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An AI-based Digital Twin Framework for Intelligent Traffic Management in Singapore

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***Abstract*—Urban centers worldwide grapple with the intricate challenge of traffic congestion, necessitating sophisticated solutions grounded in real-time data analytics. This paper presents a cutting-edge Digital Twin (DT) framework tailored for urban traffic management, with a focus on the context of Singapore's technologically advanced landscape. By seamlessly integrating live weather data and on-road camera information, the proposed framework offers insights into traffic dynamics, enabling adaptive decision-making. Leveraging a modular architecture and advanced artificial intelligence (AI) algorithms, the framework aims to optimize traffic flow, mitigate accidents, and ensure resilient commuting experiences, even amidst adverse weather conditions. Evaluation of individual components showcases promising performance metrics, albeit contingent upon data availability and user engagement. Future research endeavors will explore scalability, user-centric design enhancements, and the longitudinal efficacy of the proposed framework, positioning it as a novel solution for urban traffic management.**

***Index Terms*—intelligent transportation system, artificial intelligence, digital twin, image analysis, traffic management**

I. Introduction

In today's rapidly growing urban centers, traffic congestion has become an increasingly critical challenge for city authorities. Traffic management and forecasting are challenging tasks affected by various factors such as weather patterns, seasonal events, and rush hours. Therefore, traffic monitoring for immediate decision-making based on tangible data is crucial for ever-growing cities. Both pedestrian and vehicular traffic constitute dynamic systems that can be modeled and monitored [1]–[5]. Furthermore, the increasing frequency of extreme weather phenomena, affecting traffic incidents [6], makes it necessary to predict and address traffic congestion spots. A helpful concept in this regard is the Digital Twin (DT), which can be used as a basis for system modeling, monitoring, and simulation.

In the past years, Singapore has heavily invested in innovative technologies to establish itself as a model smart city of the future. Positioned in a disaster-prone area, the Asian coastal megacity frequently confronts natural disasters, such as intense flooding due to yearly monsoon rains [7]. This situation is expected to worsen with more intense weather phenomena due to climate change and population growth [8], leading to a growing risk of hydrological hazards through uncontrolled urban development and exposure to intensified storms. The impact of natural disasters on people's lives becomes a critical point that could be minimized with digitalization [9] and proper impact monitoring systems [10], [11]. Although human casualties have remained low due to the state's concentrated monitoring efforts [12], costs associated with socio-economic impact have steadily risen [13].

Bustling urban environments, like Singapore, present a multitude of challenges, such as fluctuating traffic patterns, infrastructural wear and tear, population movement, and dynamic environmental conditions. Incidents, accidents, as well as extreme weather events [13] can occur independently across the city, in a "patchy" manner. Big data collections [14] require point-by-point monitoring of individual locations to obtain a complete picture of the circumstances of the entire city [15], [16]. A comprehensive approach to address this issue is to employ a multi-modular architecture for a DT of the target city. DT [17] is based on the simple idea of linking a physical object with its digital counterpart accurately and in real-time [18]. 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 [19]–[21].

A DT framework consists of three components: the digital model describing the physical object, a knowledge base used to build the framework, and an analytics component used to

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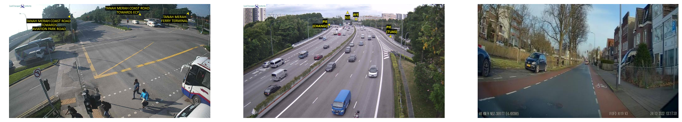
assess its performance. Utilizing real-time data, the system should be able to communicate accurately, predict its state, and react. Additionally, DT has been proposed for city information visualization [22], urban climate simulation [23], energy consumption modeling [24], building operation and maintenance [25], and citizen-inclusive urban planning [26]. The influence of weather conditions on traffic evolution using state-of-the-art deep learning and neural networks has been previously explored [27]. A common issue with DT implementations is the integration of data from different sources [28].

This study proposes a novel DT framework for a traffic monitoring platform that is human-centric and adaptive to extreme weather disruptions. It goes beyond conventional traffic cameras and sensors on fixed infrastructure, leveraging emerging technologies such as Artificial Intelligence (AI) processing, and GPS-enabled dashcams to gather real-time information from vehicles on the road. The modular architecture of the DT produces an accurate and adaptable representation of a smart city's physical space. New modules can be incorporated swiftly, and old modules can be retired, depending on the monitoring authority's requirements. Individual AI layers of processing inform the DT constantly, updating its state and information. Integration of live weather data provides a unique and adaptive approach to traffic management, allowing the system to respond dynamically to changing environmental factors. It not only monitors the current state but also provides predictions, enhancing decision-making capabilities for urban authorities. This study serves as a proof of concept for a DT framework, which provides accurate, adaptive, and real-time solutions to the complex challenges of urban traffic management.

II. Methods and Materials

A. Data Sources

Datasets are recovered from Datamall [29], a collection of dynamic datasets related to public transport and traffic metrics maintained by the Singapore Government Agency. Because the application takes into consideration weather data, OpenWeather [30] is used for weather data collection for Singapore. Data collection took place in irregular periods between 2023-06-09 and 2023-09-10. From this dataset, 63% of the samples were used for training, 27% for validation, and 10% for testing of the various modules. Additional open datasets from mobile dashcams [31] are utilized for the initial proof of work. Furthermore, dashcam footage from Singapore was sourced from YouTube.com, to customize models for the specific Singapore use case. Examples of images from the different camera sources are shown in Figure 1.



(a) (b) (c)

Fig. 1: Example images from different camera sources, (a) expressway camera with high pedestrian traffic, (b) expressway camera with high vehicle traffic, and (c) mobile dashcam.

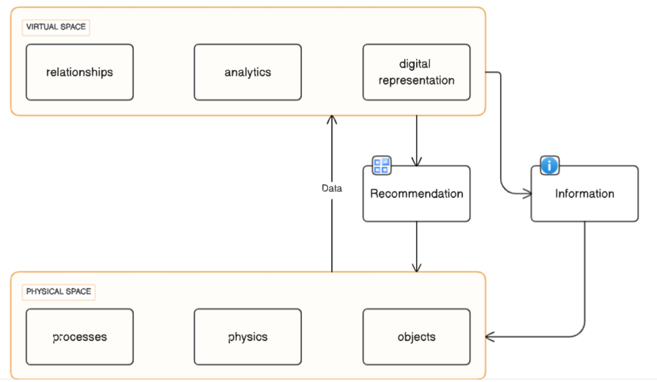


Fig. 2: A schematic of the DT concept.

B. System Architecture

A DT is expected to be a copy of the objects, processes, and physics in the physical space. Data from the physical space influence the construction of a twin in the virtual space, including digital representations, relationships, and analytics. In turn, the twin influences the physical space, by providing information or recommendations for decision making. This process is described in Figure 2. The proposed DT, should take the information from live datasets as input, process it and extract as output a description of the current situation as well as predictions, as shown in Figure 3. The input layer will handle data from live APIs and on-the-road dashcams so that this information will inform the DT. A processing layer of AI converts smart city data to create a user-friendly DT. An Extract, Transform, Load (ETL) pipeline is prepared, in order to first transform data on the server, and then load them at a data warehouse for permanent storage and further processing. An output layer represents the current state of multiple monitoring locations in the city as a collection of dynamic virtual points. An additional output layer represents predictions for the upcoming state of the above monitoring locations in the near future.

The AI Layer can be modular, including several components that can be run in parallel, which can be enabled or disabled according to requirements. Individual modules can be updated while the system is live, either by re-training or fine-tuning processing models periodically with updated datasets, or by using reinforcement learning [32], [33]. A rule can be set to update the models after fine-tuning with the latest data every three months. Sustainability and adaptability are further enhanced by the incorporation of mobile monitoring points via the use of the smart dashcam. This way, current and future state representation is not limited to the static locations of expressway cameras but can be adjusted on the go by dispatching a dashcam-equipped vehicle to the target location.

In the proposed framework care is taken to assist data

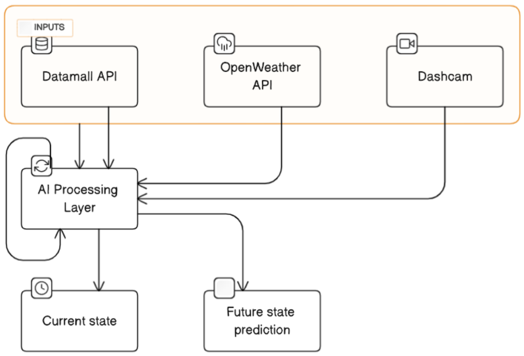


Fig. 3: The proposed system architecture.

integration from different sources in the DT. Therefore, separate models are trained for classification and prediction tasks where the source is either static expressway cameras or mobile dashcams. Furthermore, different update times for the various data sources cause issues with data synchronization. This can be solved using interpolation and extrapolation with the latest available data at each time point.

C. Individual Components

Developing a smart city platform, with the requirements of the monitoring authority in mind, would involve several goals and subprojects. The proposed architecture with the AI processing layer allows for a modular selection of subtasks, which can be developed as independent components. Modules described in Table I have been included in our proposed architecture, based on the available datasets and the context of Singapore. This is not an exhaustive list, and modules can be enhanced or increased as time goes by and requirements change. In some cases, a standalone image is used as direct input to a module, whereas in other cases time series features, such as vehicle counts are extracted from a set of images.

- **Data Anonymization:** Human faces and license plates of vehicles that are visible in the images should be blurred before data processing and storage, to be compatible with the EU General Data Protection Regulation (GDPR) guidelines [34]. This is achieved by using a pair of cascading classifiers [35] that detect first vehicles and people and then faces and license plates.
- **Vehicle Monitoring:** The location, type, and count of vehicles on the road at each time moment are detected from an image. The YOLO-v7 model [36], which performs on-the-fly object detection from the entire image, was fine-tuned for vehicle and pedestrian detection.
- **Taxi Congestion:** Clusters of congested taxi vehicles indicate locations of increased foot traffic. These clusters can be detected using KMeans clustering [37] for n=10 clusters for the top-10 congested locations.
- **Localized Weather Detection:** This module extracts weather phenomena from an image of a specific location instead of a city-wide sensor network. This is achieved with the application of transfer learning [38] on an EfficientNet-b8 model to classify weather as [clear, clouds, rain, thunderstorm].
- **Road Surface Monitoring:** The same process as the previous module using a ResNet50 model is applied with target classes [dry, wet, storm].
- **Anomaly Incident Detection:** Incidents such as road works, accidents, or flooding should be detected so that an alarm can be set. An anomaly label and heatmap can be generated using the Reverse Distillation algorithm [39].
- **Traffic Flow Prediction:** Historical values and a look-back window of actual traffic flow in the past few time steps, as well as current weather, can be used to predict future traffic flow in the next time step. This is achieved using a single-step Convolutional Neural Network (CNN) trained on historical traffic data and weather data.

D. Evaluation

There is an increased variety in the tasks being fulfilled by the individual modules of the DT. For this reason, each module is to be evaluated independently with appropriate metrics. Object detection tasks are difficult to evaluate in terms of accuracy due to a lack of labeled data. Therefore, a metric describing the Average Detected (AD) objects per class across all images is used. The AD for pedestrians in pedestrian crossings and dashcam scenes should be increased compared to expressway scenes. For classification tasks where labeled data are available, metrics such as multi-class Accuracy and F1Score, as well as training metrics such as ROC AUC, Train Loss, and Test Loss [40] can be used. For predictive tasks, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are used [41]. A smaller error of the trained model against a baseline model indicates better performance. In addition to the above evaluation measures, a demo tool that runs all developed modules has been developed to test the DT using random inputs from various time points. The insights provided by the DT can then be evaluated both visually, as well as against against the ground truth at the target time point.

III. Results

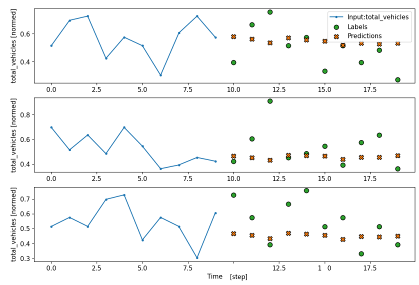
In order to demonstrate the effectiveness of the proposed architecture, a DT of Singapore based on the available datasets was developed. Modules can be validated and tested individually, without loss of generality. This is appropriate because each module addresses a different type of task and a variety of evaluation metrics is required. A condensed table of evaluation findings is presented in Table II. During development, we experimented with various models and chose the most suitable, based on performance, rapid implementation, and fast response. An example of three independent modules is shown in Figure 4.

The preliminary evaluation results for each module are presented in Table II. In the Data Anonymization module, AD values show that in dashcam images slightly more vehicles were detected compared to pedestrians, as expected. For the case of expressway cameras, the AD for vehicles was substantially higher, with a lower value for a camera that displayed

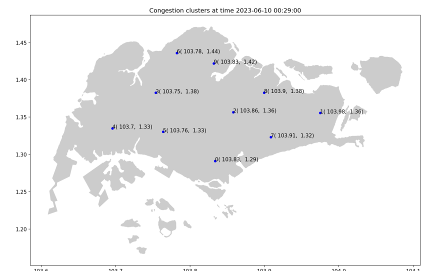
TABLE I: Available Modules

Problem Type	Module Function	Data Type	Implementation
Preprocessing	Data Anonymization	Image	MobileNet v1+Cascading Classifiers
Description	Vehicle Traffic Monitoring	Image	Yolo-v7+Fine-Tuning
Description	Pedestrian Traffic Monitoring	Image	Yolo-v7+Fine-Tuning
Description	Taxi Congestion Detection	Time Series	KMeans Clustering
Classification	Localized Weather Detection	Image	EfficientNetb7+Transfer Learning
Classification	Road Surface Monitoring	Image	ResNet50+Transfer Learning
Classification	Anomaly Incident Detection	Image	Reverse Distillation
Prediction	Predictive Modeling for Traffic Flow	Image Series	Single-step/Multi-step CNN


(a) Anonymization



(b) Vehicle Flow Prediction



(c) Taxi congestion

Fig. 4: Example outputs for individual modules

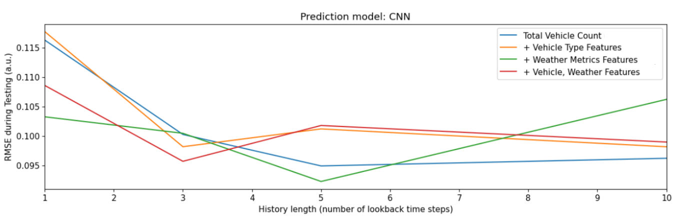


Fig. 5: Influence of using weather information and different history time steps in predictive modeling.

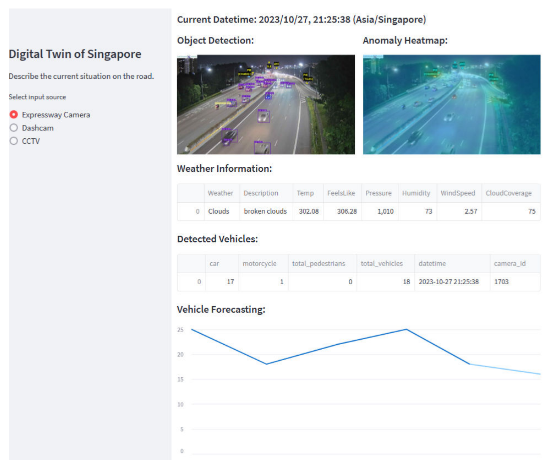


Fig. 6: A demonstration of the proposed DT in action.

vehicles passing through a pedestrian crossing. The module for Localized Weather Detection, achieved a decent accuracy of 86.2% considering its small training dataset. Road surface detection achieved an 82.1% accuracy score. For Anomaly Incident Detection, the ROC AUC was 0.9526 and the F1 Score was 85.41%. Predictive Modeling for Vehicle Flow performed better than the equivalent for Pedestrian Flow, as expected due to the increased availability of vehicle traffic data. These results demonstrate the effectiveness of the developed modules across various functionalists, with notable performance metrics attained in each category.

Regarding traffic flow prediction, several factors in the system architecture design face influence performance. The inclusion of vehicle counts by type hinders performance and increases the model's error. In Figure 5, it is evident that when the total number of vehicles and weather metrics are used as features, then the RMSE decreases. Additionally, performance improves as a moderate lookback period is used, in this case 5 time step which is equivalent to the last 25 minutes (for an update rate of 5 minutes).

A demonstration of how the information board of the DT could be displayed to the end user is shown in Figure 6. Using a live image at a specific location as input, as well as a set of previously captured images, the information in the DT for that location is updated and insights for decision-making are provided. In this case, the following modules are presented: vehicle detection, local weather detection, road anomaly detection, and future traffic flow prediction.

IV. Discussion

The implementation of the proposed architecture as an innovative urban mobility and transport platform represents a significant step forward in the field of traffic management. Its modular approach, with individual modules functioning independently and in parallel, offers a versatile and adaptable

TABLE II: Evaluation per Module

Module Function	Test Size	Performance during Testing
Data Anonymization from dashcam	4468 images	$AD_{person} = 0.92$, $AD_{face} = 0.07$, $AD_{car} = 1.15$, $AD_{plate} = 0.08$ [a]
Traffic Monitoring from expressway camera	5013 images	$AD_{vehicle} = 37.71$, $AD_{pedestrian} = 1.02$
Traffic Monitoring from pedestrian crossing camera	5187 images	$AD_{vehicle} = 12.41$, $AD_{pedestrian} = 1.20$
Traffic Monitoring from dashcam	4468 images	$AD_{vehicle} = 10.78$, $AD_{pedestrian} = 2.59$
Taxi Congestion Detection	500 records	not applicable
Localized Weather Detection from expressway camera	617 images	$Accuracy = 86.2\%$
Road Surface Monitoring from dashcam	6081	$Accuracy = 82.1\%$
Anomaly Incident Detection	1550 images	$ROCAUC = 0.9526$, $F1Score = 85.41\%$
Predictive Modeling for Vehicle Flow	80 time steps	$MAE = 0.072$, $RMSE = 0.092$, $MAE_{baseline} = 0.114$
Predictive Modeling for Pedestrian Flow	85 time steps	$MAE = 0.038$, $RMSE = 0.052$, $RMSE_{baseline} = 0.062$

[a] Average Detected (AD_{target}) objects of class 'target' per image.

system capable of rapid updates to meet evolving monitoring requirements. One of the key distinguishing features is its ability to incorporate real-time weather information and dashcam-based on-the-ground info into its decision-making process. Unlike conventional traffic monitoring systems that rely primarily on historical data and predefined algorithms, this system dynamically responds to changing environmental factors, ensuring adaptive traffic management.

DT allows for the simulation of plans before implementing them, exposing problems before they become a reality, as well as allowing to address emergencies in real-time as they arise. Not only will this solution empower traffic management and optimize infrastructure planning, but it will also enhance public safety, reduce commuting times, prevent disruptions from natural disasters, and improve the overall quality of life for residents and commuters alike. Moreover, the adaptability and learning capabilities of the proposed architecture mean that it can evolve to address the changing dynamics of urban mobility and traffic management. As it accumulates more data and experience, it is expected to become an increasingly valuable tool for city authorities, offering invaluable insights for informed decision-making and long-term planning. This system stands to benefit city authorities, commuters, public transport operators, and emergency services, making it an indispensable tool for creating smarter, safer, and more efficient cities.

This study is subject to several limitations. Due to time constraints, models of each module were trained and tested once, without any follow-up period. Data collection was limited to a few months, therefore year-round seasonality in traffic and weather patterns was not explored to its full potential. In regions with limited weather monitoring infrastructure or unreliable data sources, the system's performance may be compromised. However, the module that detects road surface and weather conditions from road images was prepared especially to provide accuracy in such cases. Additionally, the success of the framework also depends on the willingness of users to participate in data sharing through connected vehicles and dashcams. Privacy concerns and data security issues may hinder the adoption of such technologies, potentially limiting the system's access to valuable live data. However, this can be overcome, by using state-authorized vehicles, such as police or patrol vehicles for live traffic data collection. Furthermore, the implementation of this framework requires significant infrastructure and technological investments. Not all cities may have the resources or capabilities to adopt this advanced system, leading to disparities in urban traffic management solutions.

During future work, the performance of the DT needs to be evaluated in detail and for a long period, so that seasonal patterns are visible. The proposed architecture can be considerably enhanced with the implementation of Reinforcement or Federated learning in order to constantly update the DT. Additionally, the focus should be shifted to live data-driven and self-learning models, so that the implication of engineers to periodically update models can be minimized. Strategies should be devised to make the system scalable and feasible using lower processing requirements and for a broader range of cities, including those with limited resources. Big data handling, such as storing only extracted analytics from the processed image instead of the entire captured image can greatly improve storage and data throughput.

V. Conclusion

In summary, this study proposed a novel DT framework as an innovative approach to urban traffic management in Singapore. Its modular architecture, real-time weather integration, and reliance on live on-the-road image data signify a departure from traditional traffic monitoring systems. The framework's adaptability and learning capabilities hold the promise of improving traffic congestion, reducing accidents, handling natural disasters, and ensuring safe commuting even in adverse weather conditions. Future work should focus on evaluating the framework's real-time effectiveness and addressing scalability and big data challenges.

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