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Scalable Cloud and AI Integration for Intelligent Transportation Safety Systems

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ABSTRACT: Cyber-Physical Systems (CPSs) integrate connected sensing (e.g., LiDAR, cameras), control, computing, wireless communication, and actuation components with physical objects and processes to achieve interactive and adaptive capacity. CPSs can improve safety for autonomous systems, such as Autonomous Land Vehicles (ALVs) and Uncrewed Aerial Vehicles (UAVs), by identifying and avoiding hazardous events during operation.

However, the recent surge of application scenarios, traffic data requirements, and the number and size of interactive CPS participants have led to significant challenges in improving and ensuring operational safety for these intelligent CPSs. These challenges have prompted scholars and practitioners to integrate cloud infrastructure and Artificial Intelligence (AI) services with CPSs to create new cloud-enabled Cyber-Physical Systems (C-CPSs). These C-CPSs can reduce the validation and training cost of intelligence models and intelligently respond to unsafe events for traffic safety enhancement. In the context of Intelligent Transportation Systems, the combination of C-CPSs, Drones as a Service (DaaS), and ALV safety is addressed.

KEYWORDS: Cyber-Physical Systems (CPS), Cloud-Enabled CPS (C-CPS), Intelligent Transportation Systems, Autonomous Land Vehicles (ALVs), Uncrewed Aerial Vehicles (UAVs), Drones as a Service (DaaS), AI-Integrated Safety Systems, LiDAR and Vision Sensing Fusion, Cloud-Based Model Training, Traffic Safety Enhancement, Edge-to-Cloud CPS Architectures, Hazard Event Detection, Real-Time Autonomous Control, Scalable CPS Infrastructure, AI-Driven Traffic Analytics, Connected Vehicle Ecosystems, Adaptive Safety Mechanisms, Distributed Sensing and Actuation, Operational Risk Mitigation in CPS, Intelligent Mobility Platforms.

I. INTRODUCTION

The emergence of the “anytime, anywhere” paradigm is revolutionising the way services in areas such as computer networks, telecommunications, supply chain management, finance, electric power generation, transportation systems and medicine are developed, constructed, operated and exploited. The application areas for which the services are generated require ubiquitous, low-cost, seamless, pay-per-use access to managed resources, The dramatic growth in the number of users and devices has confirmed the expectation that pervasive demands would be made on systems in all areas of human activity. In order to satisfy this demand, more and more users are turning to distributed “cloud” services. The work presented in this section examines how cloud-based solutions and systems implemented in intelligent distributed systems relying on artificial intelligence techniques.

Intelligent Transportation Systems represent one area of human activity experiencing such rapid growth.The transportation domain plays an important role in the economy as well as security and disaster control. Intelligent Transportation Systems being implemented cover all modes of transport and make extensive use of sensors and wireless communications to collect real-time data and information about road or traffic status, vehicle behaviour, and driver intention for the complete transport activities of all the road users. Such systems enable the detection of unusual traffic situations, allowing abnormal behaviour to be swiftly studied and appropriate measures taken. Data from heterogeneous sources can also be aggregated in near real-time during an emergency to support disaster management operations.

A. Overview and Objectives

This work develops a scalable cloud and AI integration framework to support the design and adoption of Intelligent Transportation Safety Systems (ITSS). To achieve such a framework, the Internet of Things paradigm is employed in connection with Web 2.0 principles to enhance collaboration among roadside infrastructures and users. The result is a fully scalable ITSS ready for deployment in urban environments that also serves as a common foundation for targeted

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ITSS applications. The latter can include dynamic lane management, impaired or distracted driving detection and alerting, speeding detection and enforcement, as well as vehicular collision and near-collision determination.

A real-world case study illustrates how the integration framework enables the development of WebGIS capabilities to further exploit available sensed information. The proposed approach also consolidates the services envisioned by traditional and future ITSS within a single deployment scheme. By facilitating interconnection through service provision and consumption, Intelligent Transportation Systems based on cloud and IoT technologies overcome the limitations of geographic scope, cost and effort of maintenance and implementation associated with traditional systems.

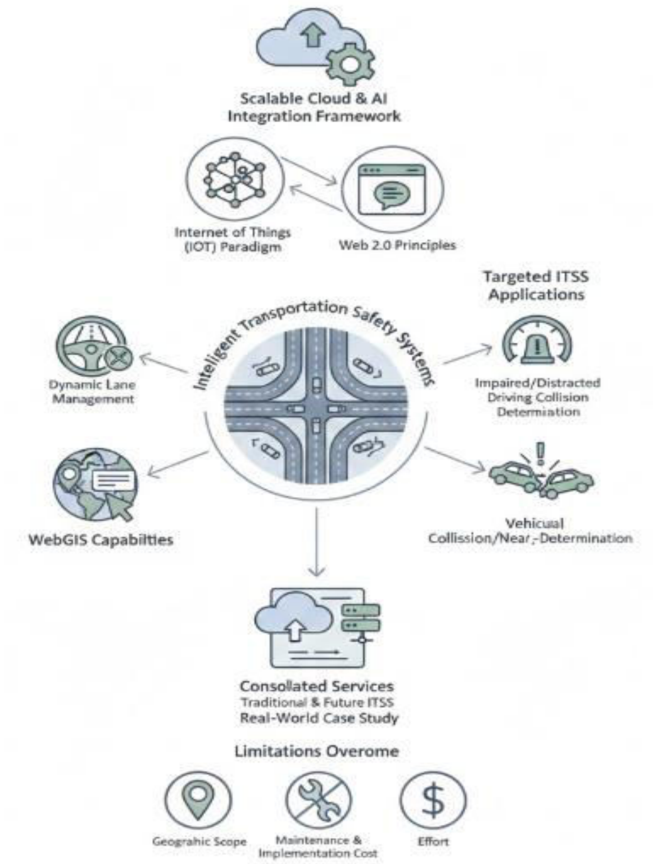

Fig 1: A Unified Cloud-IoT Integration Framework for Scalable Intelligent Transportation Safety Systems: Leveraging Web 2.0 and WebGIS for Urban Deployment

II. BACKGROUND AND MOTIVATION

The teeming growth of urbanization and tourism is mirrored by an exponential increase in vehicular population. Elsewhere, high computational capabilities are rendering real-time processing, analytics and subsequent decision-making on data from heterogeneous devices, both Cloud and Edge based, a compelling prospect. Cloud platforms like XaaS and Edge solutions such as Fog computing are posing hitherto unexplored opportunities for real-time intelligent safety and security services. Possibilities for amalgamating Cloud with Artificial Intelligence (AI) for Intelligent Transportation Systems (ITS) Safety become apparent when two of the major causes of road accidents, unsafe driving, and drunk driving, are analyzed. Though the need for smart safety solutions seems evident, the cost of deploying solutions at higher scales weighs heavily on service providers. A Service Oriented Architecture for Solution as a Service that provides AI models as service and supports a plug-and-play approach for third-party solutions either at Cloud or Edge is proposed.

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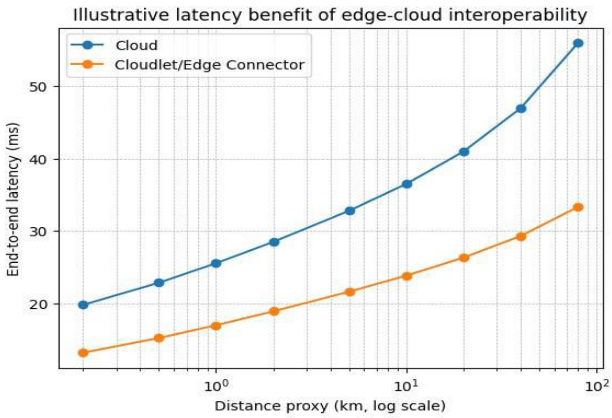
With the increase in the number of vehicles on roads, there is growing interest in using education and awareness as preventive measures. Several automated educational initiatives are based on Intelligent Transportation Systems (ITS) and hence consider the entire driving process. ITS integrates automated, connected, shared, and electrified vehicles infrastructure for improved public safety. ITS-enabling technologies like the Global Navigation Satellite System (GNSS) and Cloud computing give rise to a new generation of educational applications. These road-sign and road-advantage-aware applications notify users of danger zones several kilometers in advance.



Equation 1) Sensor fusion + standardization equations

1.1 Standardization (normalization into a common schema)

Let sensor i output a raw measurement r_i in its native units.

A common approach is to map each raw stream into a normalized feature:

$$x_i = \frac{r_i - \mu_i}{\sigma_i}$$

Step-by-step

1. Collect calibration data for sensor i.
2. Compute mean μ_i and std. deviation σ_i.
3. Convert each incoming raw reading r_i to x_i.
4. Now all x_i live in a comparable numeric scale for fusion.

1.2 Reliability-weighted fusion (scalar case)

If multiple standardized sensors estimate the same quantity (e.g., object distance), let their estimates be $x_1, \dots, x_n$ with uncertainty variances $\sigma_1^2, \dots, \sigma_n^2$.

Set inverse-variance weights:

$$w_i = \frac{1/\sigma_i^2}{\sum_{j=1}^{n} 1/\sigma_j^2}$$

Then the fused estimate is:

$$\hat{x} = \sum_{i=1}^{n} w_i x_i$$

A. Research Context and Significance

The relevance of this investigation within the field of intelligent transportation systems lies in its aim to create a cloud-based artificial intelligence and autonomous robots development framework coupling an edge computing network. These tools are pivotal for the education sector, allowing students to develop a project from scratch to deployment. These systems easily scale with little hardware effort, providing both calculation and communication for systems that require such services. As the project gains momentum, students or teams will cycle through different tasks within the system: preparing the artificial intelligence training, developing and executing the robots, and real environment deployment. The final stage prepares the necessary documentation for the whole project to make it reproducible by future students or different educational institutions.

Although intelligent transportation systems have been applied in real environments in the past, a simple and low-cost cloud and edge computing solution has yet to be implemented. Indeed, many improvements of mobile edge computing

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for vehicular ad-hoc networks have been proposed, but their focus is mainly on enhancing the performance of deployed systems instead of delving into how such vehicular ad-hoc networks get the necessary processing and storage capacity. A set of simple tools provisioning the intelligent transportation system cloud and edge computing structure are also needed. The approach presented here creates such tools with low hardware requirements, distributing the system's communication and processing using educational institutions' cloud computing accounts.

Distance_km	Latency_Cloud_ms	Latency_Cloudlet_ms
0.2	19.78	13.18
0.5	22.83	15.19
1.0	25.53	16.97
2.0	28.48	18.88
5.0	32.77	21.59
10.0	36.47	23.82
20.0	40.95	26.3

III. SYSTEM ARCHITECTURE AND DESIGN PRINCIPLES

The developed architecture is intended as a scalable system capable of supporting thousands of AI-powered camera sensors worldwide, processing petabytes of image data in cloud-based services with robust interaction and subscription schemes. Existing intelligent transportation system (ITS) architectures typically emphasize a general-purpose service model that considers various ITS applications, traffic and information types, and the provisioning of decision support systems. In these models, data from different terrestrial sources and sensors is centralized in a unified service platform. However, large amounts of data and a plethora of service subscriptions make this approach impractical. For instance, data from all pan-tilt-zoom surveillance cameras is centralized regardless of whether it will be used.

Conversely, the approach proposed here is tailored specifically for intelligent transportation safety systems (ITSSS), focusing on enabling the AI-based detection and forecasting of vehicle/pedestrian/bicycle interactions at various road junctions. AI application modules and road junction modules provide AI capabilities and infrastructure support services, respectively, while cloud-based communication and storage components are on top of the traffic data provisioned by the traffic authorities. The proposed architecture harnesses cloud technology for a high-volume pure-online service with dynamic subscription of interaction events by interested service consumers. Intelligent transportation safety services—mainly prediction of vehicle/pedestrian/bicycle interaction, alerting the associated road users—are provisioned. Active interaction prediction between vehicles and pedestrians/bicycles in driving direction can be ad hoc generated by the designated road junction.

A. Cloud-Based Compute and Data Management

The goal of a scalable cloud-based compute and data storage environment is explored. The approach uses serverless technology from cloud service providers (CSPs) to decrease a system architect's burden of designing an efficient cloud infrastructure. CSPs provide potentially infinite compute resources, which allows a focus on application functionality instead of server configuration. Another benefit is that developers can deploy applications written in any computer language for which a CSP provides a serverless function environment. Management of data in a NoSQL (not only SQL) database designed and optimized for cloud infrastructure allows efficient storage, querying, changing, adding, deleting and subsampling of data. Concepts of serverless cloud architecture and NoSQL databases are introduced. Resulting applications give students a visual and interactive experience with using cloud technology.

The serverless model helps outperform traditional server-based technology for some types of applications. Serverless eliminates unnecessary idle time by automatically starting and stopping functions when invoked. Scalability becomes automatic with no need for provisioning servers. The shift in responsibility increases architectural reliability by having a dedicated, full-time engineering team at the CSP. Serverless reduces operational costs because users pay only for resources actually consumed, not just provisioned, as in the traditional model. Programmer efficiency can improve since any language supported by the CSP can be used without porting. Serverless technology attracts attention and is increasingly popular.

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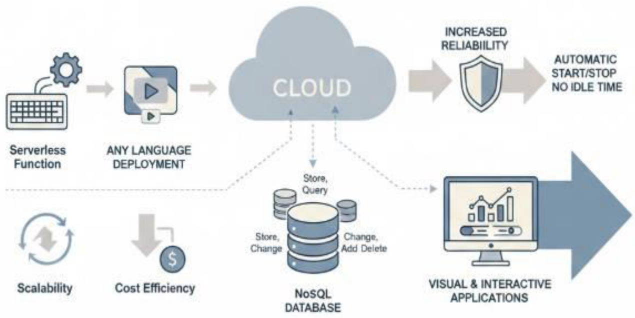

Fig 2: Optimizing Data-Intensive Applications: A Serverless and NoSQL Framework for Scalable, Cost-Efficient, and Interactive Cloud Architectures

B. Edge-Cloud Interoperability

Intelligent Transportation Systems (ITS) derived from car-to-cloud interaction technologies have great potential for full integration with cloud-based AI-systems. While the cloud is powerful, using the cloud to handle the low-latency edge services with high availability for car data delivery can easily lead to high costs or even failures. Therefore, deploying cloud-like connectors is a more cost-efficient and reliable solution. A Cloudlet can deploy cloud-based ITS services with a high availability requirement while sharing the cost with adjacent cloudlets. The data flow cost and latency can be reduced significantly with ITS cloudlets over using the normal cloud. To achieve good performance, a specialized cloud overlay is proposed to support such services dynamically. Cloud-based AI services enable traffic-related deep analiza, such as traffic risk prediction, black-spot detection, etc. Specialized data augmentation for such services is also necessary for generating data with intelligent labels.

ITS for public transportation developed in the Distributed Deep Learning Systems reduce human injuries and promote the use of non-polluting modes and car sharing services. The full integration of powerful Cloud-AI services with on-board services backup improves the usability and reduces car pollution by providing reservation services for empty rides and package delivery services when the car is empty. Providing car-to-carl services between self-driving and remote-driving services improves the traveling experience. Detecting the presence of hazardous traffic conditions or other special conditions and analyzing the reasons for the conditions help supporting both normal and effort-of-the-session services.

IV. DATA ACQUISITION, QUALITY, AND PRIVACY

Cloud-based traffic safety systems rely on real-time and historical data acquisition to accomplish their goals. Data sources include sensors, cameras, and other detection devices installed along the road, as well as data sent by connected vehicles, both relying on short-range wireless communication. Additional safety and traffic flow information is generated using AI-supported smart image analysis, which can filter out clouds, rain, or fog, or track road conditions. Data is collected and aggregated in a cloud server that serves as brain as well as data warehouse for predicting safety risks and providing real-time warnings and suggestions to vehicles. For peripheral vehicle-to-infrastructure (V2I) communication, it is important that data transmission and processing delay be minimized as far as possible.

Data quality is paramount for any data-driven application and safety-related applications in particular. As a cloud-based approach centralizes and aggregates data, the cloud becomes an attractive target for adversaries wanting to corrupt data with low risk of being detected. Possible attacks include introducing spurious or wrong data and preventing genuine data from reaching the cloud. Once introduced, corrupt data can disseminate across AI prediction and alert layers. Both application-level knowledge and user privacy considerations can be employed to minimize those risks. Well-known approaches and alternatives exist for certifying peripheral data but, so far, do not allow for real-time processing.

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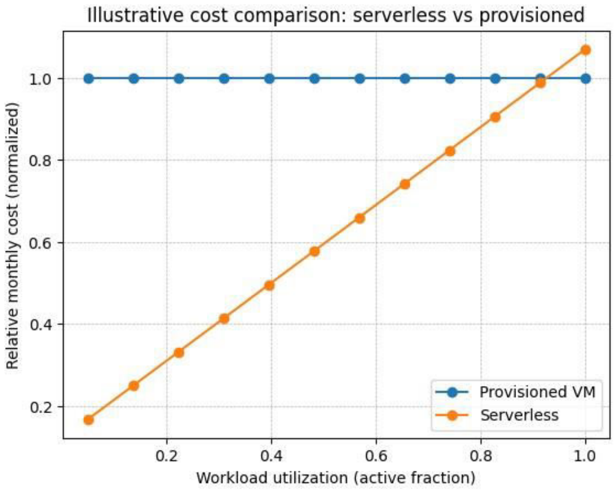

Equation 2) Trust / "cumulative distance" privacy scheme equations

A common formalization:

2.1 Distance-based trust (single interaction)

Let D be a distance/mismatch score between what was expected and what was delivered (could be spatial distance, error, or policy distance).

Define trust score:

$$T(D) = e^{-\alpha D}$$

Step-by-step

5. Choose $\alpha > 0$ (how fast trust decays).
6. If $D = 0$, trust is 1.
7. As D increases, trust exponentially decreases.

2.2 Cumulative distance trust over time

Let interactions $k = 1, \ldots, K$ have distances D_k. Define cumulative distance:

$$D_{\text{cum}} = \sum_{k=1}^{K} \lambda^{K-k} D_k \quad (0 < \lambda \leq 1)$$

Recent events count more if $\lambda < 1$.

Then:

$$T_{\text{cum}} = e^{-\alpha D_{\text{cum}}}$$

Step-by-step

1. Compute weighted history D_{cum}.
2. Convert to a bounded trust score $T_{\text{cum}} \in (0,1]$.

A. Sensor Fusion and Data Standardization

Intelligent transport systems (ITSs) rely on the integration of diverse and heterogeneous sensors placed in vehicles to create an intelligent environment for road users. Sensor measurements may cross-reference and complement one another, and data can be aggregated. Though this is an established concept, it can be structured reliably only when data coming from various sources adhere to a common standard. This step is crucial for ensuring high-scalability and high-intelligence features for intelligent ITS road-safety systems. The native differ- ent data formats coming from the sensor fusion system have to follow the same data model. This is not only necessary to avoid intersensor misleading situations, but also to accomplish a well-formed reduction of the amount of sent data in congested conditions, and further dedicated action-model-log filtering for worst-case situations recognition. It also helps in comparing the different incoming information and hereby in discovering missing information which can be deduced from the other sources. For ensuring temporal-coherency among the different fused-data-categories, dedicated syn- chronization-status parameters are added. The data-model representation is targeted primarily for any single road element or vehicle separately. Nevertheless, with slight modification and few further added supporting parameters, it can be easily extended to support whole fleets or road segments.

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Newly implemented sources and techniques have been added to the high-level dedicated road-safety intelligent system together with their corresponding data-fusion module capable of producing data adhering to a global road-safety standard. These include an a-MoD system embedded in an ITS-sharing service, a system for classifying scooters-speed–velocity configurations in urban-environment conditions, and a recognition and vehicle-speed- estimation module based on the combination of spatial-varying-object-detection-based opticalflow- estimation results. The standard framework naturally handles their heterogeneous data. An example is provided to show how the proposed preparation-step improves the classical multisource-data-fusion process.

Equation 3) Confidence-aware decision support (traffic event prediction)

3.1 Turning a model score into probability (logistic link)

Let model output be a real score s. Map to probability:

$$p = \sigma(s) = \frac{1}{1 + e^{-s}}$$

3.2 Action rule using a confidence threshold

Let p be accident (or hazard) probability and choose threshold τ.

$$\text{Take action} = \begin{cases} 1 & p \geq \tau \\ 0 & p < \tau \end{cases}$$

Step-by-step

1. Compute s from the ML model.
2. Convert $s \rightarrow p$ using sigmoid.
3. Compare to threshold τ.
4. If above threshold, tune traffic lights / alert users; else do nothing (matches the paper) .

3.3 Expected risk (probability × consequence)

Risk is often defined as:

$$R = p \cdot C$$

B. Privacy Preservation and Compliance

Unlike mobile and social networks, proximity-based applications implicitly include the user's location information in every request, which makes privacy concerns even more challenging. Therefore, this project adopts a privacy-preserving location-information-sharing scheme. To enable compliance with regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), personal information privacy should be managed by the user rather than the service provider. In addition, ideas are incorporated from key establishment and monitoring scheme so that data consumers, such as an ad company, can monitor the service trustworthiness directly without jeopardizing the data owner's privacy.

Difficulties may arise when a data consumer encounters a tolerant data supplier, i.e., D_S1 < D_T, but is still not satisfied with the help of the data supplier. To overcome this problem, the trust relationship between the data consumer and data supplier should be exploited, and the expected minimum distance of the data supplier can be relaxed. Data consumers can easily evaluate the data suppliers' services based on historical data. If the historical help site data is publicly available from a third party, the data supplier's tolerance can be further evaluated and the service trustworthiness can be assessed more accurately. The cumulative distance or service trust of the data suppliers is also an important metric for data consumers.

Confidence_threshold	Precision	Recall
0.1	0.35	0.9
0.2	0.42	0.83
0.3	0.49	0.76
0.4	0.56	0.69
0.5	0.62	0.62
0.6	0.69	0.56
0.7	0.76	0.49

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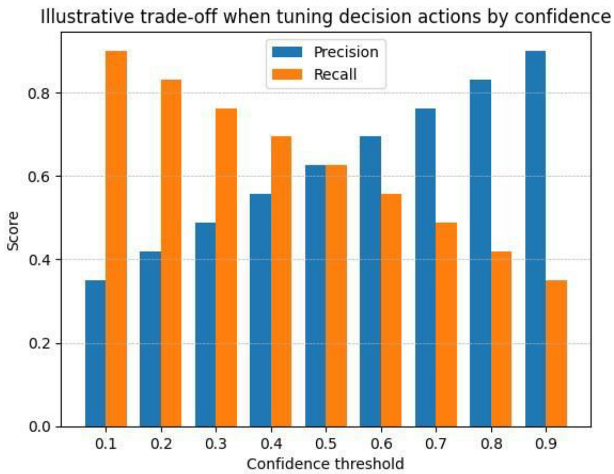
V. REAL-TIME ANALYTICS AND DECISION SUPPORT

Real-Time Analytics and Decision Support incorporates an artificial intelligence cloud integrated with decision support systems to enable road safety. Services for real-time analytics on traffic events—like vehicle congestion and accidents—use real-time traffic data and historical traffic data. After a traffic event occurs, related information is collected and saved, including weather data, the image of a traffic event from a camera, traffic flow—volume, speed, and occupancy—a time stamp and location.

To enable decision support for the control of transportation systems, data fusion algorithms and models are applied to perform prediction and hindcast on the traffic state of a road segment. Such services are addressed as state-aware services, because the predicted state of a road segment can enhance the performance of other analytic services as well as control decision-making processes. Traffic accidents are rare, but once they do happen, they have a significant impact. Therefore, road traffic event prediction—specifically traffic accident prediction—addresses road accidents. Decision-support service considers the predicted result's confidence during decision-making processes. The control of traffic lights can be tuned according to the predicted confidence, even to avoid control actions if confidence is low.



Equation 4) Safety-critical reasoning + satisfiability-style mapping

A standard quantitative mapping:

4.1 Weighted safety criticality score

Let factors f_i be normalized in $[0,1]$ (e.g., speeding, visibility, density) and weights w_i sum to 1.

$$S = \sum_{i=1}^{m} w_i f_i$$

4.2 Satisfaction / threshold check

$$\text{Safe} \Leftrightarrow S \leq \theta$$

or in risk form:

$$\text{Acceptable} \Leftrightarrow R \leq R_{max}$$

Step-by-step

1. Normalize each factor.
2. Multiply each factor by importance weight.
3. Sum to get a single score S.

A. Perception and Recognition in Transportation Environments

The recent rapid advancement in intelligent transportation systems has demonstrated a shift toward smart cities to improve road and transportation safety. Smart city systems generate substantial data and information across multiple domains, including air quality, traffic, incident detection, road condition evaluation, and surveillance. Among these developments, smart transportation systems employ radars, LIDARs, cameras, video trackers, and area monitoring UAVs to ensure operational capability in various environmental conditions. It is difficult to analyze all the sensor data

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in real-time to detect abnormal events by deploying separate systems from different organizations. Recognizing these abnormal events requires the perception, recognition, and identification of intelligent agents in the transportation environment based on the required perception range. The system must recognize cyclists, pedestrians, vehicles, and overhead images or footage of curious events from other intelligent agents. Additionally, autonomous vehicles are being developed for reliable navigation in smart transportation environments by perceiving nearby obstacles and recognizing road signs, markings, and traffic lights during driving.

The advancement of artificial intelligence provides more efficient algorithms, better model training, and recognition performance. However, environmental changes, such as shifts in season or time, still considerably affect recognition performance. Generally, detection systems recognize security or abnormal events by measuring or analyzing a significant amount of data and establishing an abnormal detection model. A data-sampling method and a machine-learning model for incident detection have been proposed. The process minimizes the amount of training data by using a data-sampling technique called "oversampling and undersampling." The system pursues the detection of a significant event caused by the interaction of intelligent agents in the transportation environment and an integrated GIS framework for managing intelligent transportation system big data based on a functional relations model and meaningful relation identification. These technologies can contribute to the advancement of intelligent transportation safety systems together with integrated cloud and AI technology.

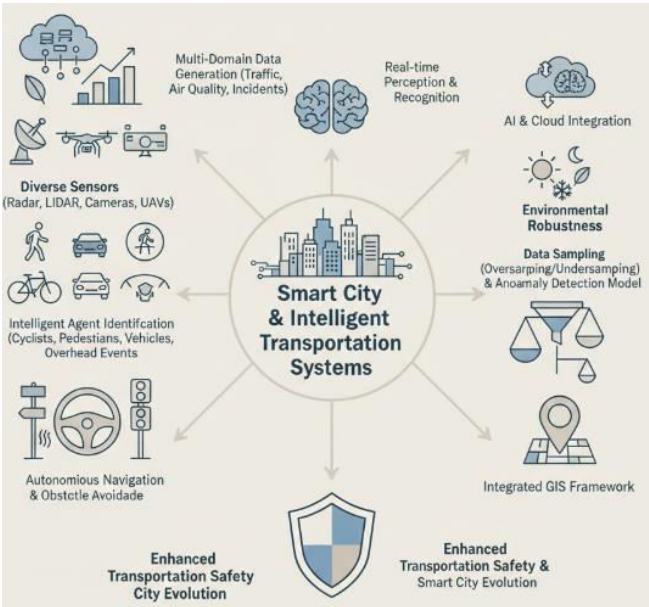

Fig 3: Integrated AI-Cloud Architectures for Smart City Resilience: Enhancing Real-Time Anomaly Detection and Environmental Robustness in Intelligent Transportation Systems

B. Safety-Critical Reasoning and Risk Assessment

The end-to-end safety-critical reasoning and risk assessment process for ITS-CPS combines safety criticality assessment with safety argument construction and evaluation. A safety criticality evaluation process maps a set of critical safety factors into a formal safety-critical model satisfiability problem that evaluates the mapping from a combination of weighted factors and observations via computational modelling and statistical predictions. Law-based systems' safety argument generation uses a set of laws augmented with knowledge inferred from an expert knowledge base and classified events to conclude either automatically constructed or formally validated safety arguments. Safety correctness is a formal proof of safety argument safety property conclusion correctness, achieved by model checking a safety argument presented as a Kripke structure.

Safety-critical reasoning and risk assessment for ITS-CPS combines two processes: a safety criticality evaluation phase that derives a safety-critical model satisfiability evaluation mapping from factors, observations, and a risk assessment phase that estimates risk probability and consequence and checks risk thresholds against system-level safety guarantees. The risk thresholds are satisfied provided a set of given safety factors holds and the event occurrence is prevented.

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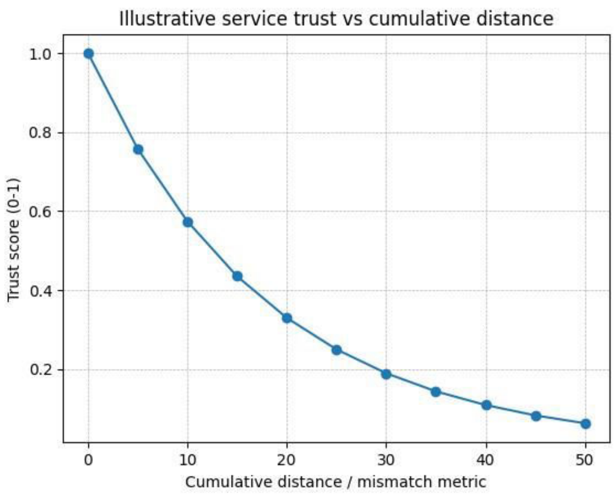
Safety criticality is formally language-independent and can, therefore, be used to guide reasoning in all investigated formal verification languages. Also provided are illustrations of the construction of safety criticality evaluation mappings and their use in law-based systems' safety argument evaluation.

VI. SCALABILITY, RELIABILITY, AND FAULT TOLERANCE

Future cloud computing applications should have the capability of scaling dynamically depending on workload behaviour. Cloud computing employs virtualization techniques to separate resources or services, so that multiple customers can share the same physical resources. VM-on-demand techniques are being developed to provision VM dynamically based on the request of customer. Fault tolerance is defined as the ability of a set of components to continue working properly in the presence of faults. It is important in cloud computing systems because of the distribution of resources, unpredictable failure rates of resources, and the precedence of availability over integrity and secrecy.

Scalability is also an important characteristic of cloud computing systems. A scalability property describes the way in which an application behaves as the resources grow or shrink. The limits on scalability are usually dictated by the core-intensive parts of the application such as popular web-service applications, such as Internet search engine and document processing. They can be scaled out by adding replicas of the core functional components, while the scripting part of the application runs locally.



Equation 5) Reinforcement learning (RL) training objective (as proposed)
5.1 Return (discounted cumulative reward)
Given reward r_t and discount $\gamma \in (0,1)$:

$$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k}$$

5.2 Objective (maximize expected return)
For policy $\pi_\theta(a|s)$:

$$J(\theta) = \mathbb{E}_{\pi_\theta}[G_0]$$

5.3 Policy gradient (one standard derivation)

$$\nabla_\theta J(\theta) = \mathbb{E}_{\pi_\theta}\left[\nabla_\theta \log\pi_\theta(a_t|s_t)\,\widehat{A}_t\right]$$

A. Orchestration, Scheduling, and Resource Allocation
The orchestration, scheduling, and resource allocation system manages physical edge nodes if needed, facilitates deployment using Docker, and instantiates MAAS managing hypervisors hosting VMs. If multiple Cloudlets are located close to each other, a Cloudlet may offload computation/storage resource virtual machine tasks to them. Cloudlets in a proximity cluster do not require a full deployment. Access devices connect with the Cloudlets. A Cloudlet consists of three parts: (1) a Scheduler that schedules applications, (2) an Orchestrator that manages

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orchestration and Scale-Up, and (3) an Edge Resource Allocator that manages the resources. Edge resources can be consumed as Docker containers to run multiple applications/services from different domains and users.

The Scheduling algorithm schedules user applications by responding to the MAAS system. Three types of applications can be scheduled: container applications running on Docker Containers, Resource-Heavy Cloud applications running on Virtual machines, and Short-Task-Based-Native Applications running on the direct MAAS resources. A Docker-image Service of the Cloudlet Pulls user-required Docker-Images from the Docker-Hub, a Docker Private Registry, or the Cloudlet-Hub, and deploys the container using the Docker Swarm manager if a Cloudlet-Cluster is formed (Docker-Swarm supports Scale-Up). The Resource Allocator provisions Physical Machine (PM) resources to Run Resource-Heavy Cloud services and Short-Task-Based-Native Applications.

B. Fault Injection and Resilience Testing

Cloud-based Intelligent Transportation Systems (ITS) rely on large numbers of vehicles and other entities in the road traffic environment to quickly collect and share real-time information. Such ITS host critical services (e.g., traffic control) that use crowdsourced data to guide important actions. To maximize safety, quality and efficiency, it's vital to understand how the system fails when it is stressed, and therefore fault injection and resilience testing are needed. Resilience testing usually requires extensive modifications or even custom tooling, and also takes considerable time and expertise. By utilizing established fault tolerance capabilities, resilience testing can be performed much more efficiently by deploying the system on a self-healing cloud-based infrastructure and injecting faults into it to test resilience. A system capable of injecting faults into a cloud-based system capable of healing itself is described, tested, and illustrated in action using multiple fault scenarios including complete VM, network, and datacenter failures. The results indicate that resilience testing need not be time-consuming.

Automated Fault-Injection Testing is Contactless and Scalable: Many services inside a cloud-based Intelligent Transportation System rely on machine learning algorithms that are trained using previous traffic data to support human decision-making. By putting a cloud-based deployment of the system at risk, the data can be corrupted, causing a user to take an unsafe or erroneous action. The ability to automatically and plausibly inject faults into trains of data without manual intervention and at scale is therefore needed. A new system that enables contactless fault-injection testing over multiple services and scaling silently in the background is described. The new test system is demonstrated by finding 136 new vulnerabilities in several machine-learning-based services of a cloud large-scale traffic-monitoring system deployed in an active environment. The results demonstrate that effective, efficient, contactless, and scalable automated fault-injection testing is achievable without resource and performance overhead.

VII. CONCLUSION

Challenges and driving approaches to Intelligent Transportation Systems (ITS) safety management are addressed. The focus is on the scalable integration of cloud and artificial intelligence infrastructures and the Open Source Version of Intelligent Transportation Safety System designed to improve social security using public transport data and protect intelligent City Assets located on/near road. Two major challenges to ITS safety management are the fast increase of attacks and the dependence of excessive AI learning by cloud companies, which are controlled by little stakeholders. First, the fast increase of attacks on cities puts a huge burden on public security. On the one hand, the public safety system cannot catch up with the increasing number of emergency empty police cars; on the other hand, because the source of these safety risks is not solved, more and more resources need to be invested. This causes a huge blank area for citizens. It is difficult for the police to protect the service assets of cities, such as subway, highway, and so on. Second, cities heavily use the service from companies' AI products, even the models such as automatic driving, but these are monopolized by only a few American companies. People in developing countries use the products that foreign companies learned the knowledge from their easily labeled cities.

A new method is needed to solve these two problems. First, the amount of data and computing resources is not a problem in AI learning. So it is possible and practical to use the accumulated computing resources of all public transport companies to learn the traffic models for better service for citizens. A reinforcement learning training process is proposed. Not only do the Cloud & AI Integration Heavy Users Careless Spend Money But Also GUI Players Who Have Complicated Visual GUI Models; are these models basic in other aspects? these three aspects are responsible for the understanding of the intelligent public transport model. These models are not deep models. Second, the public sector cannot create a blank computing resources zone on the cloud that companies do not dare to supply. This paper aims to design a type of intelligent public transport system (IPTS) for the training and detection of public safety accidents In addition, a type of cloud zone is built especially for algorithm minor cities, i.e., supporting cloud resources are provided to those places to promote the input service of appropriate supporting models to train these minor cities. A minor cloud for minor cities is provided for the public sector. Special funds are set for public safety & emergency accident detection, and these funds attract the mainly big cloud companies to provide the appropriate models that can automatically switch the services of their massive cloud application systems and provide appropriate services and safety monitoring assistants to the experiment zones.

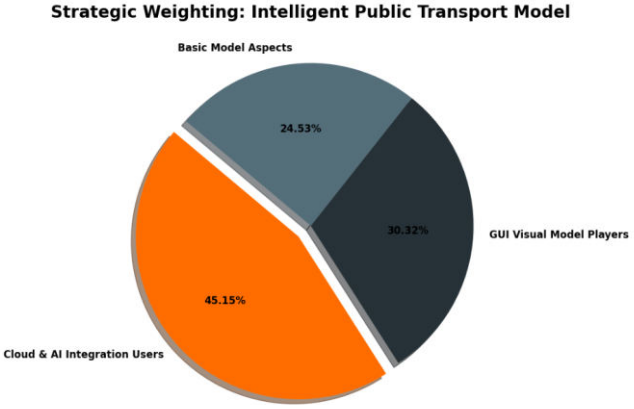

Fig 4: Strategic Weighting: Intelligent Public Transport Model

A. Future Directions and Implications

Both research focus areas can benefit from cloud technologies. The newly developed cloud-enabled Intelligent Transportation Safety System (ITSs) will be hosted on the Cloud, providing services requested by the on-board cloud and the ITS. The cloud will also carry out data fusion in the Event Detection Platform (EDP) and extract high-level features required by the AI-based applications hosted on the Edge-Cloud AI platform.

The onboard system makes use of an intelligent cloud-software application that performs advanced vehicle-cloud interaction, managing both connectivity and quality of the sensed data based on context and available resources. A Quality-Cloud (Q-C) architecture is proposed on the onboard vehicle level as an interaction layer between the vehicle and the sensors. Unlike traditional cloud-assisted systems that optimize different Quality-of-Experience (QoE) and Quality-of-Service (QoS) parameters in a segregated manner, the biomechanical characteristics of the human being are considered to optimize a subjacent Quality-of-Sensing (QoS) level. A dynamic-model-based deep sparse autoencoder neural network is employed to correlate the perceptible environment sensed by the human to the sensed environment provided by the quality-cloud, so that the perceived environment can be more effectively shared by the vehicle.

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