Thesis Proposal for MPhil Degree

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Individual Project:	Frequency-Enhanced Lightweight Framework for Multivariate Time Series Forecasting
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Part I Introduction to the Group Project

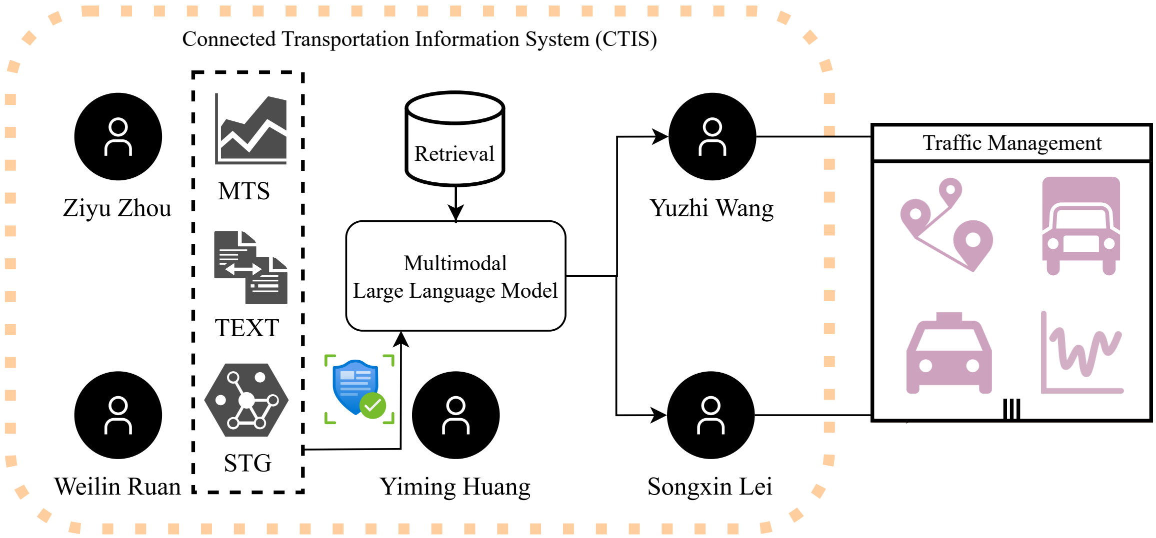


Figure 1: The outline of the composition and structure of our group project.

1.1 Background and Objective

The rapid pace of urbanization in contemporary cities has posed considerable challenges to transportation infrastructures. As population densities and vehicle usage continue to rise, urban areas increasingly experience issues such as traffic congestion, travel delays, elevated safety risks, and environmental deterioration. These persistent problems undermine transportation system efficiency, threaten public welfare, and obstruct efforts toward sustainable urban development. Effectively addressing these hurdles demands innovative strategies driven by intelligent technologies.

Intelligent Transportation Systems (ITS) have emerged as a transformative solution, integrating advanced sensing, communication, and data processing capabilities to enhance transportation frameworks. By leveraging real-time traffic surveillance, predictive modeling, and vehicle connectivity, ITS aims to streamline traffic flow, bolster safety measures, and foster environmental responsibility. ITS initiatives encompass diverse focus areas, including traffic management, autonomous mobility support, infrastructure health monitoring, and the fusion of multimodal data for urban planning and policy-making.

Within this context, our group initiative, the Connected Transportation Information System (CTIS), aspires to establish an integrated platform melding live traffic data, Vehicle-to-Everything (V2X) communication, and predictive analytics. The CTIS platform is designed to confront critical challenges in contemporary transportation, offering tools for improved traffic management, heightened safety, and diminished ecological footprints.

Modern transportation systems grapple with numerous pressing obstacles. Intensifying travel demand in urban environments generates severe congestion and prolonged travel times, incurring significant economic costs. Persistent safety concerns arise from insufficient real-time hazard detection and prevention strategies, contributing to recurring accidents. Simultaneously, inefficient route selection and traffic control raise energy consumption and carbon emissions, amplifying environmental harm. Recent incidents, such as the landslide catastrophe on the Chayang segment of the Meizhou Meida Expressway in May 2024 and the Lixinsha Bridge collapse caused by a container ship collision in February 2024, highlight the urgent need for intelligent solutions that can both mitigate such disasters and enhance emergency response.

To confront these multifaceted problems, CTIS adopts a comprehensive, interdisciplinary methodology. The project centers on deploying real-time communication and data-sharing frameworks, enabling seamless interaction among vehicles, infrastructural assets, and control centers. Advanced predictive analytics and machine learning algorithms will be utilized to interpret evolving traffic conditions, identify potential dangers, and offer actionable recommendations for improved traffic regulation. Furthermore, the inclusion of V2X communication capabilities enhances connectivity and facilitates autonomous driving functionalities, while multimodal data fusion equips urban planners with deeper insights for long-term mobility strategies.

The CTIS project is organized around the following primary objectives:

1. **Real-time Traffic Optimization:** Design and implement sophisticated algorithms for intelligent traffic control to alleviate congestion and reduce delays.

2. **Safety Enhancement:** Integrate V2X communication and continuous monitoring to strengthen hazard detection and accident prevention.

3. **Sustainability Promotion:** Enhance route planning and traffic regulation to lower energy usage and cut carbon emissions.

4. **Urban Mobility Support:** Employ multimodal data integration to furnish actionable insights for informed urban planning and decision-making.

1.2 Significance

The CTIS project represents a transformative endeavor, tackling pressing issues in urban transportation while setting the stage for the long-term progression of Intelligent Transportation Systems (ITS). Its significance stems from the seamless integration of advanced sensing, communication, and data analytics, culminating in more intelligent, safer, and environmentally responsible transportation infrastructures. By merging these cutting-edge technologies, CTIS not only addresses today's urban mobility hurdles but also lays the groundwork for meeting the future requirements of adaptive, technology-driven metropolitan environments.

The significance of this project can be outlined as follows:

- **Reducing Congestion and Improving Efficiency:** Employing real-time traffic data and predictive modeling, CTIS optimizes vehicle flow and minimizes travel delays, thereby enhancing overall transportation efficiency.
- **Improving Road Safety:** By incorporating connected vehicle technologies and continuous hazard detection, CTIS mitigates collision risks and safeguards all road users, including pedestrians and cyclists.
- **Promoting Environmental Sustainability:** More efficient traffic management and route planning reduce fuel consumption and carbon emissions, aligning with global efforts to combat climate change and ecological degradation.
- **Advancing Urban Planning:** Through multimodal, data-driven insights, CTIS empowers urban planners to design resilient, future-ready cities, strengthening long-term infrastructure and development strategies.
- **Driving Technological Innovation:** The development of CTIS fosters advancements in transportation research, generating scalable and adaptable solutions suitable for diverse urban contexts worldwide.

Beyond addressing immediate issues such as congestion and safety, CTIS offers a scalable, forward-looking framework for intelligent transportation management. Its holistic approach ensures that the platform not only responds to present-day challenges but also contributes to the ongoing evolution of ITS. By fostering more adaptive, eco-friendly, and technologically advanced transportation systems, CTIS supports the realization of a future defined by sustainable urban mobility and progressive, data-driven urban planning.

1.3 Project Composition

The project consists of a series of interconnected individual projects, with each project contributing its own unique insights and technological advancements.

1. Weilin Ruan: **Retrieval-Augmented Universal Models for Spatio-Temporal Data**
   Weilin Ruan's project focuses on Retrieval-Augmented Universal Models for Spatio-Temporal Data, which aims to design a highly efficient framework for integrating and processing large-scale spatio-temporal datasets. With the rapid growth of urban data generated from diverse sources, such as satellite imagery, traffic sensors, and public transit records, analyzing such datasets in a unified and scalable way has become a significant challenge. This project addresses these challenges by leveraging retrieval-augmented techniques to enhance the performance and interpretability of spatio-temporal data models.

2. Ziyu Zhou: **Frequency-Enhanced Lightweight Framework for Multivariate Time Series Forecasting**
   Ziyu Zhou's individual project focuses on developing WaveTS, a lightweight, wavelet-based time series forecasting model tailored for traffic prediction within the CTIS. By decomposing multivariate traffic data into multiple frequency scales, WaveTS captures both global patterns and localized fluctuations, ensuring accurate and efficient forecasts. This adaptable approach enables seamless edge deployment, supports real-time congestion forecasting, and enhances safety measures, ultimately strengthening the CTIS framework and advancing time series forecasting methodologies in complex urban settings.

3. Yiming Huang: **Hallucination Detection and Mitigation, Robustness Evaluation, and Multi-Source Information Debiasing**
   Yiming Huang's individual research mainly concentrated on utilizing underlying mechanistic interpretability to develop a more comprehensive model securing technologies and evaluation methodologies. This personal research outcome indeed matches the safety securing need in the CTIS framework. Due to textual inputs and intermediate information in the CTIS system, the sub-project of Yiming's research will help more fine-grained hallucination detection and alleviation. Besides that, Yiming's research will provide novel AI system evaluation with a unified theoreti-

cal guarantee, which is important to eval the CTIS system's performance. Yiming will also work on an AI debiasing project, which will help CTIS framework get rid of biased single-source information dependency.

4. Yuzhi Wang: **Large Language Model Enhanced Urban Agent Simulation and Application**
   Yuzhi's project aims to leverage large language models (LLMs) to enhance individual decision-making behaviors in city simulation tasks, especially in agent-based models (ABMs). Through LLM technologies like prompt, retrieval, generation and fine-tuning, the human-centered agent behaviors in the urban environment, e.g. mobility, economic and social interaction are generated, to provide micro-level research perspective to various urban evolution and optimization, such as point of interest (POI), land-use, and transportation infrastructures.

5. Songxin Lei: **Collaborative Public Resource Allocation: A Spatio-temporal Feature Extraction and Potential Game-Based Reinforcement Learning Framework**
   Songxin's work ensures that mobile public resources, such as intelligent trash bins or delivery stations, are effectively deployed to maximize coverage and meet dynamic demand. Additionally, the research investigates the collaborative relationships among resources, providing theoretical guarantees through the use of potential game theory. By integrating with spatio-temporal neural networks for feature extraction and constructing a robust reward function, this project delivers actionable strategies for intelligent decision-making. The outcomes contribute to the development of a scalable, adaptive, and intelligent transportation system, offering valuable insights for urban planners and policymakers aiming to enhance urban mobility and resource efficiency.

These interconnected projects collectively create a holistic and integrated approach to tackling the obstacles of incorporating electric vehicles into urban settings, all the while promoting sustainability, efficiency, and safety in urban mobility.

1.4 Project Connections

Each individual project within the Connected Transportation Information System interlinks to create a cohesive and efficient system:

- **Weilin's Predictive Analysis:** Weilin Ruan's project plays a pivotal role in the overall synergy of the Connected Transportation Information System (CTIS). The retrieval-augmented framework developed in this project not only enhances the efficiency of integrating and processing large-scale spatio-temporal datasets but also serves as a key enabler for many other sub-projects within CTIS. Specifically, Weilin's work dynamically retrieves and integrates relevant historical and real-time data, providing a solid foundation for downstream tasks. The retrieval-augmented framework seamlessly integrates with Ziyu Zhou's temporal models by supplying contextually relevant historical data, such as traffic patterns under similar conditions. This significantly improves the accuracy and robustness of multivariate temporal predictions while reducing uncertainty in dynamic urban environments. Moreover, the spatio-temporal graph representations generated by Weilin's project act as critical inputs for Songxin Lei's intelligent infrastructure planning. These representations enable more effective optimization of connected infrastructure layouts, such as smart traffic lights and vehicle-to-infrastructure (V2I) communication systems. Additionally, the project supports Yuzhi Wang's research on autonomous vehicle trajectory predictions by providing pre-trained universal models with strong cross-city generalization capabilities. Using these models, Yuzhi's system can better predict interactions between vehicles and pedestrians, improving the safety and reliability of autonomous navigation.
- **Ziyu's Strategic Deployment:** Ziyu's individual project focuses on modeling multivariate time series (MTS in Fig. 7) data within the CTIS ecosystem. Ziyu's predictions enrich the overall data pool that includes textual insights, spatial-temporal graphs (STG), and other sensor-derived metrics. As a result, the model's refined time series forecasts serve as a vital input stream for subsequent tasks—such as route optimization, demand forecasting for shared mobility services, or resource allocation for charging stations—handled by Yuzhi, Songxin, and other team members. In this manner, Ziyu's contributions ensure that the entire CTIS framework benefits from accurate, timely MTS forecasts, enhancing the decision-making capabilities and responsiveness of the interconnected urban transportation network.
- **Yiming's Securing Measures:** To be specific, there are at least three aspects of safety guarantee in the project: 1) By passing LLM-extracted text information

to different modules in CTIS, it unavoidably brings LLM inherent hallucination problem. One of Yiming's individual research aligns with this problem. It will help Weilin, Ziyu, and Yuzhi to reduce the hallucination of their modules' input or output. 2) To verify whether the framework is robust to noise in any kind of input data or middle intermediate information, Yiming Huang's individual research will provide the method. It aims to check the system output of Songxin's and Yuzhi's modules. 3) Due to multi-source input information and intermediate information works in the CTIS framework, it is important to ensure the framework does not rely too much on specific parts of information which results in a biased CTIS framework and wasted other kinds of information. In this aspect, Yiming will coordinate with the whole team.

- **Yuzhi's Simulation Insights:** The LLM-based urban agent simulation proposed by Yuzhi constructs a digital twin environment for CTIS from a new generative agent-based model (GABM) perspective. With the help of scalable and interactive dynamic urban simulation environments generated by LLMs, Yuzhi's work can make good use of teammates' spatio-temporal data, especially trajectory data to build agents. Besides, the simulator can be used to further provide guidance for the optimization and future evolution of transportation information systems in urban environments.
- **Songxin's Allocation Strategies:** Songxin's research serves as a critical fine-grained decision-making component within the Connected Transportation Information System. By leveraging the predictive results provided by Ziyu and Weilin, i.e., time-series population flow predictions and spatio-temporal graph-based forecasts, my work develops deployment strategies for mobile public resources. These strategies are optimized to interact with the environment, translating predictive insights into actionable decisions that maximize real-world impact.

1.5 Project Milestones

The development of the Connected Transportation Information System (CTIS) is divided into four key phases, each designed to ensure the seamless integration of individual sub-projects into a unified, scalable system. These milestones focus on data collection, model development, collaborative integration, platform testing, and deployment.

1. **Individual Data Collection and Model Development (Months 0-3)**

    - **Focus:** At this stage, each team member focuses on collecting and processing data relevant to their specific sub-project within CTIS.
    - **Key Activities:**
        - Developing initial models and algorithms for tasks such as:
            * Predictive traffic flow modeling and congestion analysis.
            * Optimizing charging infrastructure for electric vehicles.
            * Scheduling algorithms for shared-mobility services.
            * Trajectory predictions for autonomous vehicle behavior.
            * Spatio-temporal urban analysis for transportation planning.
        - Refining datasets to ensure consistency and compatibility across sub-projects.

2. **Collaborative Data Integration and Model Alignment (Months 3-6)**

    - **Focus:** This phase emphasizes collaboration among team members to integrate individual datasets and align models within the CTIS framework.
    - **Key Activities:**
        - Sharing datasets and combining insights from individual sub-projects, such as traffic flow modeling, urban analysis, and autonomous behavior predictions.
        - Synchronizing predictive models, optimization techniques, and scheduling algorithms to ensure smooth data flow and compatibility within the system.
        - Establishing a unified data pipeline to handle multimodal spatio-temporal data efficiently.

3. **Holistic Platform Integration and Initial Testing (Months 6-9)**

    - **Full Platform Integration:**
        - Combining components developed during earlier phases into a unified CTIS platform.
        - Consolidating features such as traffic flow prediction, charging infrastructure optimization, shared mobility scheduling, autonomous behavior analysis, and urban transportation insights into a cohesive system.

- **Initial Testing and Evaluation:**
  - Conducting initial testing in simulated environments to ensure the integrated platform functions cohesively.
  - Testing the platform in diverse urban scenarios to evaluate its adaptability and robustness.

4. **Comprehensive Deployment and Future Planning (Months 9-12)**

- **Deployment in Selected Areas:**
  - Rolling out the integrated CTIS platform in selected urban areas as pilot projects.
  - Collecting feedback and performance metrics to refine system components and improve operational efficiency.
- **Citywide or Multi-Area Deployment:**
  - Scaling up the system for full deployment across cities or regions based on the success of pilot implementations.
  - Ensuring the platform's scalability to support diverse urban mobility challenges.
- **Project Summary and Future Development:**
  - Compiling a comprehensive project report to document key achievements, challenges encountered, and lessons learned.
  - Proposing future development plans to enhance the CTIS platform, incorporating emerging technologies and addressing evolving urban mobility needs.

Part II Proposal of the Individual Project

2.1 Significance and Relevance of the Individual Project to the Group Project

2.1.1 Complementary Role

General Time Series Forecasting Time series data is pervasive across a variety of domains, including e-commerce, finance, and healthcare (see Fig. 2). For example, power load time series analysis helps electricity providers manage consumption patterns in factories or residential areas. However, forecasting such data is challenging due to intricate inter-series correlations and complex intra-series dependencies. While traditional deep learning models—such as Transformers [1] [2], temporal convolutional networks [3], and graph neural networks [4]—effectively capture local temporal relations, they often struggle to model global patterns.

Figure 2: Time series in the real world.

To address these limitations, frequency domain transformations—such as the Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), and Discrete Wavelet Transform (DWT)—have been integrated into neural networks [5] [6]. These techniques provide multi-scale representations, offering a more holistic understanding of time-dependent phenomena.

From Fig. 3, it can be observed that real-world time series often exhibit irregular and non-stationary characteristics. The complex fluctuations, coupled with features such as periodicity, trends, and abrupt changes, make effective modeling challenging for traditional statistical methods. Therefore, my individual project aims to propose an innovative multivariate time series prediction model with frequency transformations to achieve effective modeling of complex temporal patterns, particularly for non-stationary time series. I anticipate that this model will perform well across time series datasets from different domains and with varying distributions.

Traffic Forecasting Within the overall group project, my individual project functions as a traffic data predictor, providing real-time and accurate future forecasts for complex traffic scenarios in the CTIS project.

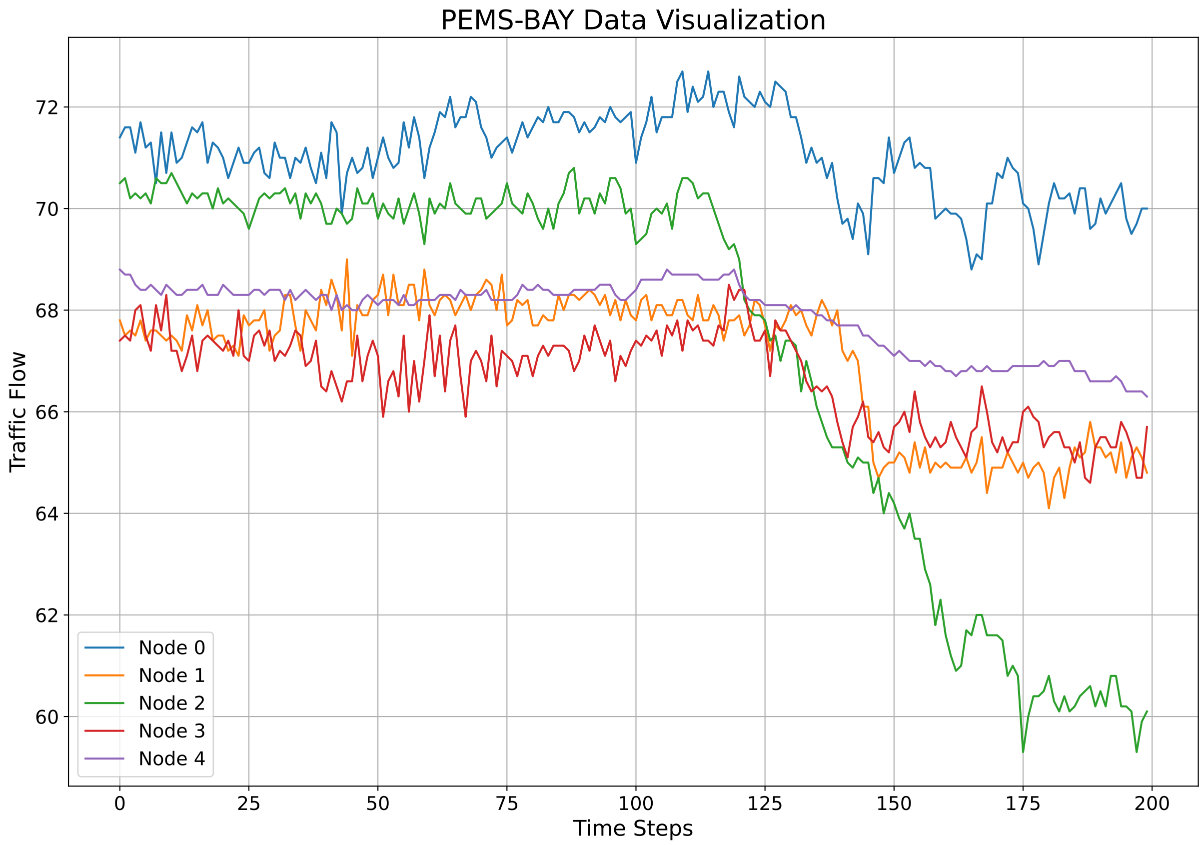
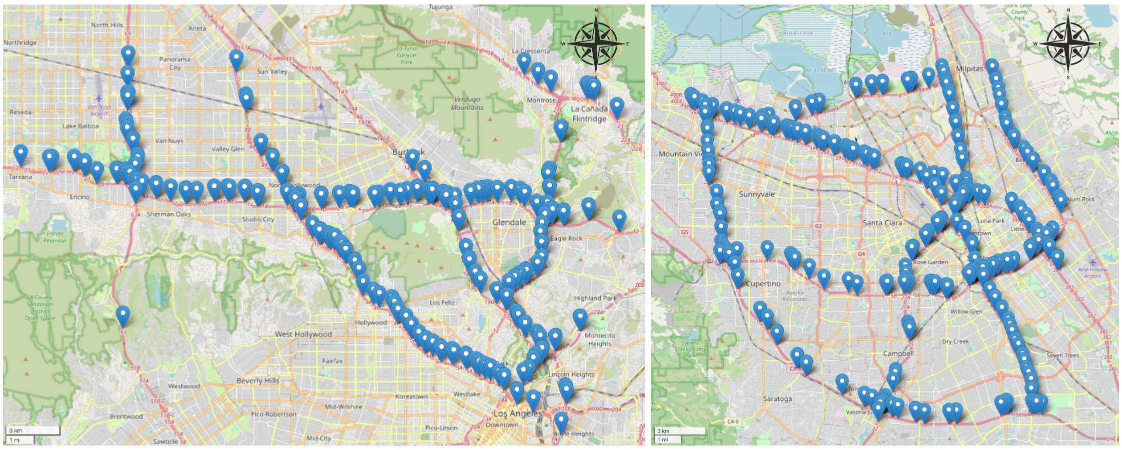


Figure 3: Time series visualization.

In the transportation domain, accurate traffic forecasting is crucial for proactive congestion management, infrastructure planning, and enhanced travel experiences [7]. Data sources such as loop detectors, surveillance cameras, and floating car data (FCD) shed light on traffic conditions (speed, volume, etc.) yet come with inherent trade-offs. Loop detectors yield precise measurements but cover only limited areas and are costly to maintain. Surveillance cameras provide rich visual cues but require complex analyses and often lack transferability across locations. FCD, obtained from GPS-equipped vehicles, is cost-effective and flexible but depends on vehicle coverage and distribution.

Real-world datasets, as shown in Fig. 4, illustrate how these sensing technologies are employed in practice. For instance, METR-LA collects data from 207 loop detectors in Los Angeles, while PEMS-BAY aggregates measurements from 325 sensors in the Bay Area. These datasets offer valuable testbeds for evaluating advanced forecasting models across diverse spatial and temporal scales. By integrating insights from general time series forecasting with these traffic datasets, the individual project contributes to the development of robust traffic prediction solutions that handle real-world constraints, heterogeneous data modalities, and evolving transportation systems.



METR-LA: 207 sensors from Mar 1st 2012 to Jun 30th 2012 in Los Angeles

PEMS-BAY: 325 sensors from Jan 1st 2017 to May 31th 2017 in the Bay Area

Figure 4: Examples of sensor distributions from benchmark datasets. (Left) METR-LA: 207 sensors in Los Angeles. (Right) PEMS-BAY: 325 sensors in the Bay Area.

2.1.2 Value Addition

The individual project leverages frequency-domain transformations and multi-scale signal analysis techniques tailored to the transportation context. While general time series forecasting methodologies offer foundational principles, the project extends and refines them for traffic prediction, incorporating characteristics such as localized disruptions, cyclical patterns, and rapid fluctuations. The resulting models are not only more accurate but also more computationally efficient, enabling deployment on edge devices within the CTIS framework. This capability directly supports the group project's objective of enhancing the CTIS. By delivering timely and reliable forecasts, the individual solution guides better route planning, congestion management, and safety interventions. It effectively bridges theoretical advancements in time series forecasting with practical transportation challenges, ensuring that improved methodologies translate into tangible societal benefits.

2.1.3 Interdependence

The relationships within the group project are inherently interdependent. The individual forecasting model relies on the CTIS to provide diverse, multi-source data streams that inform its predictions. In turn, the enhanced forecasts produced by this model benefit other CTIS components, such as traffic signal control and incident detection systems. This reciprocal flow of information and influence ensures that improvements in one area propagate throughout the

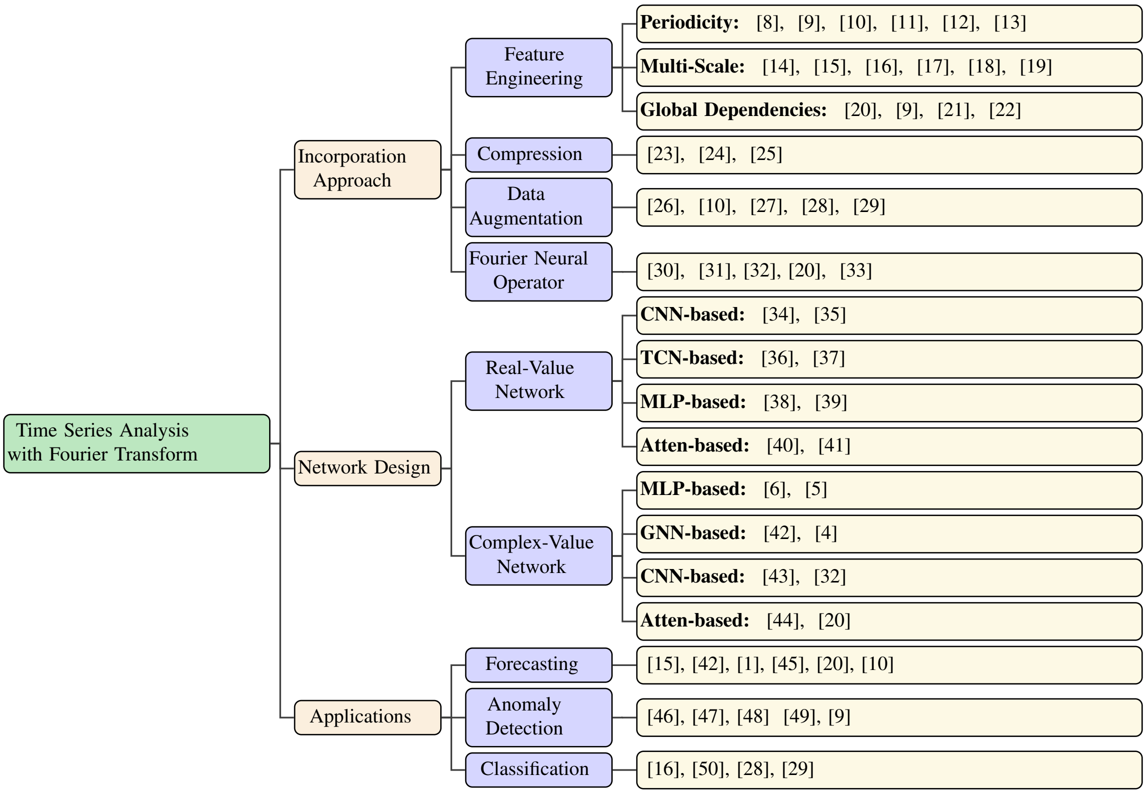


Figure 5: A comprehensive taxonomy of representative works, categorized according to Incorporation Approach, Network Design and Applications.

entire system.

In sum, the individual project's focus on frequency-domain transformations and refined forecasting techniques complements the group's broader efforts in building a connected, data-driven transportation ecosystem. By strengthening its forecasting capabilities, the project not only adds value to the CTIS but also reinforces the collaborative and interdependent nature of the group project's objectives.

2.2 Statement of the Individual Project in Details

2.2.1 Literature/Market Review and Problem Definition

This section systematically summarizes research with frequency transformations to advance time series analysis in machine learning. All the related works are categorized in Fig 5.

Incorporation Approach Frequency-domain analysis conveys crucial insights, such as periodic patterns, that complement time-domain information. For instance, [8] introduces a frequency-domain module to extract dynamic periodic patterns and integrates them into deep learning frameworks. Similarly, [9] leverages frequency-domain techniques to detect intricate anomalies, especially periodic ones. In [10], trend and seasonal components are decoupled, and seasonal patterns are learned via a Fourier layer. Likewise, [11] enhances a foundational model by incorporating features derived from the frequency domain. Further, [12] substitutes self-attention with frequency-based attention to identify seasonal behaviors, while [13] utilizes concatenated Fourier features to better model high-frequency patterns.

Modeling intricate temporal dynamics remains a formidable task. Frequency-domain strategies tackle this challenge by decomposing time series into distinct frequency components. For instance, [14] partitions RNN memory states into separate frequency states, facilitating low- and high-frequency dependency learning. Additionally, [15] decomposes trading data into multiple frequency bands to represent trading behavior. Wavelet approaches, such as [16], exploit time-frequency localization to capture patterns at multiple resolutions, while [17] utilizes a maximal overlap discrete wavelet transform to analyze individual periodicities and [18] proposes wavelet-based attention for non-stationary sequences. An end-to-end graph-enhanced wavelet model for long-sequence forecasting is introduced by [19].

Methods operating strictly in the time domain often establish only point-wise connections, thus struggling to grasp global series-level patterns. Frequency-based methods mitigate this by modeling global structures. For example, [20] integrates Fourier analysis into Transformers to better capture global temporal patterns. Likewise, [9] uses frequency analysis to discern anomalies within seasonal patterns. Furthermore, [21] and [22] incorporate spectral learning into their approaches to overcome the locality limitations of standard convolutions by employing frequency transformations for global receptive fields. FilterNet [51] exploits temporal patterns through straightforward shaping filters and contextual shaping filters.

Frequency transformations also promote sparse signal representations, assisting in noise reduction by isolating high-frequency components. For example, [23] employs Fourier transformations to filter out low-frequency noise, and [24] leverages spectral pooling to reduce dimensionality, capitalizing on the concentration of useful information at lower frequencies. Moreover, [25] introduces a learning-driven frequency selection mechanism to eliminate trivial spectral components. Recent studies have explored frequency-domain data augmentation: CoST [10] includes frequency-domain contrastive objectives to differentiate seasonal features, and BTSF [28] merges temporal and spectral characteristics to bolster representation quality. TF-C [29] advances these ideas by directly modifying the frequency spectrum to introduce frequency-based contrastive augmentation, distinguishing itself from CoST and BTSF, which apply DFT after time-domain augmentation. Another notable work, SDformer [40], proposes a Spectral Filter Transform module to improve temporal smoothness.

By the convolution theorem, differentiation in the Fourier domain reduces to multiplication [30], rendering the Discrete Fourier Transform (DFT) highly efficient for solving differential equations. Fourier Neural Operators (FNOs) [30], a prominent class of neural operators, have demonstrated strong capabilities in addressing PDEs and have more recently been applied to time series forecasting. For example, [20] incorporates Fourier-enhanced modules to capture the inherent structure of time series. [33] reformulates graph convolution in the frequency domain, achieving efficient computations on supra-graphs. DERITS [32] introduces Fourier Differential Operators to yield more stationary frequency-domain representations.

Neural Network Design DFT produces complex-valued outputs that can be represented by real and imaginary components, or alternatively, through amplitude and phase. Handling these complex values has inspired multiple strategies: for example, StemGNN [42] and ATFN [8] separately process each complex component as individual features and then apply inverse DFT, while FEDformer [20] directly performs complex multiplication in the frequency domain. Another related work is FreTS [5]. In contrast, transforms such as DCT and DWT yield purely real-valued outputs, simplifying their integration with standard architectures like RNNs and CNNs. Some methods bypass the complexity of DFT outputs by discarding one of the complex components, as demonstrated in [15]. Frequency-oriented network designs frequently focus on selecting the most informative frequency components. For instance, [25] introduces a dynamic frequency-channel selection mechanism, while [52] generalizes the concept of pooling to DCT components, enhancing feature selection. RobustPeriod [17] assesses periodicity by evaluating unbiased wavelet variance across multiple wavelet scales, effectively identifying discriminative frequency-level features.

Applications Leveraging frequency information can substantially improve forecasting accuracy and computational efficiency. For example, SFM [15] models trading behaviors across multiple frequency scales, and StemGNN [42] exploits spectral representations to enhance predictive performance. Autoformer [1] employs FFT to efficiently approximate auto-correlation, while DEPTS [45] derives periodic features through DCT. FEDformer [20] augments a model's global perspective, and additional related work includes FITS [6]. Frequency-driven methodologies are increasingly applied to anomaly detection. For instance, SR [46] uncovers anoma-

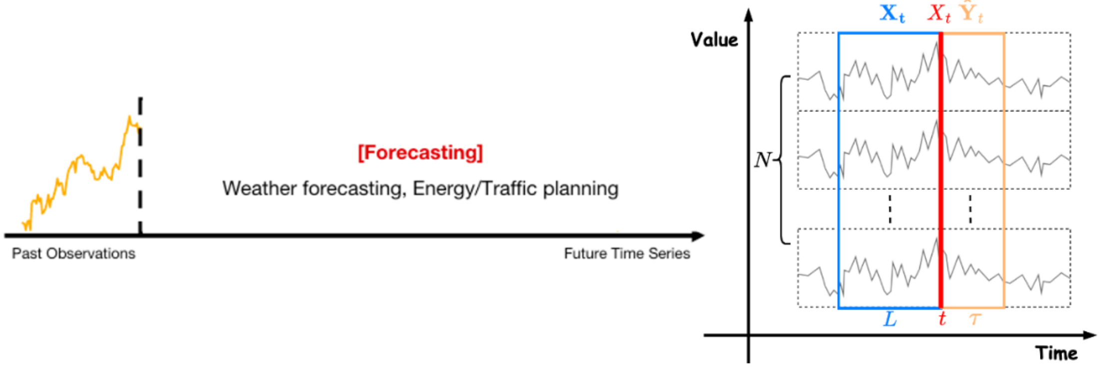


Figure 6: Problem Definition of Time Series Forecasting

lies using spectral residuals, and RobustTAD [47] relies on frequency-domain data augmentation to expand available labeled data. Likewise, PFT [49] employs partial Fourier transforms for efficient anomaly identification. FCVAE [48] innovatively integrates both global and local frequency features to ensure accurate anomaly detection. Frequency-domain techniques also strengthen classification tasks. RCF [16] capitalizes on features decomposed via DWT, while WD [50] uses adaptive wavelet scales for spectral decomposition. Additionally, BTSF [28] fuses temporal and spectral features, and TF-C [29] introduces frequency-based contrastive augmentation to maintain consistency across time-frequency representations.

Problem Formulation As shown in Fig. 6, time series forecasting takes past observations to predict the future time series. Formally speaking, we denote a multivariate time series by $[X_1, X_2, \ldots, X_T] \in \mathbb{R}^{N\times T}$, where each $X_t \in \mathbb{R}^N$ corresponds to the observations of N variates at the t-th timestamp for T total timestamps. For any given time t, the input to the model is a window of the preceding L observations, designated as $\mathbf{X_t} = [X_{t-L+1}, X_{t-L+2}, \ldots, X_t] \in \mathbb{R}^{N\times L}$. The forecasting objective at time t aims to predict the subsequent τ values, represented as $\mathbf{Y_t} = [X_{t+1}, X_{t+2}, \ldots, X_{t+\tau}] \in \mathbb{R}^{N\times\tau}$. The forecasting model, denoted by f_θ, utilizes the historical data $\mathbf{X_t}$ to estimate the future values $\hat{\mathbf{Y}}_t$, such that the forecast is given by $\hat{\mathbf{Y}}_t = f_\theta(\mathbf{X_t})$.

2.2.2 Objective and Scope of the Project

1. **Primary Objective:**

   - Develop a deep learning-based time series forecasting model that leverages wavelet differential transformations to achieve high-accuracy and efficient traffic forecasting within the Connected Transportation Information System.

2. **Secondary Objectives:**

   (a) **Model Architecture Design:** Create a multi-branch parallel architecture where each branch applies a different order of wavelet differential transformation to capture diverse temporal dynamics.

   (b) **Lightweight Implementation:** Optimize the model for lightweight design to ensure it can be deployed on edge devices, enabling real-time or near-real-time traffic predictions with limited computational resources.

   (c) **V2X Communication Enhancement:** Integrate the traffic prediction model with Vehicle-to-Everything (V2X) communication systems to improve information sharing and decision-making processes, thereby enhancing overall transportation safety and efficiency.

   (d) **Performance Evaluation:** Conduct comprehensive testing and validation of the model using real-world traffic data to assess its accuracy, reliability, and impact on transportation safety and mobility.

3. **Scope of the Project:**

   (a) **Focus Area:** Concentrate initially on enhancing transportation safety by providing accurate traffic predictions, with plans to extend the model's capabilities to other aspects of transportation management in subsequent phases.

   (b) **Technical Boundaries:** Limit the development to the design, training, and validation of the traffic prediction model, ensuring it meets the requirements for edge device deployment without delving into broader system integration tasks at this stage.

   (c) **Geographical Scope:** Implement and test the model within a specific transportation network or geographical region to demonstrate its effectiveness before considering wider application across different areas.

   (d) **Technology Utilization:** Utilize existing Transportation and Sensing and Communication Technologies to build upon current advancements, ensuring the project remains aligned with industry standards and leverages proven methodologies.

   (e) **Educational Integration:** Align the project activities with the educational goals of the Red Bird MPhil program, ensuring that the project serves as a learning platform for students to acquire relevant knowledge and skills.

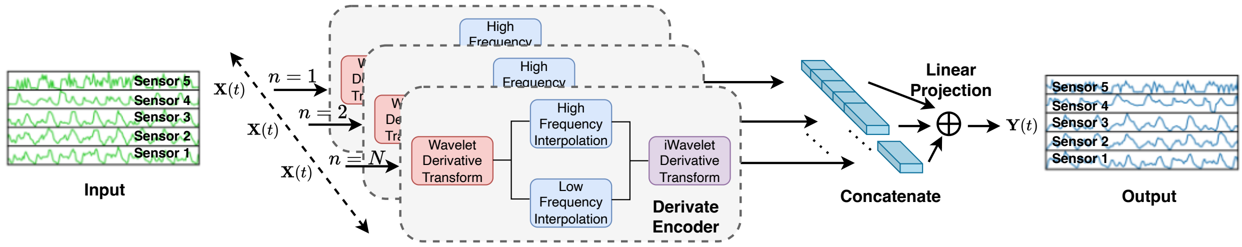


Figure 7: The proposed WaveTS architecture

2.2.3 Research Method and Justification

The proposed individual project focuses on developing a deep learning-based time series forecasting model tailored for traffic forecasting within the CTIS. The methodology integrates advanced signal processing techniques with lightweight neural network architectures to achieve accurate and efficient traffic forecasting.

Model Architecture The model processes multivariate time series data as both input and output as shown in Fig.7. The core architecture is designed with a multi-branch parallel structure, where each branch corresponds to a different order of wavelet differential transformation. Specifically, for each branch n (where $n = 1, 2, \ldots, N$), a first-order to N-th order wavelet differential transform is applied to capture various levels of signal dynamics.

Wavelet Differential Transformation Each branch begins with the application of an n-th order wavelet differential operator to decompose the input signal $X(t)$ into high-frequency and low-frequency components. Formally, the discrete wavelet transform of the n-th derivative of $X(t)$, denoted as $W_{X^{(n)}}(j,k)$, is related to the wavelet transform of $X(t)$ through the following relationship:

$$W_{X^{(n)}}(j,k) = (-1)^n 2^{nj} \tilde{W}_{j,k}^{(n)}, \tag{1}$$

where $W_{X^{(n)}}(j,k)$ represents the wavelet coefficients of the n-th derivative of $X(t)$, and $\tilde{W}_{j,k}^{(n)}$ denotes the transformed coefficients using the n-th derivative of the mother wavelet.

Frequency Component Processing The resulting high-frequency and low-frequency components from each branch are subsequently processed through complex-valued linear layers designed for spectral interpolation. This step enhances the model's ability to capture intricate patterns within the frequency domain, facilitating more precise traffic predictions.

Inverse Transformation and Prediction Following spectral interpolation, an inverse wavelet differential transformation is performed to convert the processed frequency components back to the time domain. Finally, a linear projection layer maps the transformed signals to the desired prediction horizon, yielding the forecasted traffic metrics.

Justification of the Methodology The integration of multi-order wavelet differential transformations allows the model to effectively capture both transient and steady-state characteristics of traffic data. By decomposing the signal into multiple frequency bands, the model can better handle the non-stationary nature of traffic patterns. Additionally, the use of lightweight linear layers ensures that the model remains computationally efficient, making it suitable for deployment on edge devices with limited resources. This design strikes a balance between predictive accuracy and operational efficiency, aligning with the overarching goal of enhancing transportation safety and mobility within the CTIS framework.

2.2.4 Execution Plan

1. **Data Preparation and Initial Design:** Identify and preprocess the multivariate time series dataset, ensuring it is clean, normalized, and feature-rich. Develop the preliminary model architecture, incorporating wavelet differential transformations to capture both low- and high-frequency components.

2. **Model Training and Optimization:** Train the initial model, tuning hyperparameters to improve predictive accuracy and computational efficiency. Explore techniques for model compression and lightweight design suitable for resource-constrained edge environments.

3. **Integration with CTIS Framework:** Connect the refined model to the broader Connected Transportation Information System, ensuring seamless compatibility with other project components and facilitating effective V2X communication.

4. **Testing and Validation:** Conduct thorough testing with real-world traffic scenarios to evaluate the model's performance, reliability, and ability to enhance transportation safety. Iterate based on test results to refine predictions and system responsiveness.

5. **Documentation and Dissemination:** Compile comprehensive documentation, finalize reporting materials, and integrate results into collaborative deliverables. Prepare academic publications to disseminate findings to the broader research community.

2.2.5 Intended Outcomes

By developing a lightweight, frequency-domain enhanced forecasting model, this project aims to achieve the following key outcomes:

Methods	WaveTS		iTransformer		DLinear		PatchTST		TimesNet		FEDformer		Autoformer	
Metric	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
$ETTm1$	?	?	0.407	0.410	0.403	0.407	0.387	0.400	0.400	0.406	0.448	0.452	0.588	0.517
$ETTh1$	?	?	0.454	0.447	0.456	0.452	0.469	0.454	0.458	0.450	0.440	0.460	0.496	0.487
$ETTm2$	?	?	0.291	0.334	0.350	0.401	0.255	0.327	0.291	0.333	0.305	0.349	0.327	0.371
$ETTh2$	?	?	0.384	0.407	0.559	0.515	0.380	0.406	0.414	0.427	0.437	0.449	0.450	0.459
$Weather$	?	?	0.261	0.281	0.265	0.317	0.354	0.348	0.259	0.287	0.309	0.360	0.338	0.382
ECL	?	?	0.180	0.261	0.212	0.300	0.204	0.291	0.192	0.295	0.214	0.327	0.227	0.338
$Exchange$	?	?	0.365	0.407	0.354	0.414	0.362	0.404	0.416	0.443	0.519	0.429	0.613	0.539
$Traffic$	?	?	0.423	0.282	0.625	0.383	0.480	0.304	0.620	0.336	0.610	0.376	0.628	0.379

Table 1: The intended time series long-term forecasting results.

1. **Superior Predictive Performance:** As shown in Table 1, our proposed WaveTS is expected to outperform state-of-the-art time series forecasting methods across various benchmark datasets, including challenging climate and traffic-related scenarios. The model's enhanced accuracy reflects its ability to capture both global patterns and localized dynamics more effectively than existing Transformer-based forecasting models.

2. **Efficiency and Scalability:** Beyond predictive quality, our approach emphasizes computational efficiency and resource constraints. Table 2 highlights that WaveTS's intended compact architecture, while significantly reducing the number of parameters, Multiply-Accumulate Operations, and inference time. This lightweight design enables deployment on edge devices and ensures scalability for large-scale transportation networks.

3. **Robustness Across Modalities:** By integrating multi-scale frequency-domain techniques, the model demonstrates adaptability to heterogeneous data sources, including loop detectors, floating car data, and camera-based measurements. This robustness guarantees reliable forecasting performance even as data availability and sensor configurations evolve over time.

4. **Enhanced Impact on the CTIS Ecosystem:** Through seamless integration with the Connected Transportation Information System, the improved traffic forecasts enable more informed decision-making in route planning, congestion management, and safety inter-

ventions. This translates into tangible benefits for transportation stakeholders, facilitating a more efficient and resilient mobility environment.

Table 2: Number of trainable parameters, MACs, and inference time of TSF models.

Model	Parameters	MACs	Infer. Time
TimesNet	301.7M	1226.49G	N/A
Pyraformer	241.4M	0.80G	3.4ms
Informer	14.38M	3.93G	49.3ms
Autoformer	14.91M	4.41G	164.1ms
FiLM	14.91M	5.97G	123.0ms
FEDformer	20.68M	4.41G	40.5ms
PatchTST	1.5M	5.07G	3.3ms
DLinear	139.7**K**	40M	*0.4ms* (3.05ms CPU)
FITS	4.5**K**~10**K**	1.6M~8.9M	0.6ms (2.55ms CPU)
Ours	**?K~?K**	**?M~?M**	?ms (*?ms* CPU)

2.3 Project Milestones

1. **Months 0–3 (Individual Data Collection and Model Development):**
    - **Data Preparation:** Collect and preprocess multivariate traffic data. Ensure data quality, consistency, and readiness for modeling.
    - **Preliminary Model Setup:** Implement the initial WaveTS architecture, incorporating wavelet differential transformations. Validate basic functionality and establish baseline performance metrics.
2. **Months 3–6 (Collaborative Data Integration and Model Alignment):**
    - **Model Refinement:** Fine-tune hyperparameters and improve WaveTS performance using pilot datasets. Integrate frequency-domain transformations to capture multi-scale patterns more effectively.
    - **Interoperability and Alignment:** Collaborate with team members to ensure that WaveTS outputs are compatible with other CTIS components. Harmonize data pipelines and evaluation criteria.
3. **Months 6–9 (Holistic Platform Integration and Initial Testing):**

- **Edge Optimization:** Apply model compression and optimization techniques for WaveTS deployment on resource-limited devices.
- **Multi-Modal Integration:** Incorporate loop detectors, floating car data, and camera-based inputs to enhance predictive robustness.
- **Initial System Testing:** Collaborate with the team to integrate WaveTS into the CTIS platform. Conduct initial system-level testing in simulated environments to validate compatibility and efficiency.

4. **Months 9–12 (Comprehensive Deployment and Future Planning):**

- **Full Deployment:** Deploy the optimized WaveTS model in selected urban areas, contributing to the overall CTIS pilot.
- **System-Wide Evaluation:** Assess the model's impact on traffic management, congestion mitigation, and safety enhancements within the integrated CTIS framework.
- **Documentation and Future Plans:** Finalize documentation, prepare academic papers, and propose future directions for extending WaveTS capabilities and scalability.

Milestone	**WaveTS (Individual Project)**	**Connected Transportation Information System (Group Project)**
Phase 1 (Months 0-3): Individual Data Collection and Model Development		
Milestone 1: Data Collection and Preprocessing	Collect and preprocess multivariate traffic data; implement initial WaveTS architecture for baseline validation.	Each member gathers relevant data. Begin conceptual integration of components into the CTIS infrastructure.
Phase 2 (Months 3-6): Collaborative Data Integration and Model Alignment		
Refinement of Core Forecasting & Multi-Scale Techniques	Fine-tune frequency-domain transformations, improve accuracy and efficiency. Align WaveTS outputs with other CTIS modules.	Integrate individual solutions into CTIS. Conduct initial system-level evaluations to ensure data and model compatibility.

Milestone	WaveTS (Individual Project)	Connected Transportation Information System (Group Project)
Phase 3 (Months 6-9): Holistic Platform Integration and Initial Testing		
Milestone 3: Integration with Diverse Traffic Data	Incorporate multiple data sources (loop detectors, FCD, camera feeds) for robust, multi-modal forecasts. Conduct initial edge optimization.	Combine all components into a unified CTIS platform. Test the system in simulated environments and diverse urban scenarios.
Phase 4 (Months 9-12): Comprehensive Deployment and Future Planning		
Milestone 4: Final Deployment and Evaluation	Deploy WaveTS in selected areas, evaluate adaptability and impact on traffic efficiency and safety. Document findings and propose future enhancements.	Roll out CTIS pilots in target regions, gather feedback, and refine system components. Plan for scalability and citywide/multi-area implementations.

Milestone	PQA Timeline	Current Timeline
Phase 1 (Months 0–3): Individual Data Collection and Model Development		
Milestone 1: Data Collection and Pre-processing	Collect and preprocess multivariate traffic data; implement initial WaveTS architecture for baseline validation.	Aggregate existing traffic datasets, perform essential cleaning, and push a minimal, well-documented WaveTS code skeleton to a public repository.
Phase 2 (Months 3–6): Collaborative Data Integration and Model Alignment		
Milestone 2: Refinement of Core Forecasting & Multi-Scale Techniques	Fine-tune frequency-domain transformations, improve accuracy and efficiency; align WaveTS outputs with other CTIS modules.	Release the first open-source version of WaveTS with tutorials; draft the main sections of the WaveTS paper; start preliminary tests on two additional traffic datasets.

2.4 Budget Plan

2.4.1 Estimated Budget

The total estimated budget for the individual project is approximately RMB 28,000, remaining well within the RMB 30,000 limit. This allocation provides sufficient resources for data acquisition, computation, and dissemination while ensuring cost-effectiveness.

Milestone	PQA Timeline	Current Timeline
Phase 3 (Months 6–9): Holistic Platform Integration and Initial Testing		
Milestone 3: Integration with Diverse Traffic Data	Incorporate multiple data sources (loop detectors, FCD, camera feeds) for robust, multi-modal forecasts; conduct initial edge optimisation.	Expand experiments to several new traffic datasets; refine hyper-parameters and document performance gains; update the public repo with reproducible evaluation scripts.
Phase 4 (Months 9–12): Comprehensive Deployment and Future Planning		
Milestone 4: Final Deployment and Evaluation	Deploy WaveTS in selected areas, evaluate adaptability and impact on traffic efficiency and safety; document findings and propose future enhancements.	Finalise and submit the WaveTS paper to a top venue; tag an official v1.0 release of the open-source code; prepare a brief demo and outline next-stage research plans.

2.4.2 Budget Breakdown

- **Research Materials and Equipment (RMB 10,000):** Includes data collection platforms or services (RMB 2,000), software licenses for data analysis (RMB 2,000), and access to computing equipment (RMB 6,000) to support model training and testing.
- **Data Acquisition and Preprocessing (RMB 6,000):** Covers data acquisition and storage costs (RMB 3,000) as well as preprocessing and cloud computing services (RMB 3,000) for efficient handling of large-scale traffic datasets.
- **Research Support and Services (RMB 8,000):** Allocated for student stipend (RMB 5,000), local travel expenses (RMB 2,000), and minor research-related subscriptions or publications (RMB 1,000), ensuring smooth project execution.
- **Project Presentation and Dissemination (RMB 4,000):** Funds travel expenses to domestic conferences or workshops to present research findings, fostering knowledge exchange and community engagement.

2.4.3 Cost-Effectiveness

By leveraging publicly available datasets where possible, using open-source frameworks, and employing scalable cloud computing services, the project minimizes unnecessary expenses. Additionally, focusing on lightweight model design reduces computational overhead, allowing the project to achieve its technical objectives within a moderate budget. This strategy ensures that the allocated funds are utilized efficiently, resulting in both high-quality outcomes and long-term sustainability.

2.5 Risk Analysis and Mitigation

2.5.1 Potential Risks or Challenges

- **Data Quality and Availability:** Accessing comprehensive, high-quality traffic datasets may be restricted by licensing, proprietary data, or insufficient sensor coverage. Inconsistent data formats or missing values could further complicate the preprocessing and model training stages.

- **Computational Resource Constraints:** Training deep learning models can be resource-intensive. Limited GPU/TPU availability, budget constraints, or unexpected hardware failures may slow down the iterative optimization process and hinder timely model refinement.

- **Model Generalization and Robustness:** While WaveTS aims to handle various traffic patterns, it may struggle with rare, unexpected events (e.g., severe accidents, extreme weather). Ensuring that the model remains reliable under atypical conditions can be challenging.

- **Integration Complexity with CTIS:** Aligning the individual model with the broader Connected Transportation Information System involves coordinating with multiple team members, varying data sources, and diverse system components. Incompatibilities in data schemas or communication protocols could arise.

- **Edge Deployment Limitations:** Adapting a high-performing model to run efficiently on low-power edge devices may require extensive optimization. Ineffective compression or optimization strategies could result in slow inference times, reduced accuracy, or additional deployment costs.

2.5.2 Impact of the Risks

- **Data-Related Risks:** Poor data quality or limited dataset availability can lead to suboptimal training outcomes, reduced forecasting accuracy, and delayed project timelines.

- **Resource and Performance Constraints:** Insufficient computational resources or hardware failures may prolong model experimentation and tuning processes, potentially missing critical milestones or diminishing the final model's performance.

- **Reduced Model Reliability:** If the model does not generalize well across diverse conditions, it may produce unreliable forecasts that limit its practical usefulness in real-world scenarios, undermining stakeholder confidence.

- **Integration Delays and System Inefficiencies:** Technical hurdles in integrating the forecasting model into the CTIS may delay the collective benefits of the group project, resulting in a less cohesive and efficient transportation information platform.

- **Deployment Bottlenecks:** Failure to efficiently deploy the model on edge devices could restrict real-time applications and limit the model's potential for scalability, ultimately reducing the broader impact on transportation safety and efficiency.

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