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A Digital Twin Architecture for Intelligent Traffic Management Based on Artificial Intelligence

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Abstract. This work presents a concept for an innovative Digital Twin (DT) framework for urban traffic monitoring and management, tailored for the city of Singapore. The proposed architecture leverages real-time traffic and weather data integration, AI processing, and modular design to offer adaptive and versatile traffic insights. By incorporating live information from various sources and integrating real-time weather data, the framework enables proactive traffic management and enhances safety during adverse weather conditions. The paper discusses the implementation of the framework, and its potential impact on urban mobility, and suggests future directions for research and development to facilitate the framework's implementation.

Keywords. digital twin, urban traffic monitoring, artificial intelligence, intelligent transportation systems, real-time data integration

1. Introduction

In modern city centers, dealing with traffic congestion is a major concern for authorities due to rapid urbanization. Managing and predicting traffic flow is complex, influenced by factors like weather, accidents, and rush hours. Weather changes and human activities significantly affect traffic, and extreme weather events increase the need for predicting and managing congested areas [1,2]. Both pedestrian and vehicle traffic behave dynamically and can be monitored and modeled, providing access to a real-time data stream. Hence, having real-time data for decision-making is crucial. A useful concept for this is the Digital Twin (DT), which aids in modeling, monitoring, and simulating intelligent

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transportation systems. This work presents a concept for an urban traffic management DT.

The city-state of Singapore, aiming to be a model smart city, has heavily invested in innovative technologies to optimize urban mobility. However, its location poses challenges such as frequent flooding from monsoon rains [3,4]. With climate change and population growth, these challenges are expected to worsen, leading to increased risk from natural disasters [5,6]. Balancing advanced traffic management with disaster preparedness is a priority. Digitalization and proper monitoring systems [7,8,9,10,11,12,13] can mitigate the impact of natural disasters. Singapore has focused on building adaptive frameworks and policies to address these challenges, emphasizing public responsibility in emergency response [14,15].

Urban environments, especially in busy cities like Singapore, present numerous challenges including fluctuating traffic patterns, infrastructure wear, population movement, and extreme weather events. Incidents, accidents, as well as extreme weather events [3] can occur independently across the city, in a "patchy" manner. This requires a point-by-point monitoring of individual locations to obtain a complete picture of the circumstances of the entire city. Big data collections [16] require point-by-point monitoring of individual locations to obtain a complete picture of the circumstances of the entire city [17,18]. A DT framework, consisting of a digital model, a knowledge base, and an analytics component, can accurately monitor and predict the city's state in real-time [19,20]. In the context of a smart city platform, a DT is a digital representation of real-world environments brought to life with real-time data from sensors and other data sources [21,22,23,24]. Singapore has already implemented DT for applications such as water reclamation plants [25]. Additionally, DT has been proposed for city information visualization [26], urban climate simulation [27], energy consumption modeling [28], building operation and maintenance [29], and citizen-inclusive urban planning [30]. The influence of weather conditions on traffic evolution using state-of-the-art deep learning and neural networks has been previously explored [31].

This study proposes a concept for a DT framework for a traffic monitoring platform that is human-centric and adaptive to weather disruptions. It differs from traditional traffic analytic systems by incorporating real-time weather data and employing modular design for scalability. The framework is a work-in-progress that aims to reduce traffic congestion, minimize accidents, optimize transportation routes, and ensure seamless commuting even in adverse weather conditions. The proposed framework is novel in its modular approach, allowing swift incorporation of new modules and retirement of old ones based on monitoring authority requirements. It integrates real-time weather information into traffic management, leveraging emerging technologies like connected vehicles and GPS-enabled dashcams for live data collection. Advanced AI algorithms process vast amounts of data efficiently, learning from historical patterns and user behavior to improve decision-making over time. In summary, the proposed intelligent traffic monitoring system combines real-time weather data with on-the-road live data to equip city authorities with valuable insights for informed decision-making.

2. Methodology

2.1. Digital Twin

A DT for urban mobility applications is a cyber-physical system that replicates the structure, behavior, and functionality [32,33] of a city's transportation network in a digital environment. It utilizes advanced modeling techniques, including computational algorithms, data analytics, and simulation methods, to create a dynamic and interactive representation of the urban transportation system. This digital replica is continuously updated with real-time data from various sources such as traffic sensors, GPS devices, and weather stations, allowing for accurate monitoring, analysis, and prediction of traffic flow, congestion, and other mobility-related parameters. The importance of a DT, in contrast to a Digital Shadow (DS), is that it contains information about causalities ingrained in the data [34]. Therefore, it can be utilized in a bi-directional manner, to not only virtually represent the current state of the modeled system, but also to provide recommendations back to the physical system. The DT serves as a comprehensive tool for urban planners, engineers, and policymakers to optimize transportation operations, enhance infrastructure planning, and improve overall mobility efficiency within urban areas.

2.2. System Requirements

A DT framework for urban traffic monitoring must meet several key requirements to effectively model, monitor, and analyze traffic dynamics within a city.

1. Real-Time Data Integration: The framework should be capable of seamlessly integrating real-time data from diverse sources and data types. This includes both structured and unstructured data, including series of images and periodical weather metrics and measurements.
2. Scalability: The framework should be scalable to accommodate the growing volume and variety of data generated by urban traffic systems.
3. Modularity: It should also be modular, allowing for the addition or removal of components as needed to adapt to evolving requirements and technologies.
4. Advanced Analytics and Prediction: The framework should incorporate advanced analytics and prediction capabilities to analyze historical data, identify patterns, and forecast future traffic conditions. This includes the ability to detect anomalies and predict traffic congestion and other events in real time.
5. Integration with External Systems: The framework should support integration with external systems and data sources, such as urban planning tools, and emergency response systems.
6. Security and Privacy: The framework should prioritize security and privacy measures to protect sensitive traffic data from unauthorized access, manipulation, or disclosure. This includes encryption, access controls, and compliance with data protection regulations, e.g. with the EU General Data Protection Regulation (GDPR) guidelines [35].
7. User-Friendly Interfaces: This includes interactive dashboards, maps, and reports that enable stakeholders to gain insights and make informed decisions.

8. Adaptability to Dynamic Environments: The framework should be adaptable to dynamic urban environments, including changes in traffic patterns, infrastructure, and environmental conditions. This requires continuous monitoring and calibration of models to ensure accuracy and reliability.

3. Implementation

3.1. System Architecture

A minimum DT framework tailored for urban traffic monitoring in Singapore would consist of several key components. Data processing can be implemented on an edge computing system containing several hardware devices for data collection. Live weather information from sensors in the city can be recovered with OpenWeather's API [36], which provides metrics such as temperature, humidity, wind, and precipitation, among others. The Land and Transport Authority (LTA) of Singapore provides the Datamall API [37], with current image data from static expressway cameras. These cameras stream updated images from key road arteries every 5-10 minutes, which does not fit the real-time definition. This can be enhanced by the use of mobile dashcams mounted on vehicles with fixed routes, like police patrol cars or buses. Artificial intelligence and deep learning (DL) models have proven effective in tasks such as classification, detection, and segmentation. However, DT technologies have heavy resource and power requirements such as high GPU memory and high power consumption, making processing on-board the data collection devices, i.e. cameras, difficult to implement. Therefore, data streams should be transmitted to a processing server for further analysis. To ensure compliance with privacy regulations, images should be processed so that human faces and vehicle license plates are anonymized and not visible.

The interaction between components of a DT framework aimed at traffic management in Singapore is illustrated in Figure 1. The system encompasses data collection, streaming, and processing within an edge computing framework. This framework comprises various components, including multiple mobile dashcams, stationary expressway cameras, an API for accessing live weather data, a processing server, and a database. The images from the cameras are fed to the processing server, where they are analyzed. This

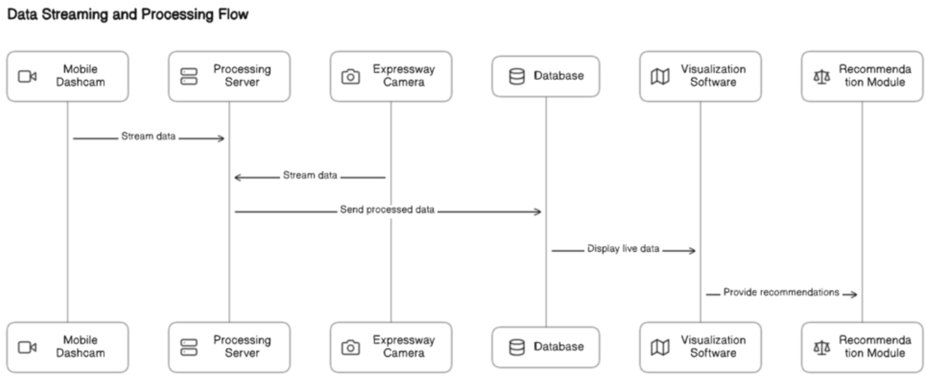

Figure 1. An interaction diagram of the DT ecosystem components.

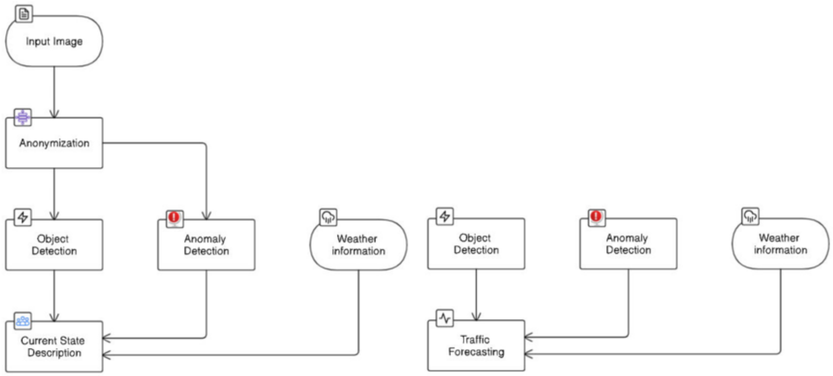

Figure 2. An example of the basic processing modules.

setup enables the efficient collection and analysis of real-time data from diverse sources, namely both traffic images and weather metrics. After data anonymization and processing, the analytics features that describe the DT's state are transmitted to a database for storage. This cycle is repeated indefinitely. To ensure a user-friendly experience, the DT's state can be visualized on a separate module using maps and 3D modeling. At a later stage, a recommendation module can be included to provide authorities and end-users with specific recommendations about the urban traffic's state, e.g. alarms about accidents. The recommendation module can be developed using a fuzzy rule-base with if-then rules, which provide warnings, alarms, and recommended courses of action [8].

3.2. Minimum Value Prototype

The processing server depicted in the architecture applies an algorithm that includes a series of sequential stages designed to analyze input image data and weather information for traffic modeling and forecasting Figure 2. Initially, input image data, captured from various sources such as mobile dashcams and stationary expressway cameras, undergoes anonymization to ensure compliance with privacy regulations. Subsequently, the object detection algorithm is applied to identify and locate relevant entities within the anonymized image data, such as vehicles, trucks, buses, and pedestrians. Furthermore, an anomaly detection module aims to identify any irregularities or deviations in traffic flow or environmental conditions, such as roadworks or flooding events. The processing results from these stages are then integrated with weather information, such as precipitation and temperature, obtained from a weather data API. Finally, traffic forecasting algorithms utilize the combined output to predict future traffic conditions.

A minimal DT of the city should at least be able to represent the number of vehicles, bicycles, and pedestrians at key checkpoints around the city every few seconds. The You Only Look Once (YOLO) [38] algorithm is a common technology that performs fast and accurate object detection and classification from live images. The YOLO algorithm works by dividing the input image into a grid of cells and predicting bounding boxes and class probabilities for objects within each cell simultaneously. It utilizes a single convolutional neural network (CNN) to process the entire image and predict the bounding boxes and class probabilities directly, instead of using multiple stages or sliding windows. YOLO optimizes speed and accuracy by jointly optimizing object detection and classification tasks, making it capable of real-time object detection in images and videos. The YOLO-v7 model which performs on-the-fly object detection from the entire image, can be fine-tuned for vehicle and pedestrian detection.

Another key analysis module is image processing for the detection of anomalies on the road, such as accidents, road works, and flooding events. Reverse distillation (RD) [39] is a powerful algorithm, which predicts anomaly heatmaps when trained on groups of normal and anomalous images. RD operates by leveraging a pre-trained mode, to distill the knowledge of normal patterns from a dataset. This distilled knowledge is then used to train a separate anomaly detection model to identify deviations from the learned normal patterns. In essence, Reverse Distillation aims to encode the knowledge of normal behavior captured by the pre-trained model into a compact representation, which is subsequently utilized to detect anomalies or outliers in new data. This approach enables effective anomaly detection without the need for labeled anomaly data during training, making it particularly useful for detecting novel or unforeseen anomalies in real-world datasets.

Using the live weather metrics from the API and object and anomaly detection from the processing modules, the DT can describe the current state of urban traffic at each point in time. Therefore, these historical data of the DTs state can be utilized to forecast a state in the future. Lastly, a forecasting module is added, which predicts the number of vehicles on the road at each checkpoint after a few time steps in the future, based on the current and past states. Time series forecasting can be implemented using an LSTM (Long Short-Term Memory) model. It works by utilizing recurrent neural network (RNN) architecture, enhanced with memory cells capable of capturing long-term dependencies in sequential data. The LSTM model processes input sequences step-by-step, updating its internal state based on both current input and past information stored in its memory cells. This enables the model to effectively learn temporal patterns and dependencies within the time series data. Through training, the LSTM model adjusts its parameters to minimize the difference between predicted and actual values, allowing it to forecast future values in the time series with high accuracy. In this case, both historical values of the total number of vehicles and weather conditions can be concatenated to form the feature vector of the forecasting model.

The modules mentioned above will be integrated into the complete system, which forms the minimal DT. This DT then needs to be attached to the data collection and data storage pipelines. After evaluating the system's state and recovering forecasted values, these forecasts will be used to provide recommendations to city authorities. The models comprising the DT will be periodically fine-tuned on updated and recent historical data, to ensure that it encompasses the most recent changes in the city's urban landscape.

4. Discussion

The implementation of the proposed DT architecture as an innovative urban mobility and transport platform marks a significant advancement in traffic management. Its modular design allows individual modules to operate independently and in parallel, providing a flexible system capable of quick updates to meet evolving monitoring needs. By harnessing live data from various APIs and data sources and integrating AI processing, the framework can identify correlations, forecast traffic disruptions, and offer tailored traffic insights for city administration. A key feature is its ability to incorporate real-time weather data, enabling adaptive traffic management in response to changing environmental conditions. This integration has the potential to greatly enhance traffic predictions and safety during adverse weather.

Developing the described system includes navigating through several challenges. First, ensuring data quality and compliance with privacy regulations while anonymizing image data for analysis is critical, so that images are not rendered unusable. Real-time processing of image and weather data demands high computational resources, balancing accuracy with speed for timely traffic modeling. Selecting and fine-tuning algorithms for object and anomaly detection and forecasting requires expertise and ongoing validation. Integrating multiple processing modules introduces complexity in data flow and communication between components. Robust data pipelines and storage solutions are necessary to handle diverse data sources efficiently. Regular maintenance and adaptation of models based on recent data are essential for system accuracy and relevance. Providing interpretable insights and actionable recommendations to city authorities enhances decision-making. Collaboration with domain experts is key to addressing these challenges effectively and ensuring the system's impact in real-world urban environments.

The combination of DT architecture and AI technology holds promise for smart cities, offering improved decision-making through data integration and visualization. Future work will focus on defining necessary modules, addressing limitations, and implementing a minimal prototype to test on the ground in Singapore. DT allows for plan simulation, preemptively addressing issues, and responding to emergencies in real time. This solution not only empowers traffic management and infrastructure planning but also enhances public safety, reduces commute times, and improves overall quality of life. The framework's adaptability and learning capabilities ensure it can evolve with changing urban dynamics, becoming an invaluable tool for informed decision-making and long-term planning. While it stands to benefit various stakeholders, including city authorities, commuters, and emergency services, its adoption may be hindered by privacy concerns, data availability, and infrastructure limitations. Overcoming these challenges and addressing limitations through ongoing research and innovation will be crucial for realizing the full potential of this framework in revolutionizing urban traffic management.

5. Conclusion

In conclusion, the conceptualization of the proposed DT framework for urban traffic monitoring in Singapore represents a significant stride forward in traffic management technology. The framework, comprising various essential components such as real-time data integration, object detection, anomaly detection, and forecasting modules, offers a versatile and adaptive solution for monitoring and managing urban traffic dynamics. The integration of DT architecture with AI technologies promises transformative benefits for smart cities, empowering city authorities and urban planners to make data-driven decisions in real time. As part of ongoing research work, with continued development and collaboration, the framework has the potential to reshape how cities tackle transportation challenges and pave the way for smarter, safer, and more efficient urban environments.

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