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An Integrated Platform using VR to Visualise and Analyse Road Traffic Conditions

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ABSTRACT

The main contribution of this paper is to introduce a framework for integrating Machine Learning (ML), Human, and Virtual Reality (VR) into one platform to promote a collaborative visualisation environment that can assist in better analysis and improve the human-machine teaming capability. This platform was demonstrated using a case study in analysing road traffic conditions. The 'Abnormal Machine Learning Road Traffic Detection in VR (AbnMLRTD-VR)' prototype system was developed to assist the human analyst. The proposed system has two main integrative components: a data-driven ML model and a 3D real-time visualisation in a VR environment. An unsupervised ML model was built using real traffic data. The AbnMLRTD-VR system highlights the outliers in the road sections in actual road contexts of a road traffic network. This gives the human analyst a 3D real-time immersive visualisation in a VR environment to evaluate road conditions. The AbnMLRTD-VR system demonstrated that it could help minimise the need for human pre-labelling of the data. It enables the visualisation of the road traffic conditions more meaningfully and to understand the context of the road traffic conditions of road sections at any given time.

1. Introduction

Road traffic accidents have caused 1.3 million deaths, and 20-50 million people have been injured yearly [1]. There is a considerable effort among researchers to combat this issue by developing systems to understand and predict traffic conditions. These systems must promptly and accurately detect abnormal road traffic conditions, which may put public safety at risk if not handled on time [2]. The abnormal road traffic conditions are usually unexpected and abrupt changes in traffic flow, such as congestion, which may lead to accidents. Road traffic anomaly detection is widely used to support and enhance road traffic prediction models [3].

One of the critical aspects of improving the reliability of Machine Learning (ML) models for anomaly detection is how accurate they are when labelling a road traffic flow as abnormal. Although anomaly detection techniques have been studied for many years, the anomaly detection problem still challenges researchers for three reasons: (1) the boundary between a normal condition and an

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abnormal condition is usually not evident, (2) the data available is often unlabelled, and, (3) some types of abnormal conditions require the understanding of the context so that the conditions can be identified [4]. For these reasons, visualising the traffic flow conditions using visual tools enables researchers and experts to precisely identify and assess anomalies and even label the anomalies.

In analysing the ML outputs of complex road traffic data, Virtual Reality (VR) is becoming popular for 3D-real-time immersive visualisation as a VR environment enables researchers and experts to perform rich visual 3D analyses [5,6]. This kind of analysis can be important when assessing the correct identification of a traffic flow condition as abnormal since domain experts' opinion is based on the context of each specific road traffic scenario. The current advancement of VR technology provides affordable, enhanced and 3D real-time immersive environments where users can be present in the VR space and have a first-hand experience of the road traffic conditions, hence a better understanding of the context in each specific road traffic situation.

Given the importance of analysing the context of an abnormal road traffic condition, this paper aims to propose and develop an AbnMLRTD-VR road traffic prototype system that could assist in defining abnormal road traffic conditions of road traffic flow that has unlabelled data. The AbnMLRTD-VR system will then show the road sections for a specific location and time and provide a 3D real-time immersive experience in a VR environment to the human analyst when analysing particular road sections. The ML technique can be any ML technique. However, a simple ML technique is developed for demonstration purposes in this paper. The ML technique used in the AbnMLRTD-VR system is based on an unsupervised technique, with no requirement for any prior labelling by humans. Once the ML technique highlights the abnormal road traffic conditions, the section of the roads can then be visualised in the VR environment. In the VR environment, the human analyst can perform further analyses and validate whether the identified abnormal road traffic conditions are valid based on the context of those road conditions and sections. The main contribution of this paper is to introduce a framework to integrate ML and VR into a single platform where the users can better analyse the data. This has enhanced the human-machine teaming capability. The proposed framework enables the human-in-the-loop approach for better collaborative analyses and predictions.

2. Analysing Road Traffic Conditions

2.1 Abnormal Conditions in Road Traffic

Road traffic flow represents the number of vehicles that pass a sensor within a time interval. This feature is one of the most common ways of analysing road traffic conditions. A trajectory is a list of point locations, for example, coordinates, where it is possible to track the path of an individual vehicle [7]. Models for abnormal condition detection have been widely used by the scientific community over the last few years [8], inclusive of road traffic prediction models [3]. A range of distinct techniques is used to identify outliers and detect anomalies in road traffic flow or trajectories.

The abnormal condition can be represented by an "outlier" (or "point anomaly"), a "contextual anomaly" (or a "collective anomaly") [9]. An outlier is a data point that is judged to be far from the closest neighbouring data points. A contextual anomaly is when the outlier is interpreted depending on the context. A collective anomaly is where observations are analysed and compared with historical patterns [9]. For example, a road traffic flow value is considered normal during rush hour traffic. In contrast, the same traffic flow value is considered abnormal when it occurs early in the morning or on public holidays in a commercial district. For context and collective anomaly, historical and observed data should be compared using the same data, time interval, and additional contexts to classify a specific traffic condition as abnormal.

Abnormal road traffic conditions can result from two types of events. The first is road traffic congestion caused by traffic incidents or overload [10]. Road traffic congestion will lead to a lower traffic flow and reduce traffic speed, but the effect lasts only for a short time. The second type is road management, such as maintenance, where there is a more prolonged effect on road traffic. This effect lasts longer and could take days, months or even years to complete maintenance.

The approaches for anomaly detection vary according to the type of model. The trajectory anomaly detection models are built using online [11] or offline processing [12], and models for detecting outliers in road traffic flow use statistical [13], similarity [14], or pattern mining techniques [15]. All these types of models can work with supervised or unsupervised models.

For supervised learning, Guo *et al.,* [16] apply different methods to improve the performance of road traffic flow prediction using abnormal traffic flow conditions. A similar approach is used by Guo [17], where disruption at the same street is manually identified, and a method of segmentation and clustering is applied before the ML predictor models. In this approach, the ML method learns from the labelled data, where incidents or known, disruptions are used to label the abnormal condition. Besides the accidents dataset used to detect an anomaly, weather conditions datasets also help detect anomalies in road traffic data [18], forming the context for the abnormal condition.

Mihaita *et al.,* [19] use outlier analysis to detect abnormal conditions for unsupervised learning. The technique consists of daily measuring of median and standard deviation. These measurements compare the current road traffic value with the historical value. The data is considered abnormal if the current value is larger than the historical value. Mihaita *et al.,* [19] consider the value of 10 times greater between the current and historical value as a large margin of difference.

Correlation in sensors is also used in past studies. Sensors are electronic devices placed on the streets so that road traffic and speed data can be collected automatically. The study presented in [20] works with the correlation between the sensors, matching the true relationship between roads regarding their traffic flow. Therefore, the closest and correlated sensors are considered abnormal when an incident occurs.

For abnormal detection models in fields other than road traffic, the evaluation can be made using traditional evaluation metrics such as accuracy and recall. This kind of measurement is only possible in supervised learning as the data is labelled. However, unsupervised abnormal detection models often require human analysis [14].

2.2 Virtual Reality for Traffic Simulation

VR has played a major role since the 1970s in specific industrial applications, particularly in the military and automobile sectors. However, with the advent of newer technologies, affordability, hardware improvements and major computer advances, new application domains also started to take advantage of the capabilities of VR [21].

The reason for this adoption is that, as opposed to traditional 2D and 3D visualisations, VR offers a 3D real-time immersive and interactive experience to the users, where they are free to intuitively explore and interact with the VR environment.

Some studies are using VR environments to simulate road traffic conditions. In many papers, VR is only used for simulating road traffic. All aspects of ML analyses, such as predicting or analysing historical data, are often performed using different systems, running in parallel and external to VR [22]. For example, Wang *et al.,* [23] use a separate ML system parallel to the VR system.

The most common approach for road traffic simulation in VR is the “microscopic” approach. This approach focuses on the microscopic level of road traffic, where each vehicle is a distinct element in the model. For example, each vehicle running in VR has its characteristics and behaviour. In this way, each vehicle can make decisions based on its characteristics and the surrounding events. If an obstacle suddenly appears on the road, the individual vehicle can decide whether to deviate from the obstacle [24]. The microscopic type is related to the road traffic psychology approach. This model often uses three models: the Car-follow model, the Generalised Force Model (GFM) and the Intelligent Drive Model (IDM). All these models attempt to reproduce human behaviour when making decisions. This decision-making process is based on three steps. First, cognitive models are built, named, and assigned to each vehicle in the VR environment. Second, an ML model, such as logistic regression, is used for decision-making. Third, the final decision-making considers the environmental events, the behaviour of drivers and the vehicle characteristics [24].

Although less popular than the microscopic approach, some studies use the “macroscopic” approach. This approach uses parameters such as road traffic volume, capacity, and density or traffic speed (overall traffic speed). Instead of treating all single vehicles individually, the macroscopic model uses collective numbers for road traffic measurements. Li *et al.,* [25] use a VR environment with coloured maps to represent the road traffic flow conditions in different road segments. The study does not approach outlier detection but road traffic flow conditions instead.

Many different tools are currently available for building virtual environments for traffic simulation. Paz *et al.,* [26] present a VR for traffic simulation using the Unity 3D game engine to build the virtual environment.

Li *et al.,* [7] use WebVRGIS for traffic analysis and visualisation in VR, and the analysis is made on abnormal conditions. In their study, the authors do not detect nor predict the abnormal condition but reproduce the anomaly in three-dimensional virtual space.

All the previous studies have been done using separate visualisation and prediction modules that are not integrated. They do not involve the active collaboration between humans and machines. Consequently, our study integrates ML and VR for analysing road traffic conditions. The main purpose of this paper is to study how ML and VR subsystems and expert humans can work together seamlessly in the human-machine loop performing traffic analysis.

3. Methodology

3.1 Interview with Domain Experts

After reviewing the literature on abnormal condition detection in road traffic and VR for traffic simulation, the first step in our design of the AbnMLRTD-VR system is to interview road traffic industry domain experts dealing with road traffic analysis. The intention is to understand how VR can be used in the road traffic domain and to ensure that our design of the AbnMLRTD-VR system can satisfy their needs and can be used. The industry domain experts were from two local companies: Metro Traffic Planning and MetroCount®.

The domain experts from Metro Traffic Planning suggest that the VR systems could help them train new employees on the process of closure of lanes, providing a good visualisation of the correct set-up of the traffic cones and signs on the road. Although the suggested functionalities are not directly related to abnormal road traffic detection, there are still some valuable comments from them. They prefer a system that can help them visualise the layout of the road and lane. They suggest that by using VR, instead of travelling to the actual location, VR can help them make a more informed decision on the set-up of the closure of the lanes beforehand.

The domain experts from MetroCount® deal with traffic analysis, and the company has a commercial software product for smart traffic analytics and survey management. This software analyses data from various sources, such as sensors placed on the streets. The do-main experts from MetroCount® want to find outliers in road traffic data, similar to what this project aimed to achieve.

The sensors measuring the flow and speed of the vehicles are placed on the ground, and they can be permanently or temporarily installed on the roads. The permanent sensors are embedded into the pavement so that the data provided by this type of sensor are more accurate. The data can be inaccurate for the temporarily installed sensors on the road if the installation is not properly done. It would be good if VR could provide better visualisation of the data collected and the ability to navigate in the 3D virtual environment to under-stand the nature of the abnormalities and the context in which they occur. Figure 1 shows a temporary sensor installed on the road.

In summary, the domain experts from both companies would like to use a VR system to help them analyse road traffic conditions without physically going to the place of interest. In addition, the potential capabilities of VR to reproduce traffic crashes and accidents were also discussed.

Fig. 1. Temporary sensor installed on a road

3.2 Road Traffic System Development

From the literature review and interviews with the domain experts, we designed the framework of the AbnMLRTD-VR system. The proposed AbnMLRTD-VR system consists of two main components with a database (Figure 2): (1) The ML module and (2) The VR module. The database module connects the two main components.

In this project, the outlier detection is performed by the ML module. A simple ML technique (k-NN) has been chosen to demonstrate the proposed integrated platform's usability. The k-NN algorithm has been implemented for the ML module as it is widely used for anomaly detection [27]. The user can dynamically change the value of the hyperparameter *k* for the k-NN algorithm. This ability enables the user to try different values for *k* directly within the AbnMLRTD-VR system and see the effects visually. The user does not have to restart the application or recompile any piece of the software.

The ML module for abnormal road traffic condition detection was written in Python. The VR module was developed using the Unity 3D game engine. Studies [28] indicate that Python ML models are effective for anomaly detection, integrate seamlessly with the Unity 3D game engine, and Unity is widely used for developing VR systems [23]. Studies [26] have also explored road traffic simulation systems using the Unity 3D game engine software, and they found this to be a suitable tool for microscopic and macroscopic road traffic simulation. The database module was created using SQLite, a small portable database suitable for studies like ours that do not require a full production database.

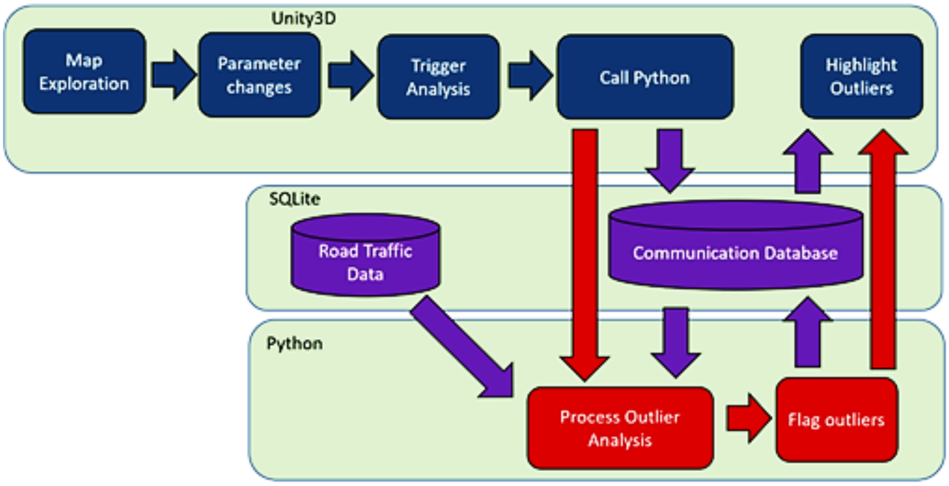

Fig. 2. The modules in the AbnMLRTD-VR system

The outliers are visualised in the VR module using a macroscopic approach. The macroscopic outlier detection uses traffic flow values where the analysis is made in the broad aspect of road traffic.

The database module has two purposes: (1) to store unlabelled data for road traffic and (2) to use it as a medium to communicate between the ML and VR modules. The AbnMLRTD-VR system is built using unlabelled data from Perth's Road traffic available from Mains Road, Western Australia. The data is migrated from a CSV file into the SQLite database. The reason is for the ML module to perform queries on the SQLite database using the PL-SQL language. This ability is crucial for data exploration and manipulation. The data contains the road traffic volume for 1,340 road segments in the urban area of Perth in 15-minute intervals. Our study used data from 2019, which contains 38,882,016 traffic flows, to demonstrate the capability of the AbnMLRTD-VR system.

The road segment selection (Figure 3) is based on the quality and number of anomalies found in the downloaded data. The intent was to reproduce the actual abnormal road traffic conditions in VR instead of producing synthetic abnormal road traffic flow conditions. Anomalies are often rare [27], and specific road segments may not contain anomalies. Therefore, attempts are made in different road segments, and outliers are discovered in one road section. Figure 3 shows the selected geographical areas used to demonstrate the AbnMLRTD-VR system.

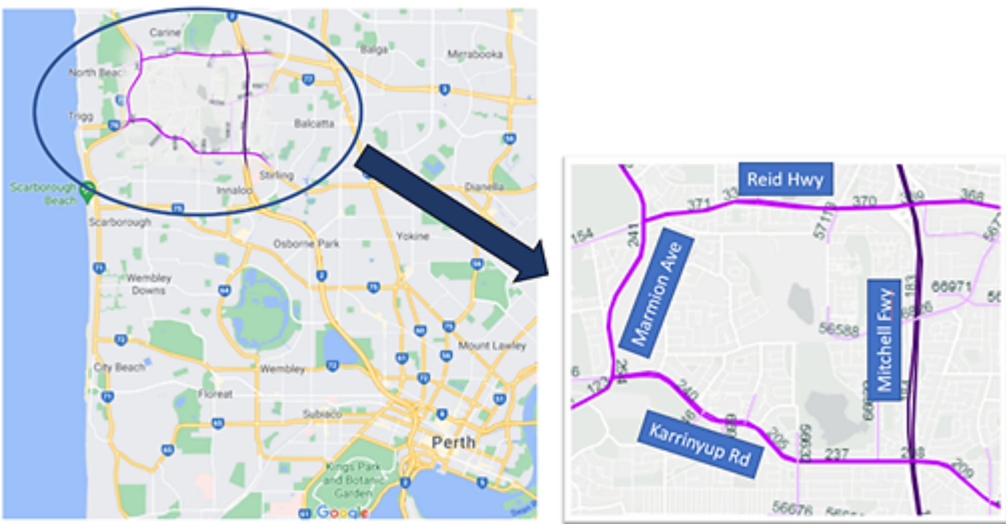

Fig. 3. Segments of road used in the demonstration

4. Results

4.1 AbnMLRTD-VR System Demostration

The system is tested on a PC with an Intel Xeon Silver 4114 CPU @2.20GHz processor, 16 GB memory RAM and a SCSI disk device. The VR headset used was Oculus Quest (Figure 4).

To demonstrate the functionalities and the purposes of the AbnMLRTD-VR system, a series of experiments were run to determine the ideal scenarios for the user to experience. We ran the ML k-NN algorithm across different road sections and DateTime intervals, and several outliers were identified.

Fig. 4. The Oculus Quest VR headset used for system testing

The selected date for the system testing was on 3rd June 2019. The selected times for the test were 5:15 a.m., 6:15 a.m., 6:30 a.m., and 8:00 a.m. At 5:15 a.m., there were no outliers identified in the road section. At 5:30 a.m., the road section 336 presented an outlier; at 6:15 a.m., a second road section 337 also presented an outlier. Fifteen minutes later, at 6:30 a.m., a third road section presented an outlier. At this time, the road section is the m-link 241. Both 336 and 337 m-links belong to Reid Hwy, while the m-link 241 belongs to Marmion Ave (Figure 3).

The first step in setting up the VR module was configuring the road sections in the Unity 3D game engine and mapping each road section (labelled “road cut” in Unity) to its code from the m-link column in the dataset. After verifying the road sections and whether the elements in each Road link are correctly mapped to the road network, the road sections are displayed on the VR headset. Figure 5 shows the highlighted road section in green for the m-link 336.

The next step is to use the VR headset and explore the VR environment. In the VR environment, there are two modes of exploration: the *panel mode* and the *immersive mode*. The two modes can be toggled between one another. The *panel mode* presents the different road networks on several virtual displays (Figure 6). The *panel mode* is used to analyse the road networks. In the *immersive mode*, a user can experience a first-person perspective view at a life-size scale (Figure 7). Figure 7 and Figure 8 shows an example of the front view and an example of the back view in VR, respectively. The outcomes of the anomalies generated from the ML can be overlayed in both modes, which are shown in red.

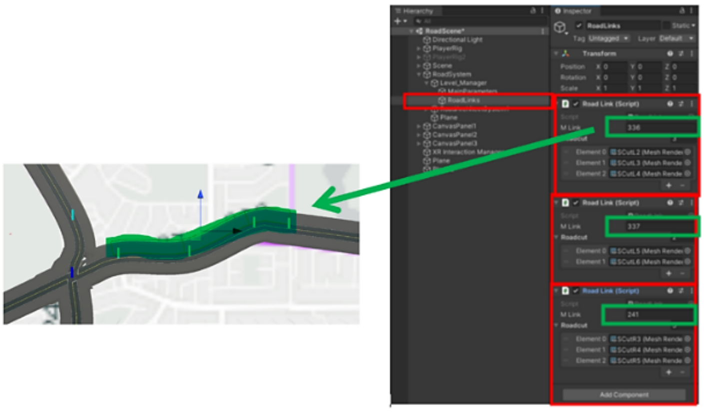

Fig. 5. Highlighted road section in green for m-link 336

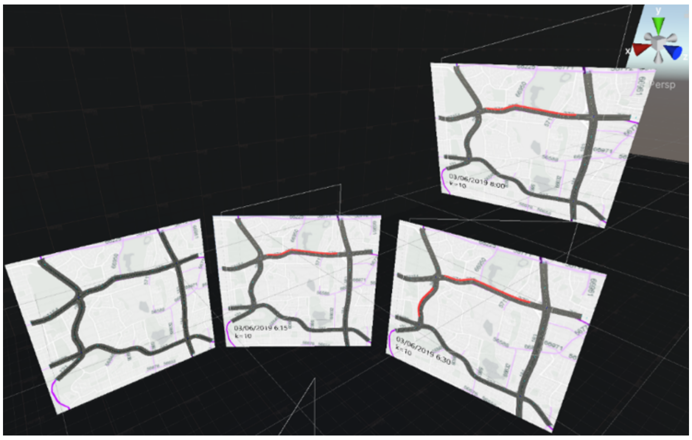

Fig. 6. Example of the *panel mode* (the red lines highlight some abnormal conditions generated from the ML)

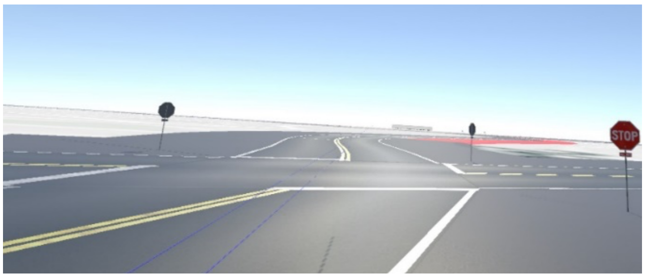

Fig. 7. Example of first-person perspective view in the *immersive mode* (The red line highlights the abnormal condition generated from the ML)

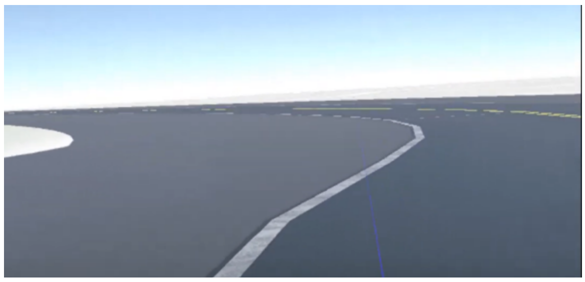

Fig. 8. Example of back view in immersive mode

These visual tools in the VR environment can help researchers and experts decide about abnormal road traffic conditions. Users can also define the thresholds for the ML models to detect abnormal road traffic conditions in the VR environment. The AbnMLRTD-VR system can help in providing the user with the ability to (1) virtually explore the road network, (2) have an immersive experience of the geographical location where the outlier is taking place, and (3) use the VR environment to create a mental map when comparing different scenarios and results of the outlier analyses. In this instance, the limited capabilities of traditional 2D or 3D visualisations are now surpassed by VR systems, where believable and immersive experience is presented.

For the contextual analysis of a given outlier, the proposed AbnMLRTD-VR system enables users to explore different road traffic scenarios. That capability gives the user an immersive experience when exploring the intersection from different perspectives. For instance, some causes of an anomaly in road traffic data are traffic incidents or overloads. Allowing users to explore the intersection in an immersive VR environment increases the perception of potential road hazards.

5. Conclusions

This paper presented a platform for integrating Machine Learning (ML), Human, and Virtual Reality (VR) into one platform to assist in better analysis. We demonstrated the proposed platform by developing a novel integrated AbnMLRTD-VR road traffic system. The AbnMLRTD-VR road traffic system is used for outlier analysis to understand abnormal road traffic conditions. Previous research from literature has shown that VR could improve the interpretability of abnormal road traffic conditions and that unsupervised ML models could help identify anomalous situations with unlabelled traffic data. However, human intervention is still important in determining road traffic situations based on context and environmental conditions. The reason is that there is no clear boundary between normal and abnormal conditions in road traffic data. In addition, the road traffic data available is often unlabelled, which restricts the options for defining the boundaries of outliers.

The development of the AbnMLRTD-VR system had two main stages. Firstly, building a VR system that can be used in a VR headset and building an ML model to quickly identify outliers from unlabelled road traffic data. System testing was conducted, providing a natural and immersive experience to analyse outliers by human analysts. Different thresholds could be defined in the AbnMLRTD-VR system interactively, and it can help the user to interpret the outliers using believable and immersive characteristics of VR.

This paper has demonstrated that using the proposed AbnMLRTD-VR system facilitates the collaboration between ML, VR, and humans in a loop to better analyse the road traffic conditions without transporting humans to the actual physical sites. Future work is to expand this framework to include analysing more road traffic conditions, implementing different efficient ML techniques, allowing multiple human users to collaborate with the ML in the VR environment, and extending the usage of the AbnMLRTD-VR system to allow for road planning purposes.

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