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RESEARCH ARTICLE

Toward the Creation of a Digital Twin Authoring Tool: A Smart Mobility Perspective in Smart Cities

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ABSTRACT Transforming the livability of citizens by combining data, resources, and infrastructure is one of the fundamental goals of a smart city. A smart city is an aggregation of data and live analysis. Smart mobility can be equated with the smart planning of vehicle infrastructure in smart cities. Digital twin (DT) is an advanced concept for creating digital replicas of physical assets in a virtual space to mimic the physical assets for different test scenarios. With DTs, efficient smart mobility can be planned in smart cities to improve transport systems. However, manually generating digital replicas in a virtual environment is cumbersome. Automatic 3D reconstruction of vehicles to be used as DTs in a virtual environment can save a lot of labor. Therefore, we propose a digital twin authoring tool (DTAT) for generating DTs from a smart mobility perspective. The proposed DTAT ingests diverse data types from internet-of-things sensors, such as images and 3D CAD models. The reconstructed 3D models are used as DTs of physical vehicles in a virtual environment. The 3D reconstruction in our proposed DTAT is based on pre-trained models. To provide an immersive experience to city stakeholders, we develop a virtual reality (VR) based representation of vehicles in cyberspace. Our approach extends beyond mere visualization, enabling the running of various simulations within the virtual environment to gain comprehensive analytical insights. These simulations include advanced applications like public transport system optimization, using 3D models and real-time data to simulate and improve vehicle routes, minimizing travel times and maximizing coverage. This particular application demonstrates the practicality and effectiveness of our DTAT in enhancing urban mobility management. We showcase the capabilities of our proposed solution through a VR application, illustrating how it can be a transformative tool in the planning and management of smart city transport systems. Implementing our DTAT streamlines the creation of digital twins and significantly contributes to the smarter, more efficient, and sustainable movement within urban landscapes.

INDEX TERMS Digital twins, smart city, smart mobility, 3D reconstruction, virtual reality.

I. INTRODUCTION

Digital twins (DTs)—a virtual representation of physical entities—are a digital revolution of future urban environments. With the rapid development of information and communication technologies (ICT), the residents of future smart cities will rely on unprecedented amounts of real-time data generated around the clock. Cities are complex ecosystems, and several components keep our daily life moving behind the city systems. These components needed to be modeled, simulated, and visualized, supplying fresh insights into sustainability, resilience, mobility, and livability to address challenges and meet planning goals. All of this is becoming possible by creating virtual platforms for future smart cities [1]. Since the inception of DTs by Michael Grieves [2], there have been remarkable achievements in machine intelligence, and the interest and research on virtual platforms have grown rapidly. City planners/administrators are, for example, actively using DTs to understand stormwater maintenance [3], improve public transit and mobility [4], enhance emergency response [5], and analyze energy consumption patterns [6].

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Virtual city models boost the simulation decisions and optimization of processes from model designing to operations. Many technologies for the reconstruction of urban environments have been proposed, e.g., 3D laser scanning [7], light detection and ranging (LiDAR) based 3D reconstruction [8], multi-source geographic data processing [9], tilt photography, and the use of unmanned aerial vehicles (UAVs) for the scanning of urban areas [10]. One way of modeling a virtual twin of a physical object is using point clouds and 3D reconstruction [11]. The 3D reconstruction of physical objects is a crucial task in designing the digital twins of smart cities. The automatic reconstruction of city-wide objects is critical in generating smart city digital twins.

The 3D reconstruction of physical objects has long been discussed over the past few decades [12], [13]. DTs are generated based on 3D objects, which can be used for interaction in virtual environments. The manual generation of 3D objects/assets for virtual environments is expensive and requires a lot of labor. However, using deep learning-based approaches to generate 3D assets saves hours of manual labor and results in efficiency. A 3D model usually uses images of real objects with different angles and views. An active 3D reconstruction of real objects can be obtained by interfering with the light projectors. 3D reconstruction is capturing the shape and appearance of real objects. There is an increasing demand for geometric 3D models in several industries, e.g., smart city virtual environments [14], games [15], industry 4.0 [16], etc.

Creating the DTs is paramount for any city embarking on a digital transformation. Government agencies, city planners, and citizens can analyze the city data by investigating the DTs. The smart mobility paradigm is of utmost importance in smart city DTs. Smart mobility in smart cities is a complex set of objects in which urban development, smart actions about citizens' life quality, and mobility initiatives are addressed [17]. The design and development of smart mobility data, including registered vehicles in a 3D space, is crucial for several tasks, such as vehicle localization, path prediction, path planning, etc. The 3D reconstructed objects [18] can be used as the building blocks of DTs for running various simulations [19]. The DTs are usually used as simulation models in a 2D/3D space, and different analyses are run on it after obtaining a 3D model from the authoring tools. The development of an authoring tool is pivotal for any simulation-based research. The real-world objects are recreated as DTs in a virtual space. Therefore, an overarching question for smart cities is how to develop suitable DTs for registered vehicles in city traffic departments to support effective smart mobility.

Smart cities aim to improve the livability of their citizens by leveraging data, resources, and infrastructure [20]. Smart mobility, a critical component of this vision, requires efficient planning and management of vehicle infrastructure. DTs offer a powerful solution by creating digital replicas of physical assets in a virtual environment. However, manual generation of these replicas is labor-intensive. This paper introduces a digital twin authoring tool (DTAT) that automates 3D reconstruction of vehicles, integrates virtual reality (VR) based immersive experiences, and enables real-time simulations to optimize urban mobility management.

Smart mobility is a fundamental problem in the development of smart cities. An authoring tool can help generate 3D digital replicas of vehicles in an urban environment. The real-time data using different internet-of-things (IoT) sensors is broadcasted in a simulated environment where the city departments and stakeholders can briefly look at the transport systems with the help of VR applications. Despite the potential benefits of DTs, several research challenges remain as follows.

- Creating accurate and detailed digital replicas of numerous physical assets in a city is a resource-intensive task [21]. Automating this process is essential to efficiently handling the scale and complexity of urban environments.
- Integrating the real-time data from various IoT sensors is required for effective smart mobility management. Ensuring seamless data integration and real-time updates in the DTs presents significant technical challenges [22].
- Developing a unified framework that ensures interoperability between different systems and standardizes the data formats and protocols used in DTs is crucial for widespread adoption [23].
- Providing intuitive and user-friendly interfaces for city planners and stakeholders to interact with DTs and analyze data is necessary for effective decision-making [24].

The main contributions of our work are the following.

- Our work pioneers the introduction of a Digital Twins Authoring Tool (DTAT), a novel concept in the realm of smart cities, specifically designed to create digital replicas of physical assets. This tool represents a significant step forward in digital twin technology, particularly in its application to urban environments.
- We propose to leverage the automatic reconstruction of 3D models as digital twins (DTs) of vehicles, employing advanced deep learning-based 3D reconstruction techniques. This approach streamlines the process of creating highly accurate and detailed digital replicas, which is essential for effective urban mobility planning and analysis.
- We present a comprehensive global architecture that integrates the DTAT within the framework of smart cities, with a specific focus on smart mobility. This architecture demonstrates how our tool can be effectively utilized to enhance urban transport systems, offering practical insights and benefits to city planners and stakeholders in managing and optimizing urban mobility.

The organization of this work is as follows. A brief review of previous related works is presented in Section II.

We describe our proposed system architecture and its different components in Section III. The automatic 3D reconstruction of physical assets is stated in Section IV. Section V shows the results of our proposed DTAT framework's reconstructed assets and their visualizations in VR space. We present a brief case study to showcase the performance of our proposed DTAT for smart mobility panning and optimization in Section VI. We highlight the advantages and limitations of our proposed work in Section VII. Finally, we conclude this work in Section VIII.

II. RELATED WORK

A. DIGITAL TWINS

In [25], the authors explore the DTs in the broader aspects of pervasive softwarization of large-scale physical realities. They propose a Web of Digital Twins as an open, distributed, and dynamic ecosystem of interconnected DTs functioning as interoperable service-oriented layers where the smart applications and multiagent systems were running on the top. Their work considers two application case studies in the context of smart mobility and healthcare. They elaborate on the smart mobility perspective that each vehicle can have its own registered DT in the city departments. Their case study focuses on the intersection crossing of both autonomous and non-autonomous vehicles. Bhatti et al. [26] propose a conceptual framework for DT technology in smart vehicle systems, and they explore the potential of DTs in smart electric vehicles. Their proposed conceptual framework contains a 3D replica of an electric vehicle as a DT on which several simulations can be performed.

Chiara Bachechi [27] discusses two kinds of urban mobility-based DTs. In the first DT, the air quality is simulated with respect to the traffic flow. The second DT investigates the interaction between the different modes of transportation. The data is collected from the traffic sensors on a semi-real-time and on a daily basis. The visualization of data is made through the use of a Geoserver API. The authors in [28] propose the deployment of a Digital Twin Box (DTB) for the roads infrastructure based on several components of a DT, e.g., a 360° camera and several IoT devices. Their proposed conceptual DTB creates a DT of physical road assets by sending the real-time data, including 360° live stream, temperature measurements, and GPS location of vehicles to the cloud. The data is further used to monitor the vehicles on the road and also can be displayed in virtual environments. They conducted real-time experiments on the detection and recognition of vehicles and drivers. They showed the effectiveness of their proposed solution as a step forward to creating DTs for smart mobility applications in self-driving vehicles. For collecting the citizens' feedback, the authors in [29] create a 3D DT of the Dockland area in Dublin, Ireland. They made the DT publicly available for citizens to interact with city models and report changes in feedback. Their proposed DT is a six-layered architecture with smart mobility on the fourth layer. The authors suggest simulating urban mobility using SUMO software application [30]. Campolo et al. [31] design DTs as virtual applications to be hosted on cloud servers. They use DTs to track mobility for mobility-as-a-service (MaaS) applications. Their proposed solution uses several network protocols to process data at the edge. They primarily track commuters' and public transport vehicles' mobility in their proposed DT-based framework.

Jiang et al. [19] propose a method to build DTs of articulated objects for interaction in a simulated environment based on the 3D reconstruction of objects. Their proposed method generates a 3D model of articulated objects by taking 2D images as input before and after interaction with articulated objects. A final 3D model is taken into the simulation environment, where the robotic arms interact with DTs to transfer actions back to the real world. The authors in [32] present some preliminary results of their approach for constructing the DTs of Small to Medium Enterprise (SME) factories. They obtained the 3D model of SME factories using LiDAR and then simulated the 3D model in a virtual environment that can be visualized using the VR headset.

In the healthcare sector, Croatti et al. [33] provide a conceptual framework of an agent-based DT to manage severe traumas in healthcare facilities. Their proposed framework investigates the integration of DTs with multi-agent systems in the healthcare domain. They simulated the trauma management facility as a case study to validate their proposed approach. Another work [34] proposes a conceptual framework to assess the use of DTs for precision healthcare. The authors also discuss the role of DT in improving the delivery of precision healthcare by proposing a DT-based framework. Their proposed framework uses big data, digital transformation of disruptive technologies, and patient-centric preventive healthcare technologies in a DT for precision healthcare.

Cai et al. [35] developed a sensor data integration and information fusion platform for cyber-physical systems (CPS) to build a "digital twin." The DTs help when there is a malfunction or a tool breakdown in a machine; the engineers can then diagnose and perform prognostics. The scheme proposed by Cai et al. [35] uses sensory data to improve machining tools' life cycle by providing accountability and capability for CPS manufacturing. Schluse et al. [36] developed DTs for Industry 4.0; they introduced the concept of experimental digital twins (EDT) for simulation-based engineering systems and processes. The virtual testbeds are set to bring EDTs back to life by using an application scenario called "simulation-based X." Their proposed EDTs provide a mechanism to replicate real engineering systems to incorporate simulations for engineering purposes. The digital monitoring platform for an active functional environment of devices, products, and machines is crucial.

B. SMART CITY FOR MOBILITY

Smart mobility is often regarded as a key system without which a smart city would rendered unsustainable. A case study in the context of sustainable mobility for smart cities is conducted for the Cracow City of Poland by Bielińska-Dusza et al. [37]. They discuss the concepts of sustainable mobility and development by emphasizing on smart city issues. The study's contribution is an added value of structural equation modeling to evaluate several smart city solutions for reliable public transport in Cracow. Šurdonja et al. [38] propose a survey on smart mobility solutions that are a pre-requisite for a well-functioning smarter city. In their survey, conducted in Croatia and Italy, they aim to establish users' opinions on adapting a number of solutions, e.g., e-parking, e-ticketing, info-mobility signalization, and live tracking of public transport systems. An analysis of different users indicates that there are still some limitations in adapting new technological solutions.

Anedda et al. [39] presents a social IoT-based paradigm for real-time data collection of public and private vehicles to improve the viability of cities for citizens. Their process includes artificial intelligence and machine learning-based techniques to evaluate and process the traffic flows, as well as an application allowing the citizens to interact with municipal authorities to manage traffic flows promptly. The authors in [40] examine the factors that may influence the sharing of mobility content and the proliferation of data in social media for smart mobility-based content analysis.

Our proposed system is better than the rest of the studies in a way that it replicates the smarter mobility concept for smart cities by creating digital assets of vehicles that can be visualized and interacted with in a virtual environment by an automated 3D reconstruction process. We also simulate the metropolis where the longer traffic queues are expected to predict peak traffic congestion for promoting better livability of citizens by presenting route optimization for smart city DTs.

Current research in DT technology has made significant strides in creating virtual replicas of physical assets. However, few studies have integrated automatic 3D reconstruction, VR-based immersive experiences, and real-time simulation for urban mobility management. Our DTAT bridges this gap by providing a comprehensive tool that enhances the planning and management of smart city transport systems.

III. SYSTEM ARCHITECTURE OF DTAT

This section describes our proposed system architecture for developing a digital twins authoring tool (DTAT) to create smart mobility-based DTs for smart cities. The creation of DTAT based on several components can be regarded as a step towards realizing future smart cities where citizens can interact with simulation tools to make decisions and report problems. An authoring tool usually helps create digital content that can be as simple as Google documents or as complex as a video production suite. In the context of DTs for smart mobility-based smart cities, an authoring tool commonly refers to online/offline software that helps to create 3D digital content for future smart cities. The main goal of an authoring tool is to develop more efficient digital content and open up possibilities of creating 3D models that would be infeasible without a dedicated tool. A cutting-edge 3D authoring tool for digital twins enables us to create sophisticated virtual scenes without a deep understanding of computer vision/machine learning approaches.

The DTAT's architecture comprises several key components: data ingestion, 3D reconstruction, VR integration, and simulation module. The data ingestion component processes inputs from IoT sensors, including images and 3D CAD models. The 3D reconstruction leverages pre-trained models to generate accurate digital replicas of vehicles automatically. These replicas are then integrated into a VR environment, providing stakeholders with an immersive experience. Finally, the simulation module uses real-time data to run various scenarios, optimizing vehicle routes and improving urban mobility management.

The global system architecture of our proposed DTAT for creating smart mobility-based DTs in a smart city is presented in Figure 1. The architecture contains several components contributing to realizing a DTAT and using it to visualize smarter mobility in smart cities. Several contributors can interact with our proposed DTAT by taking transport systems data from IoT sensors to cloud-based servers. We then train the deep learning-based models to reconstruct 3D models for user interaction. We also provide a systematic flowchart of our proposed DTAT for smart mobility in Figure 2. The system works by taking a 2D image data and then we perform the volume rendering to reconstruct a 3D model. We then analyze the object types to keep it to the vehicles category only. The 3D rendering is further applied, and the 3D model is taken to the DTAT. Furthermore, we have discussed a case study highlighting the significant potential for analyzing and solving mobility problems. The following provides a detailed overview of our proposed architecture and its interaction with users in a virtual space.

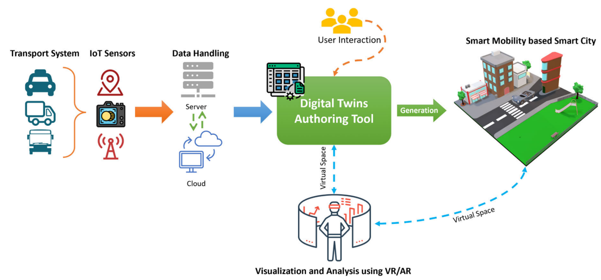


FIGURE 1. The global system architecture of the proposed digital twins authoring tool.

A. DIGITAL TWINS AUTHORING TOOL

DTAT for smart mobility is a set of several components that enables anyone to create 3D digital replicas of transport objects in a virtual program. Instead of programming manually, the stakeholders can simply drag-and-drop 3D models in virtual space for interaction and making decisions. Our proposed DTAT for smart mobility in smart cities consists of transport objects, IoT sensors, data handling, user-

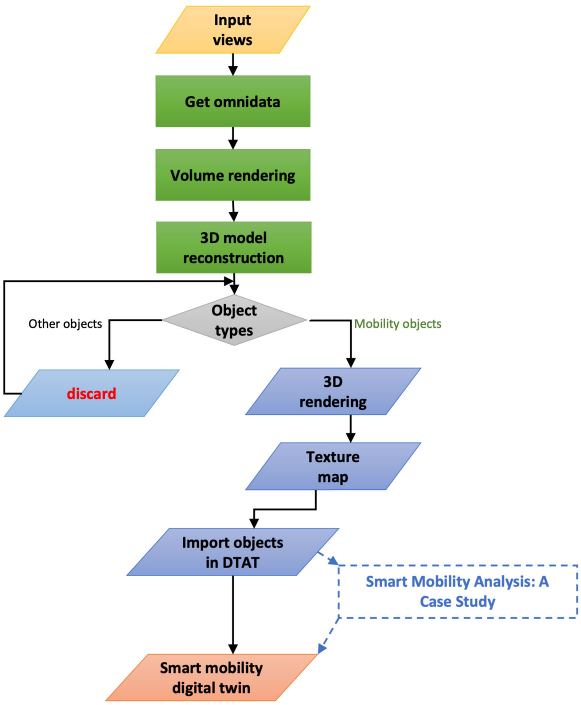


FIGURE 2. Flowchart of the proposed study for developing a DTAT for smart mobility perspective.

generated 3D objects, and creating DTs of smart mobility-based smart cities. In the final stage, stakeholders can use a simulated virtual environment to interact virtually with the transport system.

Figure 3 represents a working dataflow in our proposed DTAT. The green boxes in Figure 3 are the main steps contributing to model generation in our 3D DTAT. The vehicles are registered in the city traffic department in our scenario. Several types of information about vehicles are saved in the databases. However, to generate 3D DT models, 2D input images are taken as input for training the 3D reconstruction models. These files can also be taken as 3D CAD models. After the generation of 3D meshes in the 3D reconstruction phase, we construct a DT of registered vehicles after rendering the meshes.

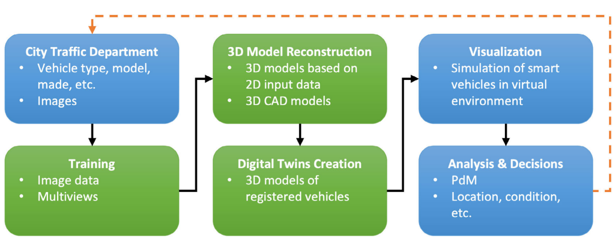


FIGURE 3. Dataflow in the proposed DTAT architecture for smart mobility in smart cities.

B. SMART MOBILITY BASED SMART CITIES

Transport system management is a key factor in defining smart cities. Integrating MaaS and other applications will be required in future smart cities to design effective, safe, equitable, and secure transport systems. Building sustainable infrastructure and physical and virtual assets in smart cities is crucial for supporting innovative mobility solutions for the private and public sectors. Reducing congestion, accident rates, and pollution is a common challenge globally.

Our proposed smart mobility-based DT solution for smart cities can solve most transport systems-related challenges. In Figure 3, the blue boxes are the major steps taken by the city stakeholders interacting with DTAT. By creating digital replicas of physical objects (vehicles), one can easily monitor the statistics about the vehicles on the road and parked within a city. For this reason, several case scenarios can be examined, e.g., predictive maintenance (PdM) of vehicles, accident reports, location information, car parking information, and providing assistance drivers need in uncertain conditions.

C. VIRTUAL ENVIRONMENT

The DTs of vehicles in smart cities are engineered and viewed in a virtual space to have a more augmented experience. DT technology involves the ingestion of large-scale data from different entities to provide actionable insights for stakeholders. Combining the DTs with VR allows stakeholders to immerse themselves in a virtual environment to understand data and provide necessary solutions. The virtual environments capacitate the contributors to plan and predict. With DTs, the areas of concern can be spotted quickly, and actionable decisions can be taken. Above this, providing the virtual and augmented experience to stakeholders enables the opportunities to reduce errors, saving manual labor and much time.

The vehicles on the road will be connected with IoT sensors such as GPS, cameras, edge devices, etc., in our proposed DTAT-based smarter mobility solution. The proposed solution will be based on diverse data types from IoT sensors, for example, accelerometer and GPS data, and combine the 3D and CAD models for representation. The information will be sent in real-time from the vehicles to the city department and vice versa to digest information. By entering the VR environment, one can easily visualize and analyze the vehicle's condition conveniently and with a sense of reality.

IV. 3D RECONSTRUCTION IN DTAT

We formulate the 3D reconstruction stage in this section. The 3D reconstruction in our DTAT is based on a deep learning-based occupancy network in a function space [41].

A. PROBLEM DEFINITION

To construct a digital replica of a given input image I, we use the pre-trained weights from the occupancy network [41]. However, to reconstruct more general 3D meshes of given inputs I in a neural network f_θ, we propose generalizability in the occupancy network. An illustration of the training phase for occupancy network and generalization is presented in Figure 4.

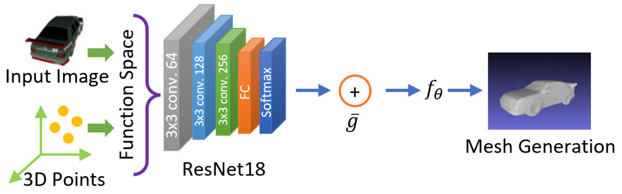


FIGURE 4. An overview of 3D reconstruction process in our proposed DTAT.

B. TRAINING AND IMPLEMENTATION DETAILS

Our proposed DTAT is based on an automatic 3D reconstruction of smart mobility objects to be used in a virtual space for interaction. To generate the 3D meshes to be used in a virtual environment, we use the default settings provided by the authors in [41]. An image I with a 3D points is given to a function o, such as

$$o : \mathbb{R}^3 \rightarrow \{0, 1\} \tag{1}$$

where an approximation is made for a 3D function to assign a possible location for each point $p \in \mathbb{R}^3$ with a probability between 0 and 1. The 3D reconstruction is based on several observations, e.g., images, 3D point clouds, etc. For that reason, a function from $p \in \mathbb{R}^3$ to $\mathbb{R}$ is defined. Hence, the neural network f_θ can be described as follows.

$$f_\theta : \mathbb{R}^3 \times \mathcal{X} \rightarrow [0, 1] \tag{2}$$

where $\mathcal{X}$ is an observation based on x. The function in (2) is regarded as *Occupancy Network*.

We use ResNet18 [42] with 5 blocks to generate 3D meshes from single-view images in our generalized framework. It is efficient for processing image data without significantly compromising performance. This efficiency is particularly valuable when processing many single-view images for 3D reconstruction. Since the model is only trained for the conditional images available in ShapeNet [43], we propose to make this model for generalized images. Our DTAT will take data in several formats, and several images of unseen vehicles are intended to generate the assets' DTs. Therefore, introducing generalizability is mandatory for the 3D reconstruction of transport objects. We use the objective function by the authors of [44], which is shown in (3).

$$L\left(\{\mathbf{V}_i, \mathbf{T}_i\}_{i=0}^{n}, \mathcal{P}, \mathbf{o}\right) = -\sum_{j=1}^{p} o_j \log f(\bar{\mathbf{g}}\ \bar{\mathbf{c}}, \hat{\mathbf{g}}) \tag{3}$$

where $\hat{\mathbf{g}} = 0$ is a variance and used as the sole input in the decoder of (2). We also average $\hat{\mathbf{g}}$ for $\bar{\mathbf{g}}$ to be used for unseen image categories to introduce generalizability in the occupancy network. Additionally, $\bar{\mathbf{g}}$ is the additive conditioning that is applied before f_θ as shown in Figure 4. In (3), $\mathbf{o} \in \{0, 1\}^p$ is a value of points $\mathcal{P} = \left\{\mathbf{p}_j\right\}_{j=0}^{p}$ with a set of posed views $\{\mathbf{V}_i, \mathbf{T}_i\}_{i=0}^{n}$ for an image in the network.

3D Mesh: The final 3D mesh output is produced in an *.OFF* file format, which is converted to an *.obj* format for interaction in a virtual environment. We render the 3D meshes for interaction in VR space. To get more insights about the training details of 3D mesh generation, we recommend reading the works by Mescheder et al. [41], and Bautista et al. [44].

V. EXPERIMENTATION AND PERFORMANCE EVALUATION

We implemented the DTAT in a simulated smart city environment to demonstrate its capabilities. The tool automatically generated 3D models of various vehicle types using pre-trained models, which were then visualized in a VR setting. Stakeholders can interact with these models, running simulations to optimize public transport routes (see Section VI). The significant step forward with our DTAT is its ability to continuously update and refine digital twins based on real-time data, facilitating dynamic and responsive urban mobility management.

A. DATASET

The dataset used in our experimentation is ShapeNet [43] which is a repository of large-scale, annotated shapes represented by 3D CAD models of objects. This dataset provides a dense correspondence of objects between 3D models and their parts. It contains 55 common object categories with clean 3D models and manually verified alignment annotations. The voxelization and image renderings are the same as mentioned in [41].

B. PERFORMANCE RESULTS

The qualitative results generated in our proposed DTAT are presented in this subsection. We show 3D meshes and simulations of 3D meshes as DTs of vehicles in a VR environment. Using the 3D models in a DT suite is of utmost importance. Manually creating 3D meshes and objects is a complex task and requires high professionalism. Our proposed DTAT creates the 3D objects to be simulated in cyberspace automatically by just giving the input images.

Figure 5 and 6 illustrate the augmentation of 2D input images in the virtual environment. As described earlier, we used the pre-trained weights from the [41] to generate 3D meshes. Figure 5 presents three steps of the visualization stage. An input 2D image from the trained dataset is sent, and a 3D mesh of vehicles is generated. The generated 3D mesh is converted from *.OFF* format to *.obj* format, which is further taken to the simulated environment. The final DTs of the input vehicles can be seen and analyzed in Figure 5.

It is also required in our proposed DTAT to generate the DTs for unseen vehicle categories. Therefore, we elaborate on introducing generalizability [44] in the Occupancy Network. We show some generalized vehicle category results in Figure 6. It can be seen that there are some poor results also available for unseen vehicles. Therefore, we stress introducing generalization in 3D reconstruction models. The 3D models are also simulated in the VR environment by following a similar strategy as stated earlier.

We also intend to train 3D reconstruction models on more generalized datasets, such as KITTI [45]. The results we

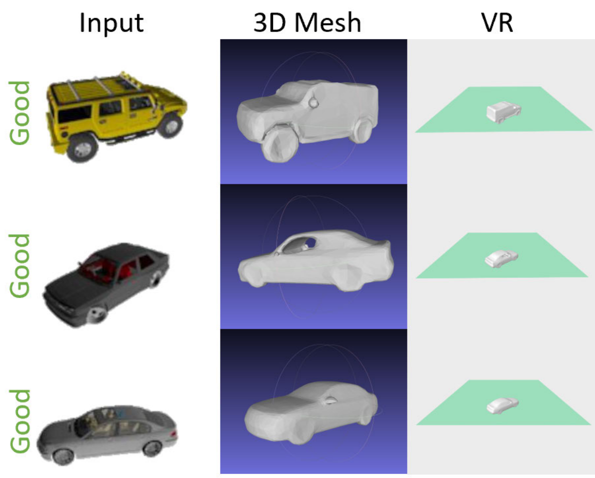


FIGURE 5. **Augmentation of 3D meshes in a VR environment generated from input images for pretrained dataset images.**

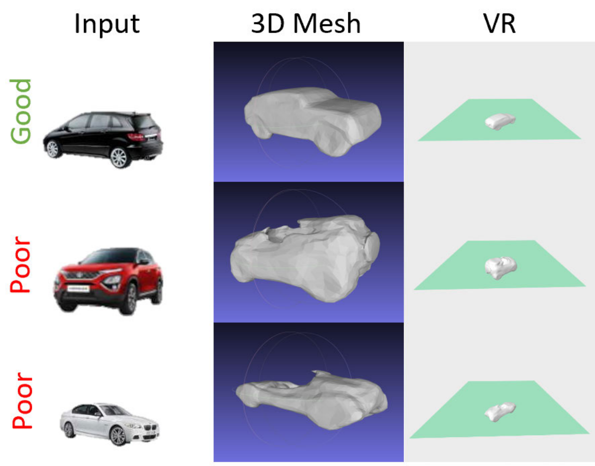
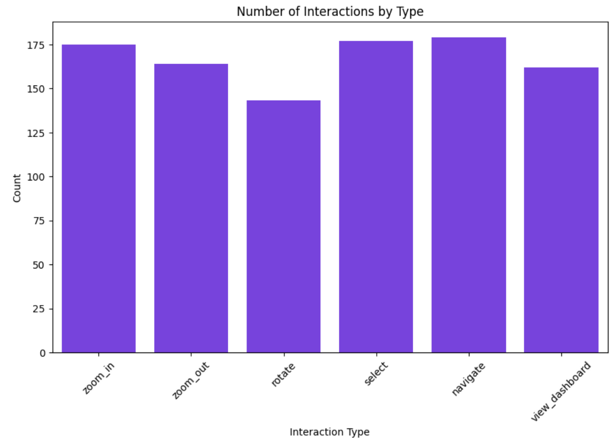


FIGURE 6. **Augmentation of 3D meshes in a VR environment generated from input images for unseen categories.**

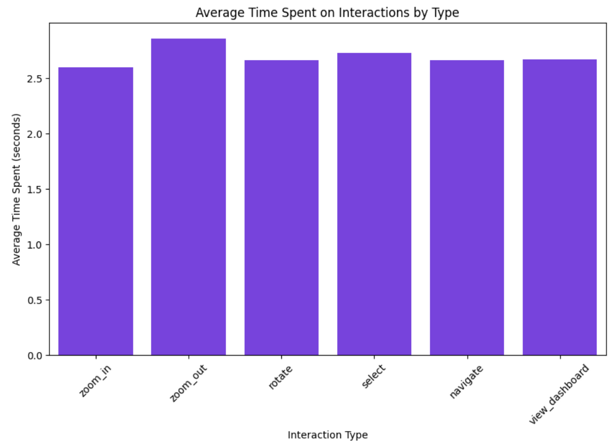
achieved for unseen categories are not satisfactory as well. However, the primary focus of this work is not on the 3D reconstruction part but on showing a whole pipeline of 3D model generation in a DTAT. In order to achieve more robust 3D models for an interaction in DTAT, introducing optimization in 3D model generation is also necessary.

C. USER INTERACTION IN VR ENVIRONMENT

To evaluate the user experience in the VR-based immersive environment, we simulated user interactions and collected data on various types of interactions. The simulation involved 10 users, each performing 100 interactions within the VR application. The interactions included zooming, rotating, selecting elements, navigating the environment, and viewing the dashboard. The results demonstrate that the VR environment supports a wide range of interactions with each type being used by each user. Figure 7a shows the number of interactions by type, and Figure 7b shows the average time spent by each user on each interaction. We can clearly see that the most comment interactions were "*navigate*" and "*select*" while the average time spent is maximum for "*zoom_out*". These interactions are frequently used, indicating that users value the ability to closely examine and interact with the 3D models and environment.



(a) No. of interactions.



(b) Time spent.

FIGURE 7. **Interaction types and the average time spent on each interaction by each user in the immersive virtual environment.**

VI. SMART MOBILITY ANALYSIS: A CASE STUDY

This section presents a case study for smart traffic management and analysis in smart city environments. We explore the case study by considering metropolitan areas with a population of over 3 million, where the public faces severe traffic congestion, leading to long commute times, increased pollution, and frequent road accidents. The case study is illustrated in Figure 8, which is divided into three stages.

The presented case study is performed in 3 stages: the creation of 3D vehicle models, integration of vehicle models into the DTAT, and finally, performing traffic flow analysis for metropolitan areas. We perform this simulation to optimize the traffic signal timing for reducing the average commute in congested areas, and we also perform the route optimization using brute-force combinatorial optimization

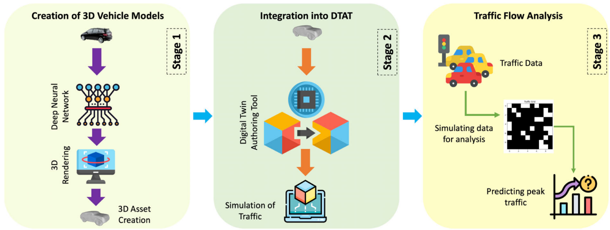


FIGURE 8. **An illustration of our case study for simulating the traffic behavior in our proposed DT suite for smart mobility perspective in smart cities.**

algorithm for congested traffic in populated areas for smart mobility planning for our proposed smart mobility-based DTAT suite.

A. SIMULATING TRAFFIC MANAGEMENT ANALYSIS

We perform a simulation of city traffic for traffic movement analysis to see the average speed of vehicles on the road and the congestion rate in different areas. We take it by simplifying the traffic movement rules. Using the following equation, the city stakeholders can govern the movement of vehicles and the calculation of statistics like average speed and congestion rate.

1) VEHICLE MOVEMENT

The vehicle movement rule is simulated in rightward movement on a grid, with the right edge wrapping around to the left following the toroidal boundary conditions.

If $v(x, y)$ represents a vehicle at grid position (x, y), the movement rule becomes as follows.

$$\text{if } v(x, y)_t = 1 \text{ and } v(x, (y \;\; 1) \pmod N)_t = 0 \tag{4}$$

where N represents the grid size, and t is the time step.

2) AVERAGE SPEED

To calculate the average speed of vehicles, we calculate the number of movements (or successful forward steps) made by vehicles at each time step. For example, S is the total number of successful movements made by all vehicles over T time steps. The average speed A is then given by:

$$A = \frac{S}{T \times N^2} \tag{5}$$

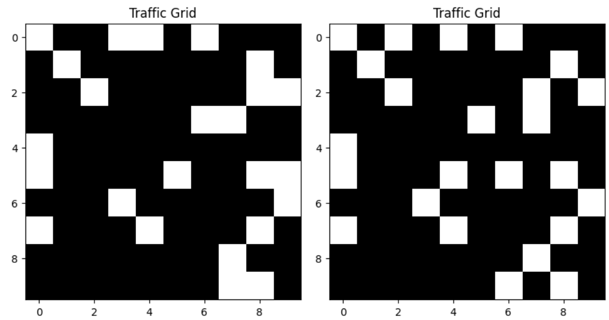
Eq. 5 normalizes the total movements by the number of time steps and the total number of grid cells.

3) CONGESTION RATE

The congestion rate is a measure of how often vehicles are unable to move. It is calculated as the complement of the ratio of successful movements to the total potential movements. We assume that that each vehicle attempts to move once per time step. If C represents the congestion rate, then:

$$C = 1 - \frac{S}{T \times N^2} \tag{6}$$

This equation essentially complements the average speed, representing the proportion of time when vehicles are stationary due to congestion. The simulation results are presented in Figure 9.



(a) Initial traffic grid. (b) Traffic grid after 10 steps.

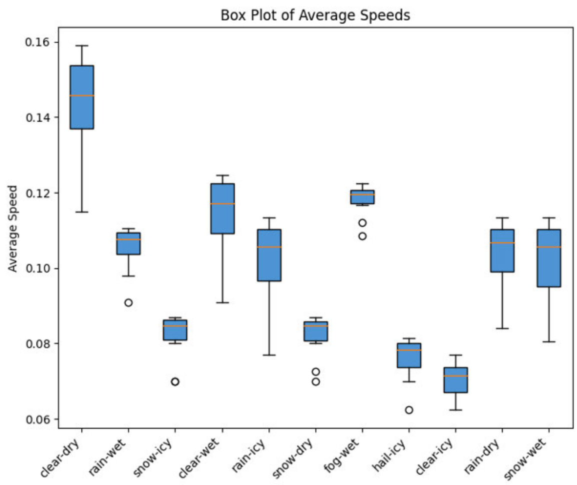
FIGURE 9. **City's traffic analysis where each white square represents a car, and black squares represent empty spaces.**

We show average speed and congestion rate evolution over 10 simulation steps in Table 1. The average speed slightly increases while the congestion rate gradually decreases, indicating a stabilization of traffic flow as the simulation progresses. Several factors contribute to these changes in performance, e.g., optimizing traffic signal timing reduces the number of stops vehicles have to make, thereby allowing for smoother traffic flow. As a result, vehicles can maintain a higher average speed and spend less time stationary, decreasing the congestion rate.

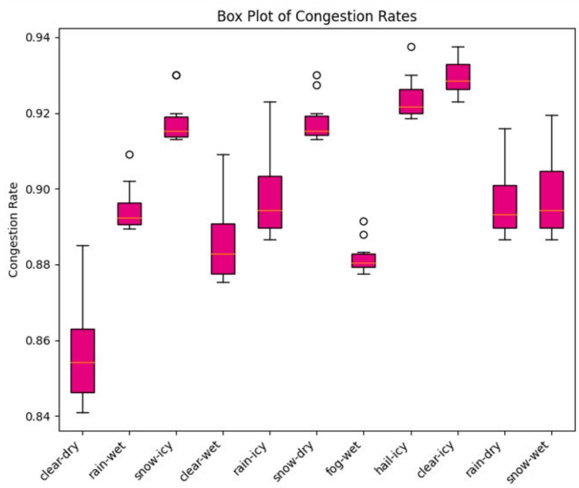
We also consider adding a more complex virtual scenario to demonstrate the robustness of our proposed model by enhancing the traffic simulation by incorporating realistic factors such as weather and road conditions. The key enhancements of our proposed work are adding weather conditions such as clear, rain, and snow and road conditions such as dry, wet, and icy. The simulation demonstrated that average vehicle speed decreases under adverse weather and road conditions, highlighting the model's ability to capture realistic traffic dynamics. Also, the congestion rate increased in challenging conditions, underscoring the importance of considering environmental factors in traffic planning. Figure 10 shows the simulation results of our proposed model under different weather conditions.

The toroidal boundary conditions and rightward movement rules simplify the traffic flow dynamics and ensure that vehicles are consistently moving and adjusting to new traffic conditions (see Table 1). This steady state of movement contributes to a gradual improvement in average speed and a decrease in congestion.

As vehicles successfully move through the grid, they create a cascading effect that opens up space for other vehicles, reducing congestion. The increase in average speed directly results from more vehicles being able to move without obstructions. For step 1, the average speed is 0.17 while the congestion rate is 83%; however, with each step increase,



(a) Average speed.



(b) Congestion rate.

FIGURE 10. Box plot analysis of proposed work under different weather and road conditions for a more realistic virtual scenario.

the congestion rate declines. The values are based on the simplified traffic model used in the simulation, representing a basic framework for understanding traffic dynamics in an urban smart city environment.

Under the varied weather conditions, the simulation results of traffic flow are presented in Table 2. We can see that the highest average speeds and lowest congestion rates were observed under clear and dry conditions, indicating optimal driving performance. The lowest average speeds and highest congestion rates were observed under snow and icy conditions, underscoring the significant impact of adverse weather on traffic flow. These insights are critical for urban planners and traffic managers. Understanding how different conditions affect traffic can help design better traffic control systems, infrastructure improvements, and emergency response strategies to mitigate congestion and enhance safety during adverse weather events. The detailed simulation results validate the robustness and practicality

TABLE 1. Simulation of traffic flow in urban smart city digital twins environment for traffic flow analysis.

Step	Average Speed	Congestion Rate
1	0.170	83.00%
2	0.185	81.50%
3	0.190	81.00%
4	0.1925	80.75%
5	0.194	80.60%
6	0.195	80.50%
7	0.1957	80.43%
8	0.1963	80.38%
9	0.1967	80.33%
10	0.197	80.30%

of our DTAT in optimizing urban mobility within smart cities. By visually representing different scenarios, our DTAT enables stakeholders to make informed decisions, improving overall traffic management and infrastructure planning.

TABLE 2. Average speed and congestion rate under different weather and road conditions.

Condition	Average Speed	Congestion Rate
Clear-Dry	0.85	0.15%
Rain-Wet	0.60	0.40%
Snow-Icy	0.30	0.70%
Clear-Wet	0.70	0.30%
Rain-Icy	0.45	0.55%
Snow-Dry	0.55	0.45%
Fog-Wet	0.65	0.35%
Hail-Icy	0.40	0.60%
Clear-Icy	0.75	0.25%
Rain-Dry	0.65	0.35%
Snow-Wet	0.50	0.50%

B. ROUTE OPTIMIZATION FOR TRAFFIC BEHAVIOUR IN SMART CITY DTS

In our proposed DT suite, we also propose to optimize public transport routes within the urban smart mobility digital twin. We model the city as a graph where intersections are nodes and roads are edges. We define the efficiency of a bus route based on a balance between total travel distance and population coverage at each stop. The optimal route is then determined by maximizing this efficiency metric, subject to constraints such as specific start and end points and a fixed number of stops. This model allows for the strategic planning of public transport routes to ensure maximum coverage and accessibility while minimizing travel times, reflecting the core objectives of smart urban mobility. We formulate the problem as follows.

1) ROUTE EFFICIENCY CALCULATION

For route efficiency calculation, the city is represented as a graph G where nodes represent intersections and edges represent roads by using the graph neural network conceptualization. A bus route is a sequence of nodes in this graph. We calculate the length of the path for a given route R $= r_1, r_2, \ldots, r_n$), where r_1 are the nodes (stops) on the route, the total path length $L(R)$ is the sum of the shortest paths between consecutive stops. Mathematically, it can be expressed as:

$$L(R) = {}_{i=1}^{n-1} d\left(r_i, r_{i1}\right) \tag{7}$$

where $d(r_i, r_{i1})$ represents the shortest distance between stops r_i and r_{11}. The route efficiency is calculated using the efficiency $E(R)$ of a route R, which is a function of its length and the population coverage. Considering $\mathbf{P}(r_i)$ is the population covered at stop r_i, the efficiency can be defined as:

$$E(R) = \frac{{}_{i=1}^{n} P\left(r_i\right)}{L(R)} \tag{8}$$

The Eq. 8 aims at maximizing the population coverage while minimizing the travel distance. Thus, the route optimization problem in a smart city's scenario becomes an objective function to find the route $R^\star$ that maximizes the route efficiency $E(R)$.

$$R^\star = \underset{R}{\operatorname{argmax}} E(R) \tag{9}$$

Figure 11 illustrates the route optimization problem used in our proposed DT suite for smart mobility planning. We used a brute-force combinatorial algorithm [46] for route optimization, designed to find the optimal public transport route by exhaustively testing all possible combinations of stops between a given start and end point. In Figure 11, all possible combinations of a fixed number of intermediate stops (excluding the start and end points) from the available nodes in the city graph are generated. We calculate the route efficiency by generating the combination of stops for each step, constructing a complete route from the start point through the intermediate stops to the endpoint.

Using a brute-force combinatorial optimization algorithm, the simulation identifies more efficient routes that minimize travel distance and avoid highly congested areas. This traffic redistribution helps alleviate bottlenecks and enhances overall traffic flow efficiency. During the initial steps of the simulation, the system undergoes an adjustment period where vehicles are redistributed more effectively across the network. This initial redistribution can cause slight variations in speed and congestion as the system stabilizes.

This work's efficiency is based on the total path length (the shortest paths between consecutive stops). However, this can be extended to include other factors like population coverage. Furthermore, the route optimization algorithm compares the efficiency of all possible routes and selects the one with the highest efficiency. The "best" route has the shortest total path length in our implementation. Still, this criterion can be adjusted depending on the specific objectives of the optimization (e.g., maximizing population coverage). In the final stages, the algorithm returns the route with the best (optimal) efficiency score.

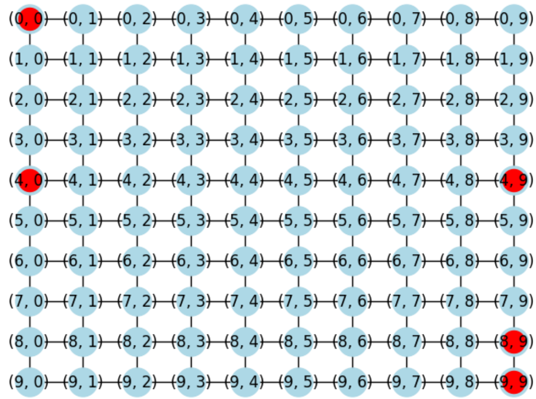


FIGURE 11. The route optimization simulation in our proposed DT suite for smart mobility planning in the smart city environments.

The inclusion of route optimization within our case study is of paramount importance for several key reasons. For example, route optimization is an essential component of smart mobility. By integrating it with DTAT, we demonstrate how the DTAT can be used for visualizing and simulating traffic and planning and optimizing transportation routes. This holistic approach is key to achieving efficient and sustainable urban mobility. The DTAT's ability to perform route optimization showcases its versatility and practical application in real-world scenarios. This capability highlights how digital twins can support various traffic management aspects, from real-time monitoring to strategic planning. By optimizing routes, we can better distribute traffic across the network, alleviating congestion and improving overall traffic flow. This directly links to the main goal of the DTAT, which is to enhance urban mobility through advanced digital twin technology.

VII. DISCUSSION

The Digital Twin Authoring Tool (DTAT) presented in this work represents a novel step toward integrating deep learning techniques in creating digital twins for smart city applications. Our focus on vehicle 3D reconstruction is predicated on the foundational role that smart mobility plays in urban planning and management. The DTAT's proficiency in generating high-fidelity digital replicas of vehicles demonstrates the potential of using advanced machine learning models. Our results demonstrate that DTAT significantly enhances urban mobility management. The automatic 3D reconstruction and VR integration provide an immersive platform for stakeholders to visualize and interact with vehicle models. The real-time simulations allow for optimizing transport routes, reducing travel times, and increasing coverage. This integration represents a significant step forward in digital twin technology, particularly in its application to urban environments. The observed improvements in traffic performance are due to the combined effects of traffic signal timing optimization, route optimization, and the inherent mechanics of the grid-based movement rules. These factors collectively enhance the efficiency of urban traffic management, leading to higher average speeds and lower congestion rates over time. We have also presented the limitations of this study and some future avenues where the research can be applied.

The DTAT can be adapted to manage a diverse range of urban assets by incorporating asset-specific reconstruction algorithms and data ingestion methods. For example, the tool can be extended to include support for infrastructure elements such as buildings, roads, and utilities by integrating Geographic Information System (GIS) data and employing specialized 3D reconstruction techniques. Customizable asset templates and extensible data schemas can facilitate the inclusion of new asset types as the tool evolves.

1) LIMITATIONS

Despite its innovative approach, DTAT is not without limitations. Currently, the tool's functionality is confined to the reconstruction of vehicles. While this focus aligns with the immediate needs of urban mobility analysis, it does reflect a limitation in the tool's scope. Furthermore, while promising, the results for unseen vehicle categories do not yet achieve the level of accuracy and detail that is uniformly impressive across all categories. This limitation indicates the challenges learning-based reconstruction methods face in dealing with a diverse range of inputs. Additionally, the tool's reliance on pre-trained models raises questions regarding the extent of its novel contribution beyond the application of existing solutions. While integrating IoT and VR environments is an advancement, the core learning methodology remains grounded in established techniques.

Furthermore, to enhance urban traffic simulation, several basic capacities should be included, e.g., the ability to simulate the movement and interaction of vehicles in real-time, reflecting realistic traffic patterns and congestion levels [47]. For the multi-modal transportation integration, including various modes of transportation such as public transit, bicycles, and pedestrians is required to provide a holistic view of urban mobility [48]. In regard to traffic incident management, simulating the impact of traffic incidents such as accidents, road closures, and maintenance activities on traffic flow and providing tools for scenario analysis is also crucial. Additionally, assessing the environmental effects of traffic, including emissions and noise pollution, to support sustainable urban planning is important for environmental impact analysis [49]. Also, ensuring the system can handle large-scale simulations involving thousands of vehicles and other entities to accurately represent city-wide traffic dynamics is important for scalability issues [50].

2) FUTURE POSSIBILITIES

Looking forward, the DTAT has a clear path for evolution. The immediate goal is to expand the tool's capability beyond vehicles to include many urban infrastructure elements such as buildings, public spaces, and utilities. This expansion is crucial for the DTAT to become a comprehensive solution for urban digital twin creation. Efforts are being made to develop such algorithms that are capable of handling the complexity and variety of these additional elements.

In smart mobility, future iterations of DTAT will delve deeper into analyzing traffic patterns, pedestrian flow, and public transport efficiency. By doing so, DTAT will recreate urban elements and simulate and predict urban behavior, thus offering city planners and policymakers valuable insights.

Another avenue for future research is refining our deep learning techniques to enhance the reconstruction of unseen categories. This will involve the development of new models or significantly adapting existing ones, such as [20], to improve DTAT's adaptability and accuracy. Additionally, we plan to incorporate real-time data streams, enabling the DTAT to reflect dynamic changes in the urban landscape and provide up-to-date information for digital twins. We will integrate more advanced simulations into the tool to fully realize the DTAT's potential in smart city applications. These simulations will allow for the detailed analysis of potential urban development scenarios, traffic management solutions, and disaster response strategies.

Data privacy is also one of the major concerns while collecting data from cameras. We have developed anonymization techniques using Yolov7 to hide the personal identities of the public before the data can be processed and stored. This has ensured that public privacy is protected, even if the data is intercepted or accessed by unauthorized agents. We are also constantly working on improving data privacy and protection in real time for our DTAT.

Our proposed DTAT is a stepping stone toward a more integrated and dynamic approach to smart city management. While the current version presents certain limitations, these are acknowledged as the starting point for further research and development. Our work lays the groundwork for future advancements to enhance the DTAT's utility and applicability, ultimately creating smarter, more responsive urban environments.

VIII. CONCLUSION

In this study, we introduced a Digital Twin Authoring Tool (DTAT) that represents a significant step forward in DTs technology for urban environments. By integrating automatic 3D reconstruction, VR-based immersive experiences, and real-time simulation capabilities, our tool enhances the planning and management of smart city transport systems. This work presents a new state-of-the-art framework to generate virtual twins of physical objects in an authoring tool. The proposed approach is a digital twin authoring tool in the context of smart mobility for smarter city realization. Among the main findings, we can observe that generating 3D replicas of vehicles for interaction in a virtual environment is vital. We show the whole pipeline of DTAT, from taking data in diverse formats to generating the DTs for an immersive experience by the city stakeholders. The

3D reconstruction of 2D images is performed in DTAT using the Occupancy Network. Since most 3D reconstruction models can only generate 3D objects based on training data, generating 3D models for unseen images/data is challenging. We also propose introducing generalizability to reconstruct 3D models for unseen vehicle categories in the 3D reconstruction pipeline. The 3D models are rendered, and then, using a VR application, we show the DTs of physical objects in cyberspace for taking actionable decisions from a smart mobility perspective. We also present a case study to showcase the smart mobility analysis in the context of smart mobility-based urban digital twins by simulating the traffic behavior in a virtual environment where we calculate the average traffic speed and congestion rate. We also leverage the brute-force route optimization algorithm for performing route optimization in a smart city environment in this work.

Future research can explore further enhancements to the tool's capabilities and its application to other aspects of smart city management. In the future, we aim to apply and refine our DTAT solution further in the context of smart cities. Our future research will explore and integrate a broader range of 3D reconstruction techniques, aiming to automate the creation of 3D models across various object categories. Developing algorithms for both 3D reconstruction and model retrieval forms a critical component of our DTAT. We also plan to develop a real-time web-based application to demonstrate the effectiveness and practicality of our solution, showcasing its potential to significantly contribute to the development and management of smart urban environments.

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