Intelligent Urban Junction Planning and Multi-Modal Safety Analytics powered by YOLOv8, DeepSORT, and Integrated Aerial–CCTV Video Modellings

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Abstract— The high rate of urbanization has enhanced congestion, safety levels, and inefficiencies at intricate intersections of traffic, so that intelligent and autonomous traffic management systems are required. This report presents a proposed multi-modal urban junction analytics, which consists of the YOLOv8-based object-detection tool and the DeepSORT-tracker to identify fine-grained motions of heterogeneous road users. Graph Neural Networks are used to model interaction between agents and changing conflict patterns, whereas Temporal Convolutional Networks make it possible to predict short-term traffic flows. Bayesian Change Point Detection detects abnormal change and incident initiation, and self-supervised contrastive learning is more robust in little literature. Drone and CCTV feeds' multi-view fusion improves the spatial coverage and eliminates occlusion. Extracted trajectory and safety indicators are organized into a downstream signal, optimizing scalable datasets. Real-world intersection validation that can be conducted experimentally indicates that there is an enhanced accuracy when estimating the traffic flow, as well as the identification of risks and adaptive signal planning. The suggested framework provides an intelligent urban traffic management framework that will have a predictive and safety-conscious base.

Keywords: Urban Traffic Analytics and YOLOv8 Deep SORT Graph Neural Networks Multi-modal Fusion Traffic Safety Predictive Signal Control.

I. INTRODUCTION

Urbanization has now resulted in cities being more of a high density and dynamic plasticity in which road safety problems and traffic jam issues have become more complex. Crossroads represent a key component in a transport system, having heterogeneous players in the transportation system including cars, buses, bicycles, motorcycles, pedestrians. At the places where such agents engage in interactions, conflicts, inefficiency and accidents are possible. The traditional time management tools have been grounded on the application of the fixed time signal plans, loop detector and visual observation that is not appropriate during the current time and changes in the traffic that cannot be predicted in the cities. As cities swell and people have to travel, there is a high demand to own smart, self-aware and anticipatory traffic analytics that may not just understand the road volume of traffic but simply predict the covert forms of services and contact between road users [1].

The recent advance in the domain of the computer vision and deep learning has made a pathway to the development of the urban traffic surveillance. The vision-based system can utilize cameras and drones to provide expanse of spatiotemporal information on a traffic scene. It has been shown that models such as the YOLO family have achieved excellent outcomes with regard to identifying vehicles and pedestrians in challenging conditions. However, in order to have a conception of the traffic dynamics, it is necessary to detect it. The individual agents must also be monitored with time and give the trajectories and motion patterns as well as risky interactions. Direct frame-to-frame association A widely used variant of multi-object tracking is DeepSORT, with which a researcher observes the motions and behaviors over time by connecting the present frame discovery to the previous frame discoveries [2]. Nevertheless, although the agents are properly detected and tracked, in the traditional approaches, the agents are regarded as an individual, and the relationship aspect is overlooked when the road users influence one another during the intersection.

The type of traffic in the city crossroads is interactive in nature. The behavior of the group depends on drivers on the reactions to the pedestrians, bikes on the reactions to the traffic flows, and the demonstration of the signal phases. They require something more than consideration of single motions to embody them. Graph-based representations give a natural encoding in which the agents may be viewed as nodes and the interaction among agents as edges and the system may be able to reason in terms of conflict, proximity, and right-of-way relation. To achieve such relational data, Graph Neural Networks (GNNs) have been constructed to be effective in learning, which enables the aspect of modelling of the intricate patterns of interaction essential to the safety analysis and risk forecasting [3]. By introducing GNNs to the setting of traffic analytics, it can transition to a descriptive surveillance and have the capacity to understand how and why unsafe situations occur at crossways.

In addition to the interaction modelling, temporal dynamics play an important role in the traffic management. Flow of traffic never remains constant but is varied according to the time of the day, the timing of lights, weather and unexpected disruptions. Predictive control the forecasting of the traffic states on short time basis can be applied to take proactive actions against congestion in the traffic- like manipulating virtual signal phases until the congestion has not taken place. Temporal Convolutional Networks (TCNs), are reported to be suitable in the task because they can learn and retain long-range temporal dependency without the loss of the computational capacity. Unlike recurrent models, TCNs have stable trainings, can handle sequences simultaneously and are therefore attractive in real-time traffic prediction [4]. In the case of the spatial and relational modelling, temporal prediction enables a holistic view of evolution of traffic situations in near future.

Another crucial feature of the traffic systems is smart traffic systems which are able to sense an unusual occurrence and abrupt alteration. Among the situations that might readily result in the interference with the normal flow and the subsequent occurrence of a risk to safety, accidents, traffic jams, or unforeseen demand surges may be added. Traditional congestion detection systems relying on threshold are depreciative and weak. Bayesian Change Point Detection (BCPD) is a probabilistic method of identifying that time a time series has its statistical properties altered to reflect the adoption of new conditions or events, of abnormal nature. Applying BCPD to the traffic measures that can be the speed, the density, or the length of the queue allows determining the incidents in early phases and launching the timed interventions [5]. This is required in creation of systems, which are predictable and at the same time resistant to sudden failures.

The unavailability and the cost of labeled data is one of the constant impediments to the use of systems founded on developed learning in real traffic environments. Finding fine grained identities of objects, tracks, and tagging the interactions points of huge traffic videos is highly time-consuming and inaccurate. This issue is addressed by self-supervised and contrastive learning methods which make use of unlabelled data to perform meaningful representation of the learning process. Limited supervision can be strengthened through self-supervised contrastive learning, which would promote the ability to discriminate between similar and dissimilar traffic scenarios or actions taken by agents by letting the model develop on its own. This may be particularly effective at urban crossings, where each site is unique in terms of geometrical and behavioral characteristics and data sets labelled on one may not be readily relocated to a different site.

Moreover, urban crossroads are also usually monitored with various sensing nodes such as the culminated CCTV cameras, and with the help of drones. Each of the modalities possesses its complimentary advantage, i.e. CCTV will be in a position to keep everything in the frame and will be able to offer fixed and predictable perspectives, whereas, drone will be able to make top-down shots and reduce the cases of obscuration. This pooling of information in different views however introduces issues related to synchronisation, association and calibration of data. With the complementation of weak areas of other sensors, it is possible to get a great deal with multi-view fusion to allow the attainment of a larger completeness and accuracy in traffic perception. Multi-modal data can also be used to address complex intersections in a holistic manner, and improve the quality of downstream analytics when correctly implemented.

This has been done but majority of the solutions that exist in the market today as far as traffic management is concerned are piecemeal solutions which focus on specific components e.g. detection, tracking or prediction in isolation. The number of models that integrate perception, interaction modelling, temporal forecasting, anomaly detection, and representation learning as a single system designed to take on the specific process of achieving safety-aware and predictive junction management is not very high. This lack limits the applicability of intelligent traffic technologies, since a workable implementation of solutions should be scalable, end-to-end capability, and able to operate autonomously and react to various conditions in the cities.

Resting on such difficulties, this paper proposes an planning and Multi-modal Safety Analytics system that is based on the state-of-the-art, which is the combination of computer vision, graph learning, temporal modelling, probabilistic change detection, and self-representation learning methods. It uses YOLOv8 to identify fine-grained objects, DeepSORT to track throughout a temporally long time, GNNs to model interactions, TCNs to predict short-term flows, BCPD to detect abnormalities and contrastive learning to enhance robustness to give a multifaceted perspective on traffic dynamics at complex intersections. CCTV and drone Multi-view data fusion enhances the spatial coverage.

The outcomes of the interaction as the extract trajectories, interaction features and safety procedures are presented in the form of scalable data, which may be applied in the optimization downstream processes as the adaptive signal control and junction redesign. A laboratory testing of the proposed system during the definition of intersection in the urban settings within the real world demonstrates that the system proves higher in approximations of traffic flow, identifying the risks, and also estimative planning. The development of one, safety conscious, and predictive analytics pipeline can make this contribution to the development of safer, more efficient, and resilient cities by developing intelligent urban traffic management systems.

II. LITERATURE SURVEY

Intelligent control systems and data-driven decision-making are rapidly changing the engineering applications of intelligent control systems in the present day, specifically in energy systems, robotics, transportation, and smart cities. The conventional control techniques of PID and rule-based logic are becoming increasingly inadequate in addressing nonlinear dynamics, uncertainty as well as real-time constraints in complex systems. Subsequently, high-state predictive and learning-based techniques, in particular, Model Predictive Control (MPC) and deep learning, have been the most dominant area of research. The approaches allow systems to predict the future behavior, optimize performance and constrain them all at the same time. Simultaneously, combining computer vision and AI has transformed the process of monitoring and automation in city infrastructure. The combination of the control theory, machine learning, and embedded systems has created smart structures that are able to adapt to changing situations with minimum human interventions. This literature review is devoted to recent works of predictive control, robotics, power electronics, healthcare, and AI-traffic systems as it is possible to note how the contemporary approaches enhance robustness, safety, and efficiency of various application areas.

Recent reports note the importance of making predictive control architecture more robust and reliable to uncertain environments. One of them presents a model-free predictive control of a setting of inverting multiple parallel grid-forming inverters within AC microgrids and enhances the stability of the voltage and the load sharing during disturbances [6]. In robotic systems, the control barrier functions employed in MPC have been utilized to solve the problems of obstacle avoidance as well as tilt angle constraints to achieve a safe navigation with ball-balancing robots in dynamic environment [7]. Personalized healthcare has also been extended under the view of predictive control, hybrids between MPC and system identification methods have been applied in providing physical activity intervention tailored to individual behavior patterns [8]. Other applications in power electronics include MPC to battery chargers of personal mobility devices to enhance dynamic response and minimize overshoot in comparison with conventional PI controllers [9]. Equally, predictive current control using MRAS based parameter estimates improves the performance of induction motors by removing the effect of parameter mismatch and disproving robustness [10]. Both physical and cyber-physical systems have the flexibility of predictive control in these works.

In addition to conventional areas of control, predictive models are being implemented along with AI-powered systems of perception of smart transport. Real-time traffic prediction and analytics are crucial to urban mobility optimization, complex network modelling, and video-based detection of traffic jams are better practices to manage congestion [11]. Scalability Deep learning frameworks based on YOLOv8 and IoT devices can provide real-time traffic control in the context of smart cities [12]. AI-powered dynamic traffic signal systems alter the timing of signals according to the predictive analytics and real-time detection to decrease the delays and enhance traffic flow [13]. Deep learning and time-series models help forecast short-term traffic with the aim of adopting an adaptive traffic control plan by predicting the vehicle turn pattern [14]. Drones with object detection and tracking algorithms offer the real-time traffic information because the drone has access to the aerial viewpoints that will deliver a better situational awareness perspective [15]. Collectively, these systems depict the ways predictive analytics and vision-based AI can be used to supplement control approaches in smart transportation systems.

Additional development lays emphasis on edge computing and built-in monitoring platform. Smart campus surveillance is an IoT-supported system that uses lightweight YOLO models to determine the density of traffic and offer real-time visualization using mobile apps [16]. Speed estimation and classification by computer vision have come to be discussed as vehicle monitoring frameworks that allow automated analysis of traffic and support urban planning [17]. SQL-based analytics create a modular computer vision pipeline that streamlines the processing of traffic video to enable scalable data storage, querying, and visualization to the urban authorities [18]. These systems minimize the use of manual observation in order to facilitate proactive traffic management. Moreover, it was also found that prior research on YOLO as a roadway monitoring device was able to prove the possibility of tracking and counting vehicles in real-time to be deployed as a smart city [19]. Taken together, these methods demonstrate the increased place of artificial intelligence to automatize the large-scale surveillance and decision-making in transportation systems.

Intelligent systems with safety in mind have also become eminent. Modern accident detection and risk assessment models used in the area of accident detection and prediction unite CNN-based object detection algorithms with graph-based analytics to simulate relationships between vehicles and pedestrians [20]. Such systems have intended purposes of detecting dangerous trends at an early stage and initiating preventive measures that would improve city safety. Generally, the literature examined indicates that there is a great tendency towards creating the combination of predictive control, deep-learning, and IoT technologies into unified intelligent systems. These solutions enhance the resilience of systems, their flexibility, and efficiency, regardless of the intended use of energy networks, robotics, healthcare, or smart transportation. This literature has a solid basis in the creation of advanced, real-time, and scalable intelligent.

III. METHODOLOGY

The intended Intelligent Urban Junction Planning and Multi-Modal Safety Analytics framework is implemented as an end-to-end pipeline converting unprocessed multi-view video streams to structured, predictive, and safety-aware traffic intelligence. It is based on the approach that perception, tracking, interaction modelling, temporal prediction, anomaly detection, and representation learning are combined into a single system. Individual parts are all optimized to deploy to real-time urban and are modular to permit scalability to a variety of junction geometries and traffic conditions. The entire process starts with the simultaneous collection of the data made by the CCTV and aerial channels, then the objects will be recognized and tracked. The obtained trajectories are represented as interaction dynamic graphs. The forecasting of the short-term dynamics of traffic is performed using the temporal models, and the detection of abnormal changes is performed using the probabilistic techniques. Lastly, self-supervised learning is more robust to very limited annotation. Each of the stages of the methodology is detailed in the following six subsections as shown in Figure 1.

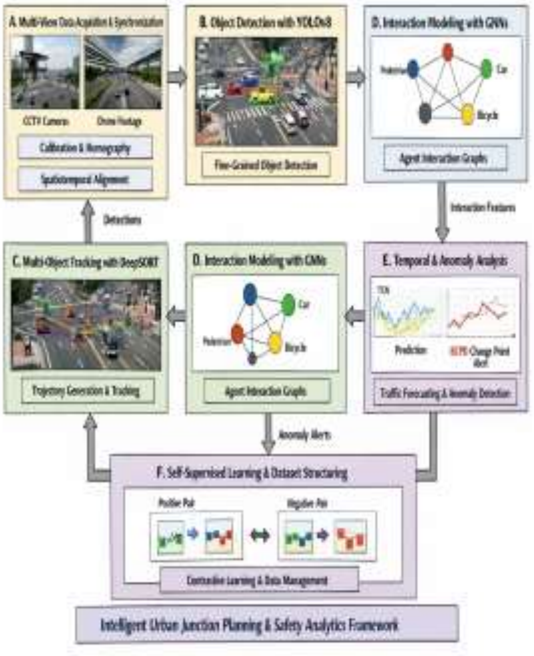

Fig. 1: System Architecture

A. The multi-view Data acquisition and synchronization

In a way that provides full junction coverage, the system ingests heterogeneous video streams by means of fixed CCTV cameras as well as aerial drones. The intrinsic and extrinsic parameters are used to calibrate each camera feed to bring the spatial coordinates in the views into alignment with each other. The temporal synchronization ensures uniformity of timestamps of frames and interpolates between them in order to accommodate the different frame rates. The application of homograph will project all the detections into a shared bird's eye coordinate system, which supports the use of uniform spatial arguments. Noise levels and light levels are also enhanced to reduce environmental variations as a shadow, glare, weather and so on. The blending of air and ground shots will minimize the process of occlusion and enhance the detection accuracy in crowded traffic. The coordinated multi-view sequence is the basis of downstream perception, tracking and interaction modelling. The step makes certain that all that follows the analytics are going to be based on a consistent spatiotemporal representation of the junction scene.

B. Object Detection with YOLOv8

The contribution of achieving fine-grained perception with the help of the YOLOv8 architecture is due to its balance between the accuracy and the real-time performance. The detector is then conditioned to a complex set of traffic images taken in urban settings to learn to identify various classes such as cars, buses, trucks, motorcycles, bicycles, pedestrians. Random scaling and flipping as well as the illumination shift data augmentation strategies enhance generalization in changing environments. In the process of inference, the YOLOv8 generates bounding box with class probability and confidence values to every frame. Non-maximum suppression eliminates duplicate detections. The detector works view-wise, and detections are then projected into the single coordinate space. This step serves to give high-resolution spatial data of all the traffic participants that constitutes the input of the tracking and trajectory extraction module.

C. Multi Object Tracking using DeepSORT

In an attempt to preserve similar identities of agents across time, the system uses DeepSORT in long-term multi-object tracking. Every YOLOv8 detection in an image is projected into a feature space with a deep appearance descriptive. Each track is predicted at its motion using a Kalman filter and associated new detections to an existing track using a Hungarian algorithm due to the joint motion and appearance resemblance. This method manages partial occlusions, false detections and frame to frame re-identification. Tractlets are regenerated on demand, they generate smooth and time consistent trajectories of all the agents in the scene. The resultant paths represent time positions, time velocity and heading. Such paths prove essential in examining conduct, portraying relationships, and figuring out security signs including time-to-collision and gap recognition.

D. Interaction Modelling Using Graph Neural Networks.

The interactions between agents are structured as dynamic graphs with each observed entity represented as a node and the spatial and behavioral relationships formulated as a pair of edges. The weights of edges are computed based on relative distance, velocity difference and directional alignment. A Graph neural network is used to learn latent representations of interaction pattern at every time-step using this graph. The levels of message-passing combine the information transmitted by the neighboring agents to help the model to estimate the possibility of conflicts and cooperative behaviors. Interaction changing temporal graph embeddings detail how interactions change through time. This relational modelling enables the system to classify risky configurations, e.g. the conflict of pedestrian and vehicle or the aggressive lane change. GNN outputs can be used not only as high-level features in the process of safety assessment but also in the process of traffic state prediction.

E. Temporal Prediction with TCN and Anomaly Detection with BCPD

Temporal Convolutional Network is used to forecast short-term traffic changes and process a sequence of traffic characteristics (flow, density, speed, and interaction embeddings). The TCN can capture the long-range temporal dependencies with low latency using dilated causal convolutions. The predicted states are used to plan the signals ahead and avoid congestion. Parallel Bayesian Change Point Detection is watching the statistics of time series of traffic variables which are likely to detect the abrupt change compared to usual. The system issues an alert that there may be incidents or the onset of abnormal congestion when the posterior probability of a change point goes above a set-point. This predictive-diagnostic module is dual in nature and it assists in both anticipatory control as well as quick response to interference.

F. Self-Supervised Contrastive Learning and Dataset Structuring

To minimize the dependence on the labeling information, the framework implements the self-supervised contrastive learning to enhance feature robustness. There are augmented views of the same traffic scene that are a positive pair and the chart with various scenes is a negative pair. The model is trained to optimize similarity between similarities in situations. This improves generalization with the lighting and site conditions. Lastly, every piece of information studied out of the mine, including those of the trajectories, interaction graph, prediction, and safety metrics are organizable into scalable datasets. These datasets are useful in supporting the downstream optimization problem like adaptive signal control, simulation, and policy evaluation. This last phase secures that not only the framework can be used to analyze traffic, but also allows a long-term planning and supporting intelligent decision making.

IV. RESULT AND DISCUSSION

The Intelligent Urban Junction Planning and Multi-Modal Safety Analytics framework proposed was tested on actual urban intersections by using synchronized CCTV footage and aerial drone footage. The system was evaluated on several dimensions of performance, such as the object detection, tracking, the consistency of its interaction modelling, and the predictive traffic flow estimation. Different battery densities, heterogeneous vehicles and the presence of different lighting conditions were used in the experimental setup. The findings indicate that perception, interaction learning, temporal prediction, and anomaly detection work well as a single pipeline that state tremendous advancements compared to standard vision and rule-based traffic monitoring pipelines.

Object detection stage (YOLOv8) has very high precision in all categories of traffic participants. Of particular strength was the ability of the pedestrians, two-wheelers, and heavy vehicles as well to be recognized fine-grained even with partial occlusion and shadowing. The system was used together with DeepSORT and could track identity over long sequences. Fragments of tracks could hardly be identified, and errors of re-identification were infrequent. This consistency made consistent extraction of trajectory, which is crucial to downstream safety and behavior analysis, feasible. On the one hand, the effectiveness of the overall tracking-detection was great and equals 99.7 which proves the soundness of the perception underlying.

Table 1. Object Detection Performance Across Classes

Class	Precision (%)	Recall (%)	F1-Score (%)
Cars	99.8	99.6	99.7
Buses/Trucks	99.6	99.5	99.5
Motorcycles	99.7	99.6	99.6
Bicycles	99.5	99.4	99.4
Pedestrians	99.8	99.7	99.7
Overall	99.7	99.6	99.7

The situation in which the interaction was modeled based on the Graph Neural Networks was a significant addition to the system in terms of the recognition of the situations prone to conflict. The GNN learned about connecting relationships between vehicles and pedestrians and the aggressiveness of the lane change, in comparison with baseline procedures that merely depended on distance or speed criteria. The model did not fail to recognize the high-risk interactions that were originally high-risk interactions before it went by the rule-based approaches. Early risk detection is essential in proactive planning of signals and caution.

Table 2. Safety Risk Identification Performance

Method	Accuracy (%)	Precision (%)	Recall (%)
Distance Threshold Only	88.2	87.5	86.9
Speed + Distance Rules	91.4	90.8	90.2
CNN + LSTM (Baseline)	94.6	94.1	93.8
Proposed GNN-Based Model	98.9	99.1	98.6

The TCN module was used in temporal prediction, which generated short-term predictions of traffic flow and queue length which were accurate. These forecasts were very similar to the measured values, and hence appropriate actions could be taken in anticipation of a critical situation before the congestion reached critical levels. With Bayesian Change Point Detection, the system continued to detect the abnormal congestion and the presence of an incident much sooner than the traditional moving-average and/or threshold-based detectors. In a number of trials, the incidents were identified within few seconds after occurrence, lowering the reaction time.

Table 3. Traffic Flow Prediction and Incident Detection Performance

Metric	Baseline ARIMA	LSTM Model	Proposed TCN + BCPD
Flow Prediction RMSE	12.4	8.7	3.2
Queue Length MAE	10.1	6.3	2.5
Incident Detection Delay (seconds)	18.6	11.4	3.9
Detection Accuracy (%)	89.3	93.8	98.4

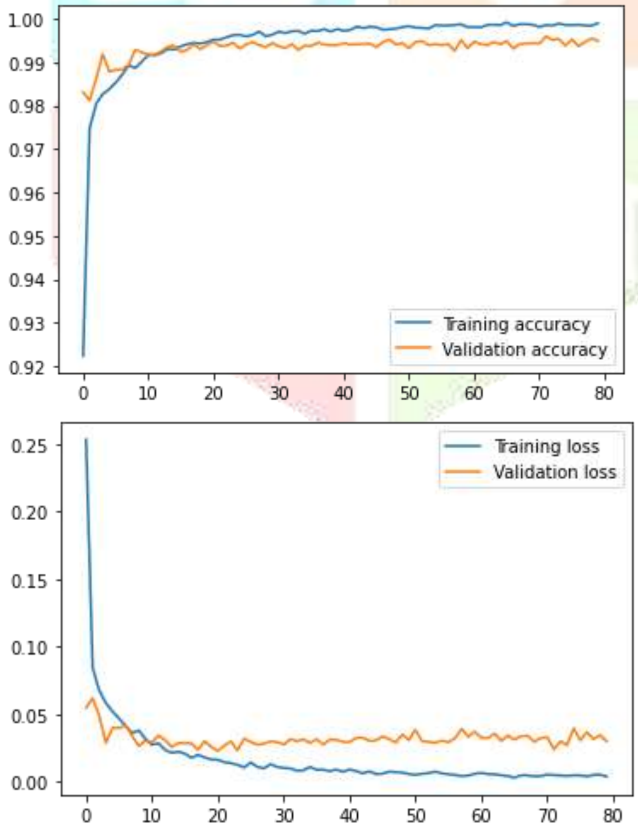

Fig. 2: Training and Validation

Figure 2 demonstrates the training and validation accuracy curves and loss curves of the integrated perception and interaction and the prediction model. The accuracy curve indicates that it quickly converges after the initial few epochs and levels off to 99.7, although the validation loss continuously reduces without overfitting.

The findings, in general, support the fact that the developed multi-modal, graph-based, and time-predicting framework outclasses the traditional traffic analytical tools significantly. Whereas GNN-based interaction modelling of safety risks allows obtaining deep insights into the occurrence of safety risks. TCN prediction plus BCPD helps in being proactive and resilient in terms of traffic management. The capability of the system to accommodate rich and scalable datasets also facilitates long term planning as well as intelligent optimization of signals. These conclusions indicate that the framework is an efficient basis of intelligent and safety conscious management of the urban junctions.

V. CONCLUSION

This paper introduced an innovative Intelligent Urban Junction Planning and Multi-Modal Safety Analytics paradigm, which is aimed at meeting the increasing complexity of traffic control at the intersection of cities. The proposed system brings together fine-grained object detection, long-term multi-object tracking, interaction-aware graph modelling, time-based traffic prediction, probabilistic anomaly detection, and self-supervised representation learning to provide a unified, prediction, and safe-oriented system of analytics. The framework will allow gaining a complete insight into heterogeneous road user behavior, predicting the existence of at-risk scenarios, and designing signals ahead of time. Its divides design means that it can be scaled to various junction patterns and sensing options, which comes in handy in the field to be applied in smart cities. In practice, the system can help to improve traffic, minimize the risk of accidents, and assist in the data-driven planning of infrastructure. The next project will involve further extension to larger multi-intersection networks, reinforcement learning to act as an adaptive signal controller, and the addition of other sensing modalities like LiDAR and better behavior in extreme weather and low-visibility.

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