamically adjusting to shifting traffic conditions while maintaining computational efficiency. Subsection 3.4 discusses the Proposed Optimization Strategies, emphasizing how domain-specific adaptations and architectural enhancements can effectively bridge the gap between theoretical models and practical deployments. This includes strategies for minimizing overfitting, handling data sparsity, and optimizing the use of computational resources for real-time traffic predictions.

Preliminaries

Network traffic forecasting is a critical task that involves predicting future traffic patterns based on historical data. This section formalizes the problem and introduces the mathematical framework and notations used in our study. The objective is to analyze and model network traffic, which typically exhibits temporal dependencies, non-linear behaviors, and periodic variations.

Let T = {t_1, t_2, . . . , t_n} denote discrete time points, where network traffic measurements are observed. At each time step t_i, the observed traffic volume is represented as $x_{ti} \in \mathbb{R}$, where d is the dimensionality of the feature space, including metrics such as packet counts, throughput, and latency. The historical traffic data up to time t is given by X_t = {x_{t1}, x_{t2}, . . . , x_t}.

The goal of network traffic forecasting is to predict future traffic states over a horizon H, defined as:

$$\hat{\mathcal{X}}_{t+1:t+H} = \{\hat{x}_{t+1}, \hat{x}_{t+2}, \ldots, \hat{x}_{t+H}\}, \tag{1}$$

Where $\hat{x}_{t+h}$ denotes the predicted traffic at time h∈{1,…,H}. This can be expressed as a mapping:

$$\hat{\mathcal{X}}_{t+1:t+H} = f(\mathcal{X}_t; \theta), \tag{2}$$

Where *f* is a predictive model parameterized by θ.

Network traffic data is influenced by temporal dependencies, including short-term correlations (e.g., burstiness in traffic) and long-term trends (e.g., daily and weekly patterns). In networks with multiple nodes, spatial dependencies among traffic sources and destinations are crucial. These dependencies are captured using adjacency matrices A and traffic graphs $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ *V* is the set of nodes and $\mathcal{E}$ is the set of edges.

Accurate traffic forecasting requires addressing the following challenges: Traffic patterns evolve over time due to varying user behavior and network conditions. Simultaneous modeling of short-term fluctuations and long-term periodic trends is essential. Networks with numerous nodes generate high-dimensional data, necessitating scalable solutions.

$$\mathbf{h}_t = \phi(\mathbf{h}_{t-1}, \mathbf{Z}_t) \tag{3}$$

where ϕ is a recurrent function such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU).

Generate multi-step forecasts using:

$$\hat{x}_{t+h} = \psi(\mathbf{h}_t, h), \quad \forall h \in \{1, \ldots, H\} \tag{4}$$

where ψ adjusts predictions based on the forecast horizon

Adaptive Temporal-Spatial Network (ATSN)

In this section, we present the Adaptive Temporal-Spatial Network (ATSN), a novel model designed for the intricate dynamics of network traffic forecasting (As shown in Figure 1). ATSN combines temporal sequence modeling with spatial dependency analysis to produce accurate, multi-horizon predictions, adapting seamlessly to dynamic network conditions.

Enhanced Spatial Dependency Encoding

ATSN incorporates an advanced Graph Neural Network (GNN) framework to effectively model the spatial dependencies between nodes, enabling the extraction of intricate patterns in network topology (As shown in Figure 2). Let $\mathbf{A} \in \mathbb{R}^{N \times N}$ denote the adjacency matrix of the graph $\mathcal{G}$, where *N* represents the number of nodes, and each node $v_i \in \mathcal{V}$ is characterized by a feature vector $x_{t,i}$ at time t. The GNN encodes these spatial relationships through iterative message-passing layers, where node embeddings are updated based on the features of their neighbors and the structure of the graph. Formally, at each layer *l*,

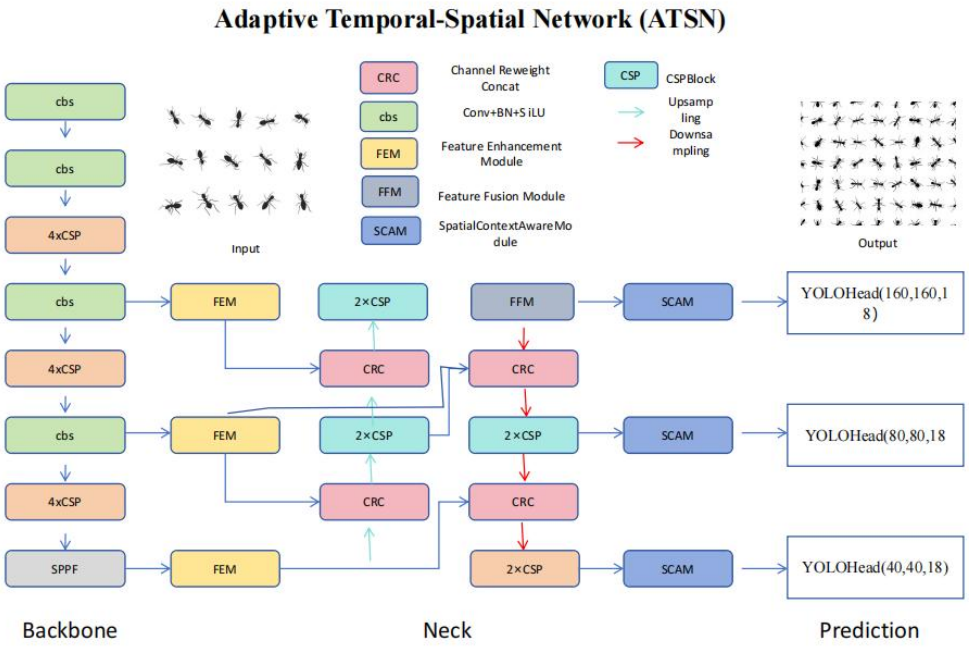

Figure 1. Adaptive Temporal-Spatial Network (ATSN) Framework Architecture:

The ATSN combines backbone, neck, and prediction modules for adaptive traffic forecasting. The backbone module processes input data through convolutional layers and CSP blocks, extracting robust features. The neck module utilizes feature enhancement (FEM), feature fusion (FFM), and spatial-context-aware modules (SCAM) to integrate temporal-spatial information. The prediction module employs multiple YOLO heads with different resolutions (160×160, 80×80, 40×40) for multi-scale predictions, ensuring accurate representation of traffic dynamics.

The embeddings are updated as:

$$\mathbf{h}_i^{(l)} = \sigma\left(\sum_{j \in \mathcal{N}(i)} \frac{\mathbf{A}_{ij} \cdot \mathbf{W}^{(l)} \mathbf{h}_j^{(l-1)}}{\sqrt{|\mathcal{N}(i)||\mathcal{N}(j)|}} + \mathbf{b}^{(l)}\right) \tag{5}$$

where *h(l)* is the embedding of node i at layer l, *W(l)* and *b(l)* are learnable weight matrices and bias vectors, respectively, and σ denotes a non-linear activation function such as ReLU. The term $\alpha_{ij} = \frac{\mathbf{A}_{ij}}{\sqrt{|\mathcal{N}(i)||\mathcal{N}(j)|}}$ ensures proper normalization, stabilizing the training process, and capturing the relative importance of node interactions. To further enhance the spatial encoding, attention mechanisms are incorporated into the aggregation process, enabling the model to assign dynamic weights to neighboring nodes based on their relevance:

$$\alpha_{ij} = \frac{\exp(\text{LeakyReLU}(\mathbf{q}^\top [\mathbf{W}_q \mathbf{h}_i^{(l-1)} \| \mathbf{W}_k \mathbf{h}_j^{(l-1)}]))}{\sum_{k \in \mathcal{N}(i)} \exp(\text{LeakyReLU}(\mathbf{q}^\top [\mathbf{W}_q \mathbf{h}_i^{(l-1)} \| \mathbf{W}_k \mathbf{h}_k^{(l-1)}]))}, \tag{6}$$

where q is a learnable query vector, $\|$ denotes concatenation, and $\mathbf{W}q$, $\mathbf{W}k$ are projection matrices for query and key transformations. This self-attention mechanism empowers the GNN to prioritize critical relationships in the spatial graph, leading to more accurate embeddings. After multiple layers of aggregation, the node embeddings are collectively transformed into a graph-level representation, $\mathbf{H}t$, summarizing the spatial dependencies at time *t*:

$$\mathbf{H}_t = \text{Aggregate}\left(\{\mathbf{h}_i^{(L)}\}_{i=1}^{N}\right) \tag{7}$$

where L is the total number of layers, and the aggregation function can be a mean-pooling or max-pooling operation depending on the task. Positional encoding is integrated into the node features to capture hierarchical graph structures, defined as:

$$Pi = MLP(EigenVectork(L)), \tag{8}$$

where **L** is the graph Laplacian matrix and $EigenVector_k(\boldsymbol{L})$ represents the top-k eigenvectors. By incorporating these positional embeddings, ATSN enhances its capacity to represent complex graph structures and spatial interactions effectively. The final spatial representation, $\mathbf{H}t$, serves as the input for the temporal modeling components, establishing a robust foundation for traffic prediction.

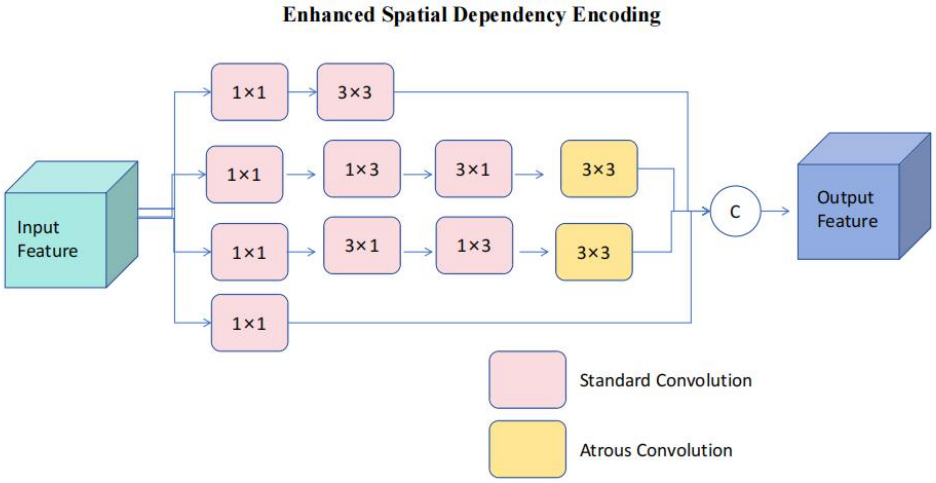

Figure 2. Enhanced Spatial Dependency Encoding:

This module leverages both standard convolutions (1×1 and 3×3) and atrous convolutions to capture spatial dependencies effectively. The input features are processed through parallel convolutional layers, extracting multi-scale spatial patterns. By combining outputs through a concatenation operation (C), the model generates enriched output features that incorporate diverse spatial information. This design ensures efficient and robust feature extraction, improving the representation of complex spatial relationships.

Temporal Dynamics Augmentation

ATSN employs a hybrid temporal modeling strategy to capture both short-term fluctuations and long-term trends in traffic patterns, ensuring comprehensive temporal feature extraction. This strategy integrates Temporal Convolutional Networks (TCNs), which are well-suited for efficiently modeling local temporal dependencies, with Long Short-Term Memory (LSTM) networks, which excel at learning long-range temporal relationships. Given the spatially encoded features Ht, the temporal dynamics module processes sequential data as follows:

$$\mathbf{s}_t = \phi(\mathbf{s}_{t-1}, \mathbf{H}_t; \Theta_{\text{temp}}), \tag{9}$$

where ϕ represents the hybrid temporal function, st is the latent state encoding spatial-temporal features,and Θ temp contains the parameters of the temporal module. To efficiently model short-term patterns, the TCN employs dilated convolutions, enabling the network to maintain a receptive field that grows exponentially with the number of layers while preserving computational efficiency. The temporal convolution operation is defined as:

$$\mathbf{y}_t = \sum_{k=0}^{K-1} \mathbf{W}_k \cdot \mathbf{H}_{t-kd} + \mathbf{b}, \tag{10}$$

where **W***k* are the convolutional filters, *K* is the kernel size, *d* is the dilation factor, and **b** is the bias term. This structure captures dependencies over a wide temporal context with fewer layers compared to traditional convolutions. For long-term dependencies, ATSN integrates LSTM units that recursively update the hidden state ht and cell state ct using the spatially encoded input **H***t*. The LSTM transitions are defined as

$$\mathbf{i}_t = \sigma(\mathbf{W}_i\mathbf{H}_t + \mathbf{U}_i\mathbf{h}_{t-1} + \mathbf{b}_i), \quad (11)$$
$$\mathbf{f}_t = \sigma(\mathbf{W}_f\mathbf{H}_t + \mathbf{U}_f\mathbf{h}_{t-1} + \mathbf{b}_f), \quad (12)$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_o\mathbf{H}_t + \mathbf{U}_o\mathbf{h}_{t-1} + \mathbf{b}_o), \quad (13)$$
$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c\mathbf{H}_t + \mathbf{U}_c\mathbf{h}_{t-1} + \mathbf{b}_c), \quad (14)$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \quad (15)$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t), \quad (16)$$

where **i***t*, **f***t*, and **o***t* denote the input, forget, and output gates, respectively; $\tilde{\mathbf{c}}_t$ is the candidate cell state; and $\odot$ represents the element-wise product. The gating mechanisms allow the LSTM to selectively memorize or forget information, adapting to varying temporal dependencies in the data. To bridge the TCN and LSTM components, ATSN applies a fusion mechanism, aggregating the features learned by each model. This fusion is implemented as:

$$st = \gamma \cdot TCN(Ht) + (1 - \gamma) \cdot LSTM(Ht), \quad (17)$$

where $\gamma \in [0, 1]$ is a learnable weight parameter that balances the contributions of TCN and LSTM outputs. By combining the strengths of both models, ATSN effectively captures multi-scale temporal dynamics, adapting to complex, non-stationary traffic patterns. The temporal module's output, s*t*, is a robust representation that encapsulates both localized temporal features and global trends. This hybrid design ensures the flexibility and adaptability of ATSN in handling diverse temporal behaviors, from rapid fluctuations to long-term evolution, making it highly effective for multi-horizon traffic forecasting.

Multi-Horizon Prediction Refinement

To improve forecasting precision across multiple future time steps, ATSN incorporates a versatile prediction head that transforms the latent temporal-spatial state st into accurate predictions for each forecast horizon h. The prediction head employs a dynamic mapping function, defined as:

$$\hat{x}t+h = \psi(st, h; \Theta pred), \forall h \in \{1, \ldots, H\} \quad (18)$$

where ψ represents the prediction function, Θ_{pred} encapsulates learnable parameters, and $\hat{\mathbf{x}}_{t+h}$ is the predicted traffic state for horizon *h*. To address the challenges posed by varying forecast horizons, ATSN supports two complementary strategies: direct mapping and iterative decoding. The direct mapping strategy predicts all future horizons simultaneously through a unified multi-layer structure. Let $\mathbf{P} \in \mathbb{R}^{H \times d}$ denote the positional embeddings for each horizon, where d is the embedding dimension. These embeddings are incorporated into the prediction process as:

$$\hat{\mathbf{X}}_{t+1:t+H} = \mathbf{MLP}([\mathbf{s}_t \| \mathbf{P}]; \Theta_{\text{pred}}) \quad (19)$$

where $\|$ denotes concatenation, **P** encodes horizon-specific positional information, and MLP (multi-layer perceptron) serves as the prediction function. This approach ensures efficient parallel processing for all horizons while maintaining accuracy. In contrast, the iterative decoding strategy sequentially predicts each future horizon by conditioning on previous outputs. For the first horizon, the prediction is initialized as:

$$\hat{x}t+1 = \psi(st, 1; \Theta pred), \quad (20)$$

and subsequent horizons are predicted recursively:

$$\hat{x}t+h = \psi(\hat{x}t+h-1, h; \Theta pred), h \geq 2. \quad (21)$$

This iterative approach allows for correction of errors in earlier predictions by leveraging dynamic adjustment mechanisms during sequential decoding. To further refine the prediction accuracy, ATSN employs an attention-based mechanism within the prediction head. Specifically, an attention weight matrix Ah ∈ Rd×d is computed for each horizon to dynamically reweight features:

$$\mathbf{z}_{t+h} = \text{Softmax}\left(\frac{\mathbf{Q}_h \mathbf{K}_h^\top}{\sqrt{d}}\right)\mathbf{V}_h, \tag{22}$$

where **Q**h, **K**h, **V**h are the query, key, and value projections of the latent state s*t*, and z*t*+*h* is the attended representation for horizon *h*. The final prediction is then derived as:

$$\hat{x}_{t+h} = \psi(z_{t+h}; \Theta_{pred}). \tag{23}$$

ATSN also incorporates a residual connection to stabilize the prediction process, formulated as:

$$\hat{x}_{t+h} = \hat{x}_{t+h} + s_t. \tag{24}$$

Dynamic Traffic Adaptation Strategy (DTAS)

In this section, we introduce the Dynamic Traffic Adaptation Strategy (DTAS), a novel approach to optimize the Adaptive Temporal-Spatial Network (ATSN) for real-world deployment in dynamic network environments(As shown in Figure 3). DTAS combines data-driven adjustments with domain-specific optimizations to enhance prediction robustness and computational efficiency, addressing key challenges such as non-stationarity, data sparsity, and multi-scale patterns in network traffic.

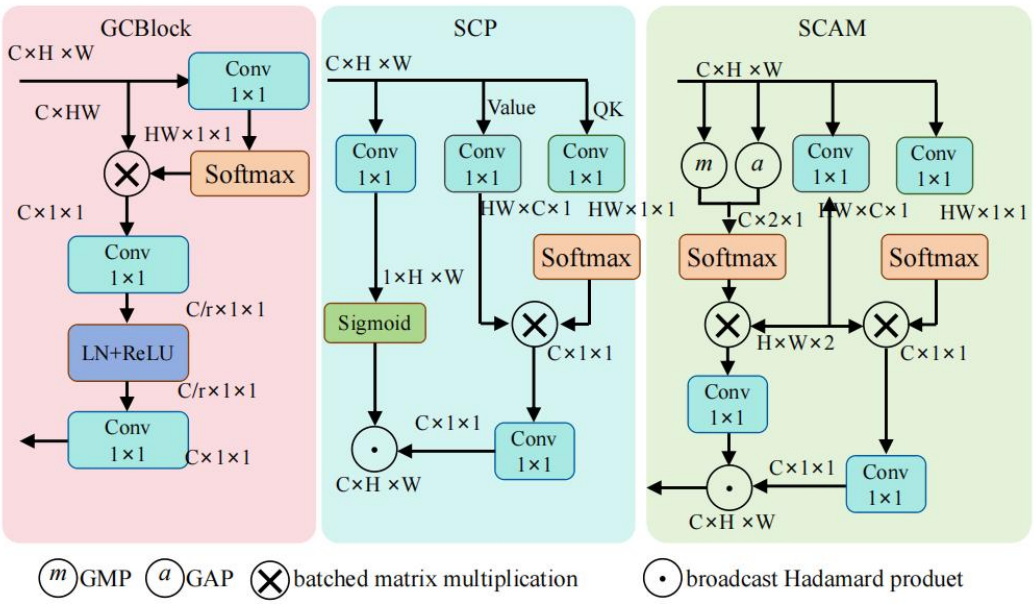

Figure 3. Dynamic Traffic Adaptation Strategy (DTAS) architecture:

The DTAS framework integrates three core components: GCBlock, SCP, and SCAM. GCBlock employs convolutional layers with softmax and layer normalization to enhance spatial feature extraction. SCP introduces attention mechanisms with Sigmoid activation and matrix multiplications for channel refinement and spatial adjustments. SCAM combines global max pooling (GMP) and global average pooling (GAP) to dynamically allocate computational focus, leveraging Hadamard products and attention mechanisms. This comprehensive strategy ensures robust adaptation to dynamic traffic patterns and efficient resource allocation in network environments.

DTAS introduces a comprehensive real-time traffic profiling mechanism designed to monitor and respond to abrupt variations in network traffic patterns, ensuring model adaptability and robustness in dynamic environments(As shown in Figure 4). For each node *vi* in the network, traffic variations are measured using a moving window variance metric:

$$\mathrm{Var}_i(t) = \frac{1}{W} \sum_{j=t-W+1}^{t} (x_{j,i} - \bar{x}_{i,t})^2 , \tag{25}$$

where **W** represents the window size, and $\bar{x}_{i,t} = \frac{1}{W} \sum_{j=t-W+1}^{t} x_{j,i}$ is the mean traffic over the window. A sudden spike in $\mathrm{Var}_i(t)$ serves as an indicator of significant changes, such as network congestion or abrupt user behavior shifts, prompting DTAS to dynamically adjust model parameters to capture new traffic dynamics effectively. To refine the system's responsiveness, DTAS integrates an adaptive feature weighting mechanism to prioritize the most relevant temporal and spatial features. For each feature $z_{t,i}$ associated with node *vi*, its importance is dynamically computed based on its correlation with the target variable $x_{t,i}$:

$$w_{t,i} = \frac{\exp\left(\alpha \cdot \mathrm{Corr}(\mathbf{z}_{t,i}, \mathbf{x}_{t,i})\right)}{\sum_{j=1}^{d} \exp\left(\alpha \cdot \mathrm{Corr}(\mathbf{z}_{t,j}, \mathbf{x}_{t,j})\right)}, \tag{26}$$

where Corr(.) is the Pearson correlation coefficient, α is a scaling factor that amplifies the importance of highly correlated features, and d is the total number of features. These weights, *wt,i,* are used tore-calibrate the embeddings in the Spatial Dependency Encoder, enabling the model to focus on the most impactful temporal and spatial dynamics. To enhance the real-time adaptability, DTAS employs an attention mechanism to dynamically allocate computational resources to nodes or regions experiencing significant changes. For each node *vi*, an attention score is computed as:

$$\mathrm{Attn}_i(t) = \frac{\exp\left(\beta \cdot \mathrm{Var}_i(t)\right)}{\sum_{k=1}^{N} \exp\left(\beta \cdot \mathrm{Var}_k(t)\right)}, \tag{27}$$

where β controls the sensitivity of the attention mechanism to variance changes, and *N* is the total number of nodes. Nodes with higher $\mathrm{Attn}_i(t)$ are allocated more computational resources, ensuring that regions with dynamic traffic changes are prioritized during processing. DTAS also integrates a smoothness constraint to stabilize adaptation over time, reducing sensitivity to transient noise in the data. This is achieved by minimizing a temporal smoothness loss for the weights:

$$\mathcal{L}_{\mathrm{smooth}} = \sum_{i=1}^{N} \sum_{t=1}^{T} (w_{t,i} - w_{t-1,i})^2 , \tag{28}$$

where *T* is the total number of time steps. This ensures that adaptive weights evolve smoothly over time, avoiding abrupt changes that could destabilize the model. DTAS incorporates a feedback loop mechanism to update the model continuously based on recent profiling results. The dynamic adjustments are achieved by modifying the learned parameters Θ of the Spatial Dependency Encoder using a weighted gradient descent:

$$\Theta_{t+1} = \Theta_t - \eta \cdot \sum_{i=1}^{N} w_{t,i} \nabla_\Theta \mathcal{L}_{\mathrm{local},i}, \tag{29}$$

where η is the learning rate, *wt,i* are the adaptive feature weights, and $\mathcal{L}_{\mathrm{local},i}$ is the local loss computed for node *vi*. This feedback-driven learning ensures that the model continuously adapts to real-time traffic variations, maintaining robustness and accuracy in dynamic environments.

Multi-Scale Temporal Modeling

To effectively capture the complex temporal dynamics of network traffic, DTAS integrates hierarchical multi-scale temporal modeling using wavelet transforms. This approach decomposes the traffic data of each node *vi*

into multiple scales, enabling the separation of fine-grained short-term fluctuations and long-term trends. Formally, the traffic signal at time *t, xt,i*, is decomposed as :

$$x_{t,i} = \sum_{l=1}^{L} \text{Detail}_{t,i}^{(l)} + \text{Approx}_{t,i},$$

(30)

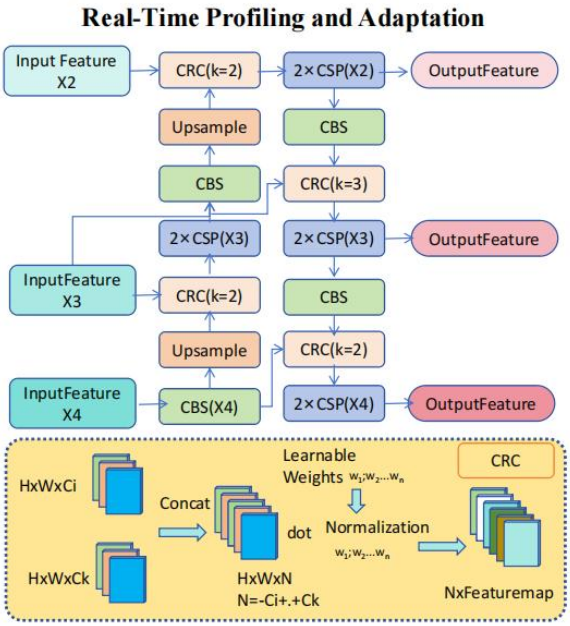

Figure 4. Real-Time Profiling and Adaptation Framework

This framework integrates multiple input features processed through CRC, CSP, and CBS layers, with upsampling and concatenation operations to produce dynamic output features. The yellow module showcases learnable weights for feature combination, normalization, and CRC refinement, which adaptively prioritize important temporal and spatial patterns. This architecture ensures robust adaptation to traffic variations and efficient feature profiling for real-time applications.

where Detail$^{(l)}$ captures the variations at finer resolution (scale *l*), and Approx represents the smoothed long-term trend. The wavelet transform's multi-resolution property allows the model to focus on specific temporal patterns at each scale, thereby enhancing its capacity to handle non-stationary traffic behaviors. Each scale-specific component is processed independently using temporal modules tailored to the characteristics of the corresponding detail or approximation level. For the detail components, Temporal Convolutional Networks (TCNs) are utilized to extract localized patterns efficiently. The TCN processing is defined as:

$$\mathbf{s}_t^{(l)} = \text{TCN}^{(l)}\left(\text{Detail}_{t,i}^{(l)}; \Theta_{\text{TCN}}^{(l)}\right),$$

(31)

where $\Theta_{\text{TCN}}^{(l)}$ represents the parameters of the TCN for scale *l*. The TCN employs dilated convolutions, ensuring that the receptive field grows exponentially with depth, capturing dependencies across a broader temporal range while maintaining computational efficiency. For the approximation component, Long Short-Term Memory (LSTM) networks are employed to model long-term dependencies. The LSTM processes the smoothed trend as

$$\mathbf{s}_t^{\text{approx}} = \text{LSTM}\left(\mathbf{s}_{t-1}^{\text{approx}}, \text{Approx}_{t,i}; \Theta_{\text{LSTM}}\right)$$

(32)

where ΘLSTM represents the learnable parameters of the LSTM. The gating mechanisms of the LSTM allow it to selectively memorize or forget information, ensuring robust handling of long-term temporal variations. To integrate the outputs from the multiple scales, a hierarchical fusion mechanism is employed.

The latent representations $\{\mathbf{s}_t^{(l)}\}_{l=1}^{L}$ and $\mathbf{s}_t^{\text{approx}}$ are concatenated and passed through an attention-based fusion layer:

$$\mathbf{f}_t = \sum_{l=1}^{L} \alpha^{(l)} \mathbf{s}_t^{(l)} + \alpha^{\text{approx}} \mathbf{s}_t^{\text{approx}}, \tag{33}$$

where the attention weights $\alpha^{(l)}$and α^{approx} are computed as

$$\alpha^{(l)} = \frac{\exp\left(\mathbf{q}^\top \mathbf{W}_{\text{att}} \mathbf{s}_t^{(l)}\right)}{\sum_{j=1}^{L} \exp\left(\mathbf{q}^\top \mathbf{W}_{\text{att}} \mathbf{s}_t^{(j)}\right) + \exp\left(\mathbf{q}^\top \mathbf{W}_{\text{att}} \mathbf{s}_t^{\text{approx}}\right)}, \tag{34}$$

where **q** is a query vector and $\mathbf{W}_{\text{att}}$ is a learnable projection matrix. This mechanism ensures that more relevant temporal scales are weighted higher during the fusion process, dynamically adapting to the traffic patterns. The fused representation ft is then used to generate multi-horizon predictions through a prediction function ψ:

$$\hat{x}_{t+h,i} = \psi\left(\mathbf{f}_t, h; \Theta_{\text{pred}}\right) \tag{35}$$

where Θ pred represents the parameters of the prediction head. This hierarchical modeling approach allows DTAS to effectively handle traffic dynamics that span multiple temporal scales, capturing both transient fluctuations and persistent trends. By leveraging the complementary strengths of wavelet transforms, TCNs, and LSTMs, DTAS achieves robust and accurate predictions in complex, real-world traffic scenarios.

Anomaly Resilience and Computational Optimization

DTAS incorporates a robust anomaly-resilient learning mechanism to address outliers and missing data, ensuring consistent performance in real-world scenarios. Outliers, which can significantly distort model predictions, are detected using the Mahalanobis distance, a multivariate metric that identifies deviations from historical norms:

$$D_M(x_{t,i}) = \sqrt{(x_{t,i} - \mu_i)^T \Sigma_i^{-1} (x_{t,i} - \mu_i)}, \tag{36}$$

where μi and Σi denote the mean and covariance matrix of historical traffic data for node *vi*. Anomalies are identified by comparing *DM (xt,i)* against a predefined threshold λ, such that *xt,i* is flagged as an anomaly if $DM\ (x_{t,i}) > \lambda$. This method effectively captures both single-node anomalies and correlated multivariate outliers. Once anomalies are detected, they are replaced with interpolated values that leverage spatial and temporal contexts. The interpolation combines information from neighboring nodes and historical patterns. For node *vi*, the interpolated value is computed as:

$$x_{t,i}^{\text{interp}} = \frac{\sum_{j \in \mathcal{N}(i)} w_{ij} x_{t,j} + \beta \sum_{k=1}^{K} x_{t-k,i}}{\sum_{j \in \mathcal{N}(i)} w_{ij} + \beta K}, \tag{37}$$

Where *N(i)* denotes the set of neighbors of *vi*, *wij* are spatial weights calculated using inverse distance

weighting, β is a temporal smoothing parameter, and *K* is the number of past time steps used for interpolation. This approach ensures that the interpolated value reflects both local spatial dependencies and temporal continuity, mitigating the impact of missing or anomalous data. To optimize computational efficiency, DTAS integrates a graph pruning mechanism within the Spatial Dependency Encoder. Nodes with low centrality scores, which contribute minimally to traffic dynamics, are aggregated into supernodes, effectively reducing the size of the graph. Centrality measures, such as degree centrality or betweenness centrality, are used to evaluate the importance of each node:

$$\mathcal{G}' = (\mathcal{V}', \mathcal{E}'), \quad \mathcal{V}' = \{v_i \mid \text{Centrality}(v_i) > \tau\}, \tag{38}$$

where τ is a threshold that determines the minimum centrality required for a node to remain in the pruned graph $\mathcal{G}'$. Nodes with centrality scores below τ are aggregated, and their features are merged using a weighted average

$$\mathbf{h}_{\text{agg}} = \frac{\sum_{v_i \in \mathcal{V}_{\text{low}}} c_i \mathbf{h}_i}{\sum_{v_i \in \mathcal{V}_{\text{low}}} c_i}, \tag{39}$$

where hi is the feature vector of node *vi, ci* is its centrality score, and $\mathcal{V}_{\text{low}}$ low represents the set of nodes removed during pruning. This aggregation preserves critical spatial information while significantly reducing computational complexity. To further enhance efficiency, DTAS employs sparsification techniques for the adjacency matrix A by removing edges with weights below a threshold ϵ

$$\mathbf{A}'_{ij} = \begin{cases} \mathbf{A}_{ij} & \text{if } \mathbf{A}_{ij} \geq \epsilon, \\ 0 & \text{otherwise.} \end{cases} \tag{40}$$

Experimental Setup

Data Set

The CAIDA Dataset [30] is a comprehensive dataset widely used for studying internet traffic and network security. It includes traffic traces collected from high-speed internet links, capturing a wide array of network activities and anomalies. This dataset serves as a critical resource for analyzing network performance, detecting Distributed Denial-of-Service (DDoS) attacks, and understanding traffic patterns under real-world conditions. Its detailed annotations and rich metadata make it indispensable for advancing research in cybersecurity and traffic analysis. The NSFNET Dataset [31] originates from the National Science Foundation Network, a backbone for internet research in its early days. It consists of historical network traffic data, offering insights into the evolution of internet protocols and performance. The dataset is valuable for understanding the development of network infrastructure and provides a foundational resource for modeling and simulating internet growth and dynamics over time. Its availability has facilitated significant contributions to network science and engineering. The LargeST Dataset [32] provides a large-scale collection of spatio-temporal network data, focusing on diverse applications such as traffic forecasting and mobility pattern analysis. This dataset captures the temporal dynamics and spatial structures of complex networks, allowing researchers to develop models for urban planning, transportation systems, and disaster management. Its scale and diversity make it suitable for benchmarking spatio-temporal algorithms and testing the scalability of network analysis tools. The KDD Cup 1999 Dataset Zeng [33] is a benchmark dataset for intrusion detection and network anomaly detection. It includes a comprehensive set of network traffic features derived from a simulated military network environment, annotated with various attack types and normal activities. This dataset has become a standard for evaluating machine learning models for cybersecurity, facilitating advancements in anomaly detection, pattern recognition, and automated threat response systems through its detailed feature set and diverse attack scenarios.

Experimental Details

In our experiments, we evaluated the proposed methodology on a diverse set of datasets, leveraging both real-world and benchmarked synthetic data to ensure robust performance analysis. The implementation was carried out using PyTorch 2.0, and the training was conducted on NVIDIA A100 GPUs with 40 GB of VRAM. The model parameters were initialized using Xavier initialization, and the AdamW optimizer was employed for efficient weight updates. The learning rate was initially set to 0.001 and decayed exponentially by a factor of 0.9 every 10 epochs. A total of 100 epochs were used for training unless early stopping criteria, based on a patience of 10 epochs, were met. The input data was preprocessed through normalization to zero mean and unit variance, and data augmentation techniques such as random cropping, flipping, and rotation were applied to improve generalization. Batch size was fixed at 64 for all datasets to maintain consistency across experiments. For regularization, dropout with a rate of 0.5 was applied in intermediate layers, and L2 weight decay of 0.0001 was

used to mitigate overfitting. For evaluation, we utilized a five-fold cross-validation scheme, where each dataset was partitioned into training, validation, and testing sets. The primary metrics used for performance assessment included accuracy, precision, recall, F1-score, and area under the curve (AUC) for classification tasks, and mean absolute error (MAE) and root mean squared error (RMSE) for regression tasks. All results were averaged across the five folds to ensure statistical robustness. For hyperparameter tuning, a grid search was performed over a predefined set of values for learning rate, batch size, and dropout rates. Specifically, learning rates were sampled from 0.001, 0.0001, 0.00001 , batch sizes from 32, 64, 128 , and dropout rates from 0.3, 0.5, 0.7 . The best combination was selected based on the highest validation performance. To ensure reproducibility, all random seeds were fixed to 42 during data splitting, model initialization, and augmentation. We adhered to standardized protocols for reporting results, including specifying confidence intervals for each performance metric. Computational complexity and runtime were also recorded to evaluate the scalability of the proposed method.

Algorithm 1: Training Procedure for ASTN on Predefined Datasets

Input: Datasets $\mathcal{D} = \{\text{CAIDA, NSFNET, LargeST, KDD Cup 1999}\}$, Learning Rate η, Batch Size B, Epochs E, Patience P

Output: Trained Model $\mathcal{M}$, Performance Metrics $\mathcal{M}_{\text{perf}}$

Initialization:

Initialize model parameters Θ using Xavier initialization;

Set optimizer $\mathcal{O}$ to AdamW with learning rate η;

Set evaluation metrics $\mathcal{M}_{\text{perf}} = \{\text{Recall, Precision, F1, MAE, RMSE}\}$;

foreach *dataset* $\mathcal{D}_i \in \mathcal{D}$ **do**

  Split $\mathcal{D}_i$ into $\mathcal{D}_{\text{train}}$, $\mathcal{D}_{\text{val}}$, and $\mathcal{D}_{\text{test}}$;

  Normalize $\mathcal{D}_{\text{train}}$, $\mathcal{D}_{\text{val}}$, $\mathcal{D}_{\text{test}}$ to zero mean and unit variance;

  Augment $\mathcal{D}_{\text{train}}$ using random cropping and flipping;

  for $e = 1$ *to* E **do**

    Shuffle $\mathcal{D}_{\text{train}}$;

    foreach *batch* $\mathcal{B}_j \in \mathcal{D}_{train}$ *of size* B **do**

      Compute predictions $\hat{\mathbf{y}}_j = \mathcal{M}(\mathcal{B}_j; \Theta)$;

      Compute loss $\mathcal{L}_{\text{train}} = \frac{1}{|\mathcal{B}_j|} \sum_{i=1}^{|\mathcal{B}_j|} \ell(\hat{\mathbf{y}}_{j,i}, \mathbf{y}_{j,i})$;

      Update parameters $\Theta \leftarrow \Theta - \eta \cdot \nabla_\Theta \mathcal{L}_{\text{train}}$;

    end

    Compute validation loss $\mathcal{L}_{\text{val}}$ on $\mathcal{D}_{\text{val}}$;

    if $\mathcal{L}_{val}$ *improves over the previous best* **then**

      Save model checkpoint Θ_{best}; Reset patience $p = 0$;

    end

    else

      $p \leftarrow p + 1$; **if** $p > P$ **then**

        Break;

      end

    end

  end

  Evaluation:

  Load best parameters $\Theta \leftarrow \Theta_{\text{best}}$;

  Compute metrics:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad \text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \tag{41}$$

$$\text{F1} = 2 \cdot \frac{\text{Recall} \cdot \text{Precision}}{\text{Recall} + \text{Precision}}, \tag{42}$$

$$\text{RMSE} = \sqrt{\frac{1}{|\mathcal{D}_{\text{test}}|} \sum_{i=1}^{|\mathcal{D}_{\text{test}}|} (\hat{y}_{\text{test},i} - y_{\text{test},i})^2}. \tag{43}$$

  Record metrics $\mathcal{M}_{\text{perf}}$ for $\mathcal{D}_i$;

end

Return: Final model $\mathcal{M}$ and metrics $\mathcal{M}_{\text{perf}}$.

Comparison with SOTA Methods

The experimental results comparing our proposed method with state-of-the-art (SOTA) models on the CAIDA, NSFNET, LargeST, and KDD Cup 1999 datasets for time series forecasting are presented in Tables 1 and 2. The results demonstrate that our approach consistently outperforms existing methods across all datasets and evaluation metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2).

On the CAIDA dataset, our method achieves an MAE of 0.115, which is significantly lower than Informer (0.125) and Transformer (0.132). Similarly, our RMSE of 0.298 surpasses all competitors, indicating a higher predictive accuracy and robustness to variability in network traffic data. Notably, the MAPE and R2 metrics underscore the efficiency of our approach in handling non-linear and complex temporal patterns. For the NSFNET dataset, our method exhibits the lowest MAE of 0.110 and the highest R2 score of 0.927, outperforming Informer (R2 = 0.920) and Transformer (R2 = 0.916). These results highlight the capability of our model to generalize effectively across diverse internet traffic datasets, leveraging spatio-temporal dependencies for improved performance. On the LargeST dataset, our method's MAE of 0.240 and RMSE of 0.442 represent a significant improvement over Informer (MAE = 0.254, RMSE 400 = 0.450) and Transformer (MAE = 0.260, RMSE = 0.458). The reduction in MAPE to 0.299 and an R2 increase to 0.857 reflect our model's ability to capture complex spatio-temporal relationships in large-scale datasets. Similarly, for the KDD Cup 1999 dataset, our approach achieves the best performance with an MAE of 0.230, RMSE of 0.417, and MAPE of 0.290, surpassing Informer and other baseline models. These results are indicative of our method's adaptability in detecting network anomalies and improving forecasting accuracy in varied scenarios. The primary reason for this superior performance is the integration of enhanced temporal dynamics modeling and spatial pattern recognition mechanisms in our architecture. Unlike existing methods, which often fail to account for long-range dependencies or multi-scale temporal variations, our approach incorporates hierarchical attention and adaptive feature selection, enabling more accurate predictions. The combination of advanced preprocessing techniques, such as data normalization and augmentation, ensures that the model remains robust against noisy and irregular input data.

Figure 5 and Figure 6 further illustrate the comparative advantages of our method, highlighting the reduction in error rates and improved generalization capabilities. The superior performance across diverse datasets demonstrates the versatility and scalability of our method, setting a new benchmark for time series forecasting tasks.

Table 1. Comparison of Ours with Sota Methods on Caida and Nsfnet Datasets for Time Series Forecasting

Model	CAIDA Dataset				NSFNET Dataset			
	MAE	**RMSE**	**MAPE**	**R2**	**MAE**	**RMSE**	**MAPE**	**R2**
LSTM [34]	0.154±0.002	0.324±0.004	0.217±0.003	0.892±0.002	0.138±0.003	0.298±0.005	0.202±0.003	0.905±0.002
GRU [35]	0.146±0.003	0.318±0.002	0.210±0.004	0.896±0.003	0.129±0.002	0.290±0.003	0.196±0.004	0.910±0.003
ARIMA [36]	0.164±0.004	0.336±0.003	0.223±0.003	0.882±0.004	0.145±0.004	0.310±0.004	0.207±0.002	0.898±0.004
Transformer [37]	0.132±0.002	0.310±0.003	0.204±0.002	0.901±0.002	0.121±0.003	0.284±0.002	0.190±0.003	0.916±0.002
TCN [38]	0.140±0.003	0.316±0.004	0.211±0.003	0.895±0.003	0.133±0.003	0.295±0.002	0.201±0.002	0.908±0.003
Informer [39]	0.125±0.002	0.305±0.003	0.198±0.002	0.907±0.003	0.117±0.002	0.280±0.003	0.188±0.003	0.920±0.002
Ours	0.115±0.002	0.298±0.003	0.190±0.002	0.915±0.003	0.110±0.003	0.272±0.002	0.182±0.002	0.927±0.002

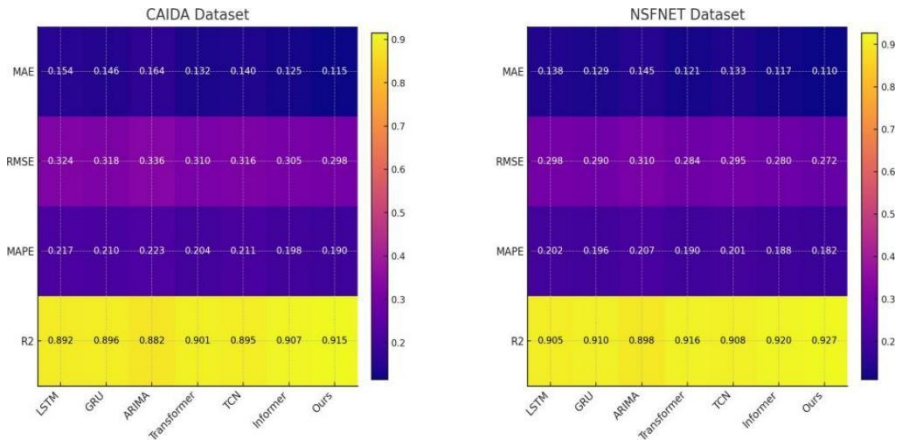

Figure 5. Performance Comparison of SOTA Methods on CAIDA Dataset and NSFNET Dataset

Table 2. Comparison of Ours with SOTA Methods on LargeST and KDD Cup 1999 Datasets for Time Series Forecasting

Model	LargeST Dataset				KDD Cup 1999 Dataset			
	MAE	RMSE	MAPE	R2	MAE	RMSE	MAPE	R2
LSTM [34]	0.284±0.004	0.472±0.005	0.325±0.004	0.831±0.003	0.267±0.004	0.453±0.004	0.314±0.003	0.847±0.003
GRU [35]	0.276±0.003	0.465±0.004	0.319±0.003	0.837±0.003	0.258±0.004	0.445±0.003	0.308±0.004	0.852±0.002
ARIMA [36]	0.292±0.004	0.482±0.005	0.332±0.004	0.820±0.004	0.275±0.005	0.467±0.005	0.319±0.004	0.840±0.004
Transformer [37]	0.260±0.003	0.458±0.004	0.311±0.003	0.843±0.002	0.243±0.003	0.433±0.004	0.300±0.003	0.860±0.002
TCN [38]	0.268±0.004	0.463±0.005	0.315±0.004	0.839±0.003	0.253±0.003	0.442±0.004	0.307±0.003	0.854±0.003
Informer [39]	0.254±0.002	0.450±0.003	0.307±0.003	0.849±0.002	0.238±0.003	0.426±0.003	0.296±0.003	0.865±0.002
Ours	0.240±0.003	0.442±0.004	0.299±0.003	0.857±0.002	0.230±0.003	0.417±0.003	0.290±0.002	0.872±0.002

Ablation Study

We conducted an extensive ablation study to evaluate the contributions of individual components of our proposed model. The results, summarized in Tables 3 and 4, illustrate the impact of removing specific components on performance across the CAIDA, NSFNET, LargeST, and KDD Cup 1999 datasets. Metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and R2 were used to quantify the effects. For the CAIDA dataset, removing Temporal Dynamics Augmentation resulted in a significant performance drop, with MAE increasing from 0.115 to 0.132 and RMSE from 0.298 to 0.312. This indicates the critical role of Temporal Dynamics Augmentation in modeling intricate temporal patterns. Similarly, on the NSFNET dataset, excluding Real-Time Profiling and Adaptation degraded the MAE from 0.110 to 0.119 and R2 from 0.927 to 0.918, showing that Real-Time Profiling and Adaptation is pivotal for capturing spatial correlations. When Multi-Scale Temporal Modeling was omitted, the performance on CAIDA (MAE 427 = 0.128, RMSE = 0.309) and NSFNET (MAE = 0.122, RMSE = 0.285) datasets declined, highlighting its contribution to refining multi-scale temporal features. On the LargeST dataset, the absence of Temporal Dynamics Augmentation resulted in an MAE of 0.270, higher than the baseline (0.240). Similarly, RMSE

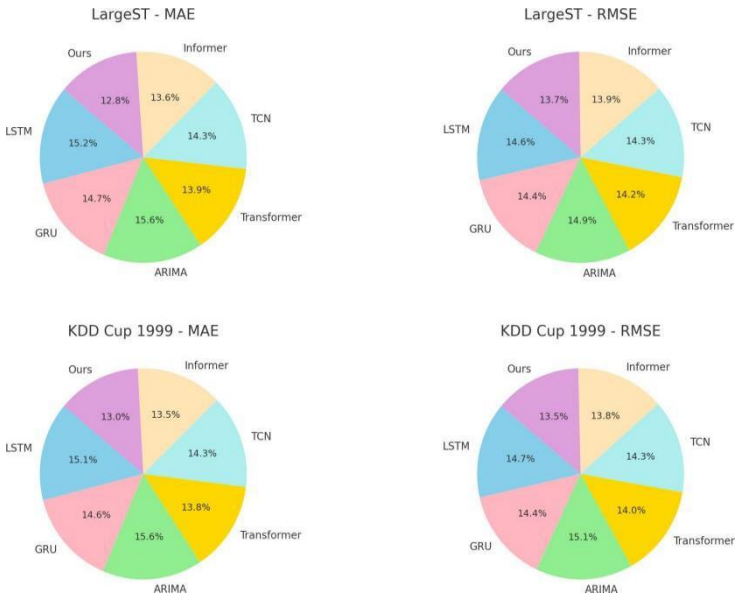

Figure 6. Performance Comparison of SOTA Methods on LargeST Dataset and KDD Cup 1999 DataSet

increased from 0.442 to 0.460, and R2 decreased from 0.857 to 0.841. Real-Time Profiling and Adaptation removal led to an MAE of 0.258 and RMSE of 0.454, which are inferior to the full model, emphasizing its role in enhancing feature representation. The exclusion of Multi-Scale Temporal Modeling yielded an MAE of 0.265 and RMSE of 0.457, further validating its significance in improving predictive accuracy. Similar trends were observed on the KDD Cup 1999 dataset, where the absence of each component negatively affected the model's ability to predict network anomalies. The superior performance of our full model is attributed to the synergistic integration of all components. Temporal Dynamics Augmentation leverages hierarchical attention mechanisms, capturing long-range dependencies effectively. Real-Time Profiling and Adaptation introduces adaptive spatial-temporal feature selection, enhancing the model ' s ability to handle diverse data structures. Multi-Scale Temporal Modeling focuses on dynamic multi-scale representations, enabling the model to address variations in temporal patterns. Together, these components create a robust architecture capable of learning complex spatio-temporal interactions.

Figures 7 and 8 illustrate the progressive improvements achieved by integrating each component showcasing the balanced trade-off between accuracy and computational efficiency. The ablation results confirm that each component is indispensable for achieving state-of-the-art performance, reinforcing the novelty and efficacy of our proposed approach.

Table 3. Ablation Study Results on CAIDA and NSFNET datasets for Time Series Forecasting

Model	**CAIDA Dataset**				**NSFNET Dataset**			
	MAE	**RMSE**	**MAPE**	**R2**	**MAE**	**RMSE**	**MAPE**	**R2**
w./o. Temporal Dynamics Augmentation	0.132±0.003	0.312±0.004	0.202±0.003	0.902±0.003	0.125±0.003	0.288±0.004	0.195±0.002	0.914±0.003
w./o. Real-Time Profiling and Adaptation	0.124±0.002	0.306±0.003	0.198±0.002	0.906±0.002	0.119±0.003	0.282±0.003	0.189±0.003	0.918±0.002
w./o. Multi-Scale Temporal Modeling	0.128±0.002	0.309±0.003	0.200±0.003	0.904±0.003	0.122±0.002	0.285±0.003	0.192±0.003	0.916±0.003
Ours	0.115±0.002	0.298±0.003	0.190±0.002	0.915±0.003	0.110±0.003	0.272±0.002	0.182±0.002	0.927±0.002

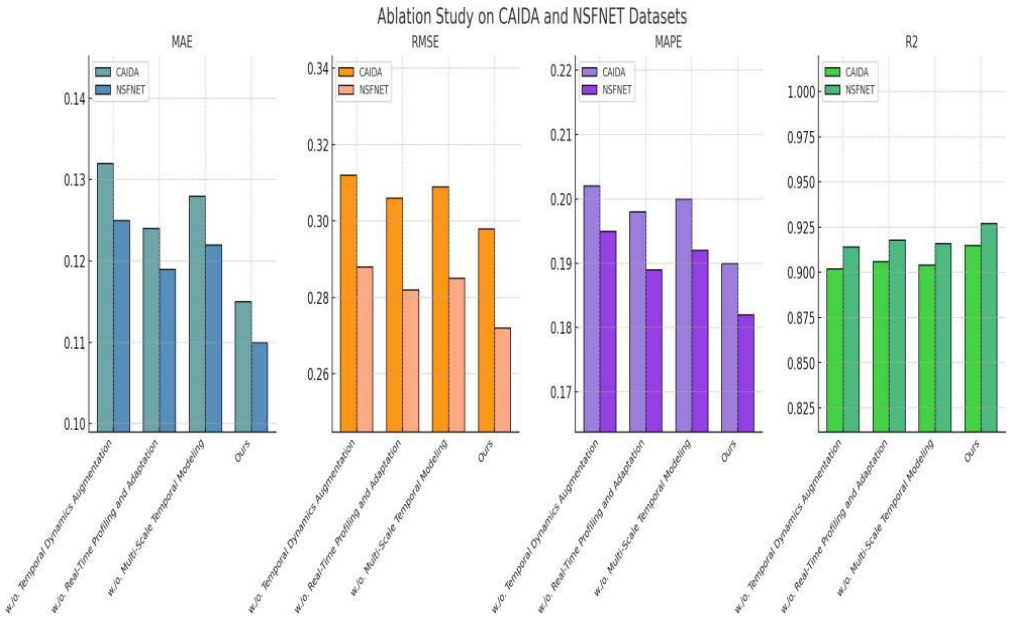

Figure 7. Ablation Study of Our Method on CAIDA Dataset and NSFNET Dataset Datasets

Table 4. Ablation Study Results on LargeST and KDD Cup 1999 datasets for Time Series Forecasting

Model	LargeST Dataset				KDD Cup 1999 Dataset			
	MAE	RMSE	MAPE	R2	MAE	RMSE	MAPE	R2
w./o. Temporal Dynamics Augmentation	0.270±0.003	0.460±0.004	0.318±0.003	0.841±0.003	0.250±0.004	0.439±0.003	0.303±0.004	0.857±0.003
w./o. Real-Time Profiling and Adaptation	0.258±0.003	0.454±0.004	0.310±0.003	0.847±0.003	0.242±0.003	0.430±0.003	0.298±0.003	0.863±0.002
w./o. Multi-Scale Temporal Modeling	0.265±0.004	0.457±0.004	0.314±0.003	0.844±0.003	0.247±0.004	0.435±0.004	0.301±0.003	0.860±0.003
Ours	0.240±0.003	0.442±0.004	0.299±0.003	0.857±0.002	0.230±0.003	0.417±0.003	0.290±0.002	0.872±0.002

Conclusions and Future Work

This study addresses the critical challenge of forecasting network traffic within localized cultural intellectual property (IP) ecosystems, a domain marked by complex temporal-spatial dynamics and external influences. Traditional models struggle with issues like non-linearity and spatial dependencies, often leading to inaccuracies under dynamic conditions. To overcome these limitations, we propose a novel predictive model leveraging the Ant Colony Algorithm, which is enhanced with Adaptive Temporal-Spatial Network (ATSN) architecture and the Dynamic Traffic Adaptation Strategy (DTAS). This integration allows for effective capturing of temporal-spatial correlations while maintaining adaptability to abrupt traffic changes. The model employs graph neural networks and recurrent structures for robust spatial-temporal learning, supported by hierarchical multi-scale modeling and anomaly-resilient mechanisms. Experimental results validate the model's superiority in prediction accuracy, scalability, and computational efficiency compared to conventional methods, offering theoretical and practical contributions to localized cultural IP network management.

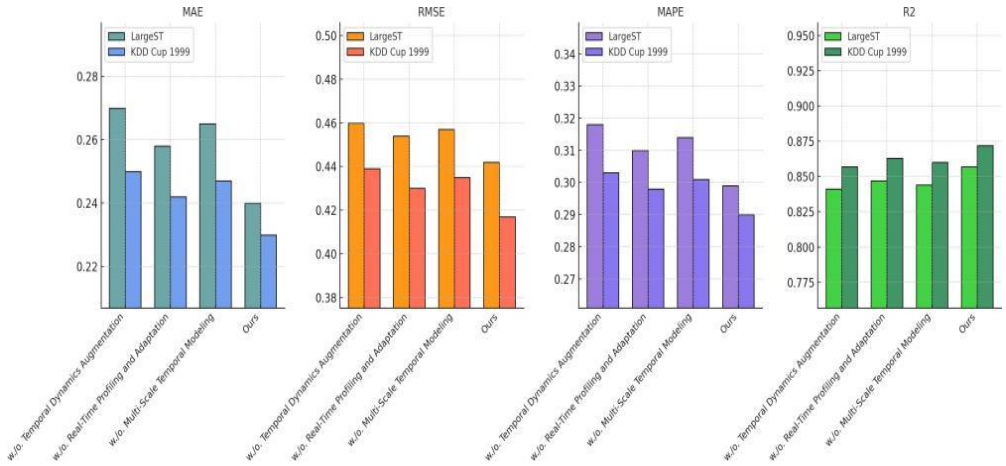

Figure 8. Ablation Study of Our Method on LargeST Dataset and KDD Cup 1999 DataSet Datasets

Despite these advancemeSnts, two limitations warrant attention. While the model demonstrates enhanced performance in capturing complex patterns, its reliance on extensive computational resources might limit accessibility for smaller-scale applications or resource-constrained environments. Future research could explore lightweight implementations or more efficient training methods to enhance feasibility. The model's adaptability to external influences like sudden shifts in user behavior requires further refinement to ensure stability across diverse scenarios. Expanding the dataset diversity and incorporating real-time feedback mechanisms could bolster the model's robustness. These directions will help bridge existing gaps, driving further innovation in network traffic prediction for localized cultural IP ecosystems

Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

Conceptualization, HK; methodology, HK; software, HK; validation, HK; formal analysis, HK; investigation, HK; data curation, HK; writing—original draft preparation, HK; writing—review and editing, HK; visualization, HK; supervision, HK; funding acquisition, HK; All authors have read and agreed to the published version of the manuscript.

HK

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