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Predictive Traffic Accident Warning System for Smart Cities: Enhancing Urban Safety with Data-Driven Insights

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Abstract

This paper introduces a predictive traffic accident warning system tailored for smart city applications, aiming to improve urban safety through advanced data analysis and contextual reporting. The proposed system employs computationally efficient algorithms to predict the severity of traffic accidents with high accuracy while maintaining robust data privacy standards. By integrating real-time traffic data with external knowledge sources, it generates detailed, actionable reports and timely warnings, enabling proactive decision-making. The system's design emphasizes effective task orchestration for seamless integration with existing urban infrastructure and optimized resource management. Evaluation results demonstrate the system's high accuracy, scalability, and practical viability in smart city environments. Future research will focus on enhancing model efficiency, leveraging transfer learning for cross-domain adaptability, and deploying real-world implementations to vali- date the system's performance.

I. INTRODUCTION

By 2050, over two-thirds of the global population is projected to live in urban areas [1]. Urbanization, driven by population growth and migration towards cities, presents both opportunities and challenges such as overpopulation and traffic congestion [2]. Developing smart cities is a strategic approach to mitigate these challenges. A ”smart city” integrates information and communication technology to enhance urban living [3]. This concept emphasizes the interconnection of com- munity, people, and technology, aiming to prioritize human needs [4]. Urban mobility and transportation are significant challenges, with traffic congestion and accidents being major concerns. Annually, traffic accidents result in 1.35 million deaths globally, underscoring the critical need for effective accident prevention measures [5]. In large-scale Internet of Things (IoT) ecosystems, efficient data processing is crucial. Centralized cloud servers face latency and security challenges for many application domains, making real-time processing difficult [6]. Edge computing aims to address these limitations by bringing computational resources closer to data sources, enabling timely processing and reducing latency [7, 8]. When edge computing is integrated with AI, known as EdgeAI, real-time urban decision-making could be facilitated [9, 10]. For example, models trained to predict road weather [11, 12] or traffic congestion can operate on edge devices located closer to the sites, providing immediate insights to traffic management systems. Nonetheless, due to the resource constraints of edge devices, certain computationally intensive tasks might still be offloaded to the cloud or other powerful nodes within the city network. That approach requires loosely-coupled architectures and distributed algorithms [13, 14]. A lot of research proposes AI support for smart transportation systems from various perspectives. For example, Bortnikov et al. [15] detect accidents by training a 3D Convolutional Network on the data generated by a video game, Uma and Eswar’s [16] develop yawning detection of the drivers, Liu et al [17] concentrate on traffic flow prediction. However, the majority of related work focuses on a single type of AI module specifically developed for the task at hand, neglecting the capabilities of integrating their approach with other kinds of AI modules to create a more comprehensive support system. Additionally, response time is often overlooked in the assessment of related work, with a primary focus on accuracy. To our knowledge, no existing work incorporates multiple types of AI modules, raising questions about the integration and applicability of these separate modules into a cohesive framework. To address these gaps, we present our integrated system, containing two AI modules: first, Federated Learning (FL) [18] model to predict traffic accident occurrences and estimate severity and second, Generative Artificial intelligence (GenAI) to generate reports and warnings. Moreover, we utilized k0s, a lightweight Kubernetes distribution, for efficient task orchestration [19]. The task orchestration capabilities of k0s are crucial for seam- Lesly integrating the FL models and Retrieval-Augmented Generation (RAG) processes across multiple edge nodes. This enables automated deployment, scaling, and management of tasks, ensuring high availability, fault tolerance, and robust performance monitoring for our accident prevention warning system. The contributions of this work can be summarized as follows:

1) We integrate two different kinds of AI modules into a coherent distributed system supporting accident prevention. We comprehensively evaluate this system and analyze the related challenges and opportunities.

2) We orchestrate tasks and monitor our system, examining its feasibility for real-world smart city environments.

The remainder of this article is organized as follows. sec related work discusses related work, while sec:design de- scribes the system design, and sec:implementation details the implementation. sec:eval then provides a detailed system evaluation and metrics, sec:discuss future discusses our findings, implications, and future research directions, and sec:conclusion concludes the work.

II Related Work

A. *Intelligent Transportation System in Smart City*

Intelligent Transportation Systems (ITS) are essential for the advancement of smart cities, with many recent studies dedicated to improving urban traffic management and safety. Here, we discuss several key works that have made significant contributions to this field. As an example, Hasan et al. [20] used the Google Distance Matrix and Directions APIs to provide advanced traffic jam alerts. Their Internet of Vehicles (IoV) module detects accidents and, with the assistance of the National Data Warehouse and a GPS module, notifies the nearest clinic. They developed an Android application for routing suggestions and employed an Arduino with a Sonar sensor, temperature sensor, gyroscope, piezo sensor, and GSM module as the core processing unit. Working on one of the most trendy applications, Bortnikov et al. [15] developed a 3D Convolutional Neural Network (CNN) to recognize accidents automatically. They trained the CNN using a custom video game to create accident scenes with various weather and lighting conditions, adding noise to diversify the data. The model was then tested on real traffic videos from YouTube. The novelty of this research lies in the use of video games to generate datasets, which are challenging to replicate in real-life scenarios. Yu et al. [21], with the same aim, proposed a Deep Spatio-Temporal Graph Convolutional Network for traffic accident prediction for Beijing traffic data, which was collected hourly over three months and includes accident records (time and location), vehicle speeds, meteorological conditions and points of interest. Recent research has considered informing other vehicles after detecting traffic accidents using IoT, IoV, and related technologies. Zhou et al. [22] proposed an accident detection algorithm based on spatiotemporal feature encoding with a multilayer neural network. This method first detects border frames as potential accident frames, then encodes the spatial relationships of detected objects to confirm an accident. The process involves using Histogram of Oriented Gradients and ordinal features initially, followed by CNN feature encoding and object relationship detection with a multilayer neural network. A trained Support Vector Machine then confirms the presence of an accident. Another approach involves efforts to reduce accidents before they occur is the work of Uma and Eswari [16], which developed a prototype using a Raspberry Pi and Pi Camera, along with sensors to monitor driver's eye movements, detect yawning, and identify toxic gases and alcohol consumption. This system, employing the Haar Cascade algorithm for face detection and calculation of Eye Aspect Ratio and Mouth Aspect Ratio, estimates risk through these feature analysis. Besides, to identify accident hot spots, Le et al. [23] used Road Traffic Accident data over three years in Hanoi, Vietnam, to develop a GIS- based statistical analysis technique. This method assesses the influence of accident severity on temporal spatial patterns, identifying accident hotspots in relation to specific times of day and seasons. Beyond the mention in [24] of the potential service supports of cloud to autonomous vehicles applications, edge computing is playing a pivotal role in reshaping traffic management in smart cities. Within this domain, Mohamed's [25] and Zhou's research groups [26] demonstrated substantial improvements in traffic management and reduced congestion durations through an edge-based model for real-time traffic data analysis. Besides, to achieve low latency and high pre- diction accuracy on vehicle identification at the edge, Wan et.al [27] have eliminated redundant frames from collected videos and presented an approach for real-time video processing. In a similar manner, Ke et al. [28] developed a multithread system for real-time detection of near-crash events in traffic, using video analytics on dashcams. Leveraging edge power, their system efficiently performs object detection and tracking directly from the video feeds on board. This approach involves removing irrelevant video to conserve bandwidth and storage while collecting diverse and valuable data for traffic safety such as road user type, vehicle trajectory, vehicle speed, brake switch, and throttle. The approach from Ke et al. demonstrates considerable promise for widespread application due to its low cost, real-time processing, high accuracy, and broad compatibility with various vehicles and camera types. Additionally, a recent work by Nguyen et al. [29] utilized Blockchain technology alongside edge computing to develop a reliable and transparent situational awareness system for autonomous vehicles. Their system broadcasts notifications and alternative route suggestions from the nearest edge station when congestion or accidents are detected by other vehicles, using various sensing data sources, including dashcam images and environmental factors like weather, temperature, and humidity. The use of Blockchain in their study ensures the data validity and integrity, as well as facilitates collaboration among different service providers. However, despite the recognized vision and applications, Zhou et al. [30] emphasized that employing edge computing in ITS always comes with inherent challenges related to sensor failure, and privacy protection concerns, which must be addressed for effective implementation.

B. *FL in ITS*

Building on the challenges identified by Zhou et al. [30] particularly concerning privacy protection, FL recently has been used more in smart cities. Amongst many applied domains within urban environments, the extension of FL applications in traffic systems is mostly leveraged for traffic monitoring and accident predictions. FedGRU - FL-based Gated Recurrent Unit (GRU) neural network [17] is one of the pioneering works for traffic flow prediction (TFP) with federated deep learning that comparably performs to other advanced competing methods without compromising the privacy and security of data. Additionally, as proved by experiments, the joint announcement protocol proposed in this paper helps in reducing communication overhead by 64.10% compared with centralized models, implicating the scalability of FedGRU for bigger networks. With the same motivation to address the privacy exposure risk of centralized machine learning, Qi et al. [31] presented a fully decentralized FL network, utilizing a Blockchain-based FL architecture as opposed to the conventional vanilla framework. The authors employed the local differential privacy technique to protect vehicle location and utilized GRU to achieve accurate TFP. Performance and security comparisons were also made among different machine learning models and with/without the use of blockchain. Qi et al. also conducted comparative analyses in terms of both performance and security, examining various machine learning models and contrasting scenarios with and without blockchain implementation. Concerning the monitoring of traffic congestion, typical systems begin by detecting vehicles and subsequently estimating traffic flow density. In their research, Xu et al. [32] employed remote sensing images for this purpose, while Chougule et al. [33] continuously used the estimated traffic density from intersection-captured images to dynamically adjust the duration of green light and schedule the timing of signals across all lanes. As one of the highlights in the narrow field of applying FL on ITS: risk detection, Yuan et al. [34] introduced FedRD, a framework combining edge-cloud computing, FL, and differential privacy techniques for intelligent road damage detection and warning. The framework not only improves detection performance and coverage area but also addresses privacy concerns through Individualized Differential Privacy with pixelization technique. Comprehensive evaluations demonstrate FedRD’s capability to deliver high detection accuracy and wider coverage while preserving user privacy, even in scenarios where edge devices have limited data. This groundbreaking effectiveness sets a new benchmark in the field.

C. *GenAI in ITS*

Recently, GenAI has garnered significant attention in several applications, including ITS, due to its advantages and flexibility. By analyzing data from various sources, such as roadside sensors, vehicles, and traffic signals, GenAI enhances urban operations by detecting patterns, identifying trends, and providing accurate predictions and advice. With the leverage of natural language processing, GenAI can present these predictions in human-understandable language, making these technologies more accessible and practical for smart services [35]. See prior works [36, 37] for examples of how GenAI integrated into many services within cities. As another example in ITS, Impedovo et al. [38] propose a deep generative model to predict weekday vehicular traffic flow to prevent accidents in the most critical areas and improve continuity by reducing traffic. More notably, RAG, first introduced by Lewis et al. in 2020 [39]l, stood out as a part of this GenAI world, representing a distinct approach to generating text, informed reasoning, and supporting decision-making. Its application in ITS is not popular, however, there are some notable works. For instance, Dai et al. [40] integrated RAG into autonomous driving systems to enhance decision- making processes. According to the authors, the use of RAG in their work addresses the problem of impractical generated content from the mainstream foundation models nowadays, such as GPT4 or LLaMa. It helps these models enhance the reliability of their outputs during the generation phase by dynamically retrieving accurate contextual information from outer databases (e.g. updated traffic rules, driving experiences, or human preference). Similarly, Ding et al. [41] utilized RAG for more controlled generation of traffic scenarios. Specifically, RealGen [41] synthesizes new scenarios by combining behaviors from multiple retrieved examples in a gradient free manner, using templates or tagged scenarios. This in-context learning framework provides versatile generative capabilities, including scenario editing, behavior composition, and the creation of critical scenarios, thus enhancing the adaptability and precision of synthetic data generation for various applications. Most recently, in his Master’s thesis, Mohanan [42] evaluated eight embedding RAG models for a chatbot tailored to Indian Motor Vehicle Law. As can be seen, prior research typically focuses on a single module, such as risk estimation or warning generation, limiting possible support for ITS. This raises an open question: ”Is it possible to integrate all diverse components into a cohesive and comprehensive ITS framework?” This is where our work positions.

II. System Design

This article presents a system for predicting and preventing traffic accidents. It is capable of predicting the possible accidents based on the traffic conditions and other available data, and provides detailed textual comments to the user explaining the grounds leading to such estimation. Figure 1 illustrates the overall system flow, highlighting the interplay between the key components: Federated Learning (FL) and Retrieval-Augmented Generation (RAG). This integrated system combines the strengths of RAG and FL to ensure high- quality outputs while maintaining data privacy and relevance. FL enhances the accident severity prediction model while maintaining data privacy. The RAG system uses integration between the warning generation model and the knowledge retrieval model to enhance the generation process with relevant external data, improving context and accuracy. Our training approach starts from data preprocessing. The preprocessed dataset is then used to train the FL model for traffic accident risk estimation. The predictions, along with the sensors’ real-time data, are utilized as input for the RAG model. The RAG model integrates advanced retrieval mechanisms with state- of-the-art language generation capabilities to produce detailed warnings and reports for traffic accidents. To efficiently man- age and deploy these components, we use a task orchestration tool. This tool ensures seamless integration and coordination among the various models, automates deployment, and scales the system as needed. Additionally, it facilitates robust performance monitoring, ensuring high availability and fault tolerance across the system.

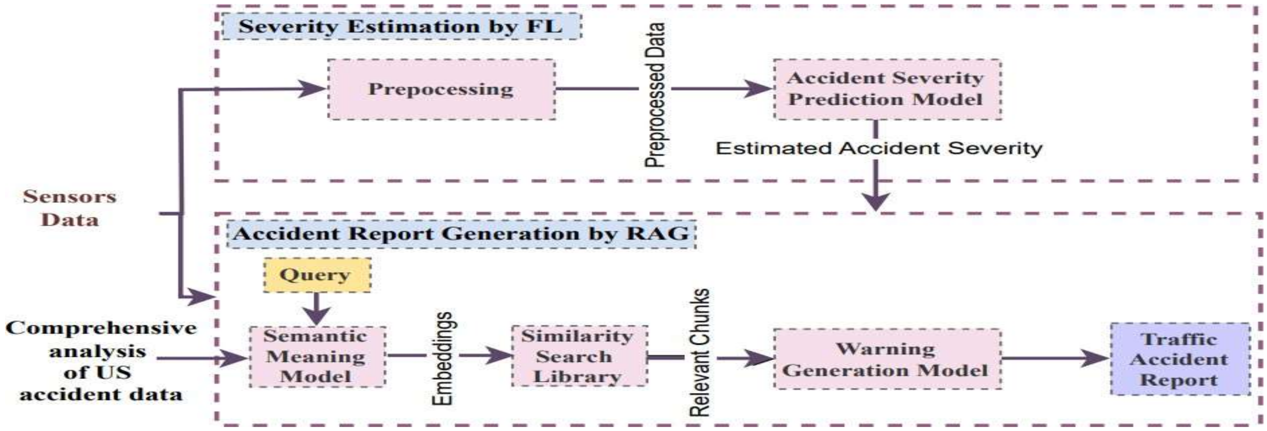

Severity Estimation by FL
Prepocessing
Preprocessed Data
Accident Severity Prediction Model
Estimated Accident Severity
Sensors Data
Accident Report Generation by RAG
Query
Comprehensive analysis of US accident data
Semantic Meaning Model
Embeddings
Similarity Search Library
Relevant Chunks
Warning Generation Model
Traffic Accident Report

Fig. 1. System workflow. This figure illustrates the key components of the core system, Federated Learning (FL) and Retrieval-Augmented Generation (RAG). Using preprocessed weather and road traffic sensors, FL predicts accident severity. Within the RAG framework, the Semantic Meaning Model creates embeddings for documents and queries. The Similarity Search Library selects the most relevant document chunks based on similarity. Finally, the Warning Generation Model generates a traffic accident report that incorporates data analysis and future recommendations.

A. Dataset

This study uses US Accidents (2016-2023) dataset 1 [43] from Kaggle, distributed under CC BY-NC-SA 4.0 license. This dataset comprises a vast collection of over 7.7 million (7,728,394) traffic accident records, covering 49 states of the USA from February 2016 to March 2023. The accident data were collected using multiple APIs that provide streaming traffic incident data captured by various entities, including the US and state departments of transportation, law enforcement agencies, traffic cameras, and traffic sensors within the road networks. The data includes detailed information on accident severity, location, time, and weather conditions. This dataset was utilized to train the FL models for traffic accident prediction.

B. *Federated Learning*

Our application relies on FL model for accident risk estimation. FL was selected based on two primary considerations: data privacy and collaborative enhancement.

1) Privacy: Addressing privacy concerns, vehicles in a real scenario do not transmit raw data, which could potentially reveal sensitive information. Instead, only model parameters will be sent, ensuring that individual data remains secure and private. This cannot be done with traditional centralized learning when all data need to be sent to a central server for training.
2) Collaboration: When a vehicle updates and shares its model parameters, it contributes to the overall learning process. This collective effort leads to an improvement in the overall model's performance, as it can learn from a wide range of diverse and localized inputs. The shared knowledge enables more accurate and robust risk estimation.

The training data features provide a detailed view of accident records, including the specifics of the accidents, the geographic locations, the prevailing weather conditions at the time of the accidents, and various environmental and contextual factors that may be relevant to analyzing the accidents. In a real scenario, the vehicle's onboard computing system uses these inputs to continuously update its local model, learning from real data. Once the training is done, the model parameters will be sent to the nearby edge server. The server, after receiving a sufficient amount of models will start doing the aggregation to get the global model, which is then sent back to the participating vehicles. When this whole process is complete, we finish one communication round and continue to the next round.

C. *Retrieval-Augmented Generation*

RAG combines an information retrieval component with a text generator model to provide situational information and guidance [44]. In the ITS context, RAG can integrate various external data sources to analyze and report traffic accidents, identifying risk factors and details [45]. This makes the system more dynamic and adaptable to new information. In our system, see Figure 1, RAG provides textual accident warnings to the end user, along with explanations of how the estimates were derived. Knowledge retrieval model It is designed to find the most relevant information from an external knowledge base in response to the query. This enhances FL model output and sensor data with relevant information. We use SentenceTransformers2 as a retrieval model based on similarity search. Warning generation model: It is designed to generate new content using language models. It uses the retrieved information by the retrieval model and FL-output details to generate a response. For our system, we use gpt- 3.5-turbo-06133 to create contextually relevant warnings and detailed reports. The accident report includes the severity of the accident, the location and traffic control procedures, and guidance and actions.

C Task Orchestration and Monitoring

Effective resource management and device health monitoring are essential for enhancing the responsiveness of smart city services. This requires comprehensive system monitoring that spans from edge devices to the cloud. The deployment of applications on edge devices necessitates advanced task orchestration platforms, which must be carefully selected based on specific requirements. Given that edge devices typically have limited resources, the chosen tool must operate smoothly under such constraints. For the proposed system, k0s4 has been selected. We selected k0s because of its minimal resource consumption on edge devices and its straightforward and rapid implementation process, supported by comprehensive docu- mentation and active developer forums. It typically operates with as little as 1 CPU and 512 MB of RAM on each controller node and 1 GB of RAM on each worker node, which aligns well with the capabilities of edge devices. However, the minimum requirements increase when the number of worker nodes is increased. Additionally, numerous monitoring options compatible with k0s are available. k0s is packaged as a single, self-extracting binary which embeds Kubernetes binaries. It has many benefits, such as it has no OS level dependencies and everything can be, and is, statically compiled.

III. System Implementation

A. Risk Estimation with FL

1) Preprocessing: **Preprocessing Phase:** The preprocessing phase for our system includes a series of essential data preparation steps to ensure the quality of the dataset for further analysis.

1) **Data Cleaning:** Duplicated and missing values were removed.
2) **Feature Engineering:** To enhance the informativeness of the dataset, a new feature called *Comfort_Index* is created as defined in Equation (1).

Comfort_Index = (Temperature − 32) *xHumidity/100 (1)*

3) **Data Resampling:** To address the imbalance issue, both random oversampling and under sampling were applied to ensure equal label distribution.
4) **Data Transformation:** Transformation was conducted based on feature type:
   - **Categorical Data:** One-hot encoding was applied to categorical columns, excluding *Street*, *State*, and the target label *Severity*.
   - **Boolean Data:** Columns with two distinct values were binarized, converting them to 0 and 1.
   - **Numeric Data:** Numeric columns were left un- changed, preserving their original values.
5) **Standardization:** The dataset was standardized using *Standard Scaler* to ensure consistent feature scales and values within a specific range.

FL Training and Prediction: To simulate a real-world scenario using our chosen dataset, we distributed the data across several nodes and established certain assumptions. This section will elaborate on those details. Distribution: The data is divided into five equal parts, corresponding to five nodes in the system. We also make sure the number of samples of each label is distributed equally among clients. Model Training: Each client trains its local model, consisting of three fully connected layers. Training specifications include the use of the cross-entropy loss function, Adam optimizer with a learning rate of 1e-3, and a batch size of 32. After ten training epochs, the locally trained models are aggregated by the server into a global model, and the global parameters are saved at each checkpoint, here at each communication round, before being sent back to the participants for training in the next round. The FL training process concludes after ten communication rounds. At this stage, various model architectures, encompassing differing layer counts and hyperparameters, were evaluated over 50 communication rounds to observe the trend and convergence in via its performance. The selected model outperformed alternatives; models with reduced layers demonstrated inferior outcomes (3- 4%), while configurations with additional layers, despite a 3% accuracy improvement, incurred prolonged training duration and converged to local, rather than global, optima. See Table 1 for details.

TABLE I COMPARISON OF RISK ESTIMATION MODELS: ACCURACY AND TRAINING TIME

Model	Simple	Chosen	Complex
Accuracy (%)	67.09	71.15	74.42
Training Time (hours)	3.461	4.042	5.603
MAE (%)	32.91	28.85	25.58

B. *Warning Generation with RAG*

Using the RAG model, we retrieve text passages using an input sequence. During the generation of the target sequence, we include these passages as additional context. Our model leverages two components, which are implemented in LangChain5. A retriever that retrieves relevant text snippets in response to a user's query or prompt based on knowledge source which is uploaded using built-in document loader from LangChain. In our system, we rely on the US traffic accident database as an external knowledge source, containing a comprehensive analysis of US traffic accident data [46]. This report provides insight into preventive measures and policy recommendations for decreasing traffic accidents in the US based on detailed analyses by state, time, and contributing factors such as weather. The retrieval process begins with loading documents using a tool in LangChain. This process is enhanced by a splitter tool, also integrated into LangChain, designed to segment extensive texts into smaller chunks based on a specified chunk size by examining characters recursively which is crucial for the efficient handling of large textual data. For the creation of text embeddings, we employ Hug- ging Face Embeddings, a specialized embedding model from the Hugging Face library6 within LangChain. This model transforms the segmented text chunks into numerical vectors, facilitating their computational handling To store these embed- ding vectors in a vector store, we utilize the FAISS library7 , a robust vector database. It enables effective similarity search by identifying text chunk vectors most similar to the question vector. This process is vital to determine which portions of the knowledge source are most pertinent to the input query. This is for later retrieval at query time based on the k argument which finds the top k most relevant text chunk vectors for each query. Table 2 summarizes the RAG parameters used. The generator creates a more detailed, factual, and relevant response based on the original input and retrieved documents. The original input represents the severity of an accident, derived from the FL output and complemented by sensor real- time data. For the generation of coherent and contextually relevant text, the original input and the retrieved documents are fed into gpt-3.5- turbo-0613, a sophisticated pre-trained language model. Based on the content of these documents, the model generates coherent and contextually relevant text grounded in real-world information. Figure 2 illustrates an example of a traffic accident report generated by RAG.

TABLE II SUMMARY OF RAG PARAMETERS USED

Parameter	Value
Text Splitter Type	RecursiveCharacterTextSplitter
Chat Model	ChatOpenAI
ChatOpenAI Model Name	gpt-3.5-turbo-0613
Vector Store	FAISS
Embeddings Type	HuggingFaceEmbeddings
Embeddings Model Name	sentence-transformers/all-mpnet-base-v2
Search Type	Similarity
Chunk Size	2000

C. *Task Orchestration and Monitoring*

As discussed in Sub-section 3.4 we opted for k0S, which is ideal for our needs and simple in implementation. We used Lens IDE8 which is a Kubernetes IDE to manage the cluster and monitoring of the whole system. It allows for comprehensive oversight of nodes, pods, and resource monitoring. Monitoring involves tracking the usage of CPU, memory, storage, and network bandwidth, and monitoring device safety and functionality to detect any potential problem. We containerized our application using Docker9 and deployed our application using Lens IDE and k0s task orchestration tool. We used Cluster metrics in the Lens IDE to monitor the resources efficiently

IV. System Evaluation

To assess the system's performance, several key metrics were employed. We want to ensure that all the components work perfectly both independently and in the integrated system. First, we monitored the accuracy of the FL model for risk estimation, assessing its ability to predict traffic accident severity. This evaluation utilized the dataset for training the model. Additionally, the quality and relevance of warnings and reports generated by the RAG model were assessed. The system's prompt responsiveness was also tested, particularly how quickly it can generate alerts and warnings based on incoming data. Furthermore, the resource management aspect was evaluated to ensure that the system's resource usage is optimized and well-maintained. The developed system was deployed and tested on a real cluster of three nodes with k0s equipped with the monitoring application.

TABLE III Traffic Accident Data on US Highway 22, NJ

Parameter	Value
Street	US Highway 22
State	NJ
Start Latitude	40.65562
Start Longitude	-74.40149
Crossing	False
Give Way	False
Junction	False
No Exit	False
Railway	False
Roundabout	False
Station	True
Stop	False
Traffic Calming	False
Traffic Signal	False
Distance (mi)	0.167
Temperature (°F)	56.09
Wind Chill (°F)	72.98
Humidity (%)	42.97
Pressure (in)	29.59
Visibility (mi)	9.99
Wind Direction	NNW
Wind Speed (mph)	9.19
Precipitation (in)	0.0016
Weather Condition	Fair
Sunrise/Sunset	Night
Comfort Index	10.35
Severity	2

A. *Risk Estimation Evaluation*

1) Accuracy: We monitor the training process of the FL model in terms of accuracy, loss, and convergence. The training for 50 communication rounds with 5 training clients takes up to 4.042 hours. Figure 3 plots the training accuracy in the upper graph and the training loss in the lower graph. The model demonstrates convergence approximately by round 30 at 71.15%, as depicted in the upper plot. Initially, model accuracy exhibits an upward trend from round 0 to 30, albeit with

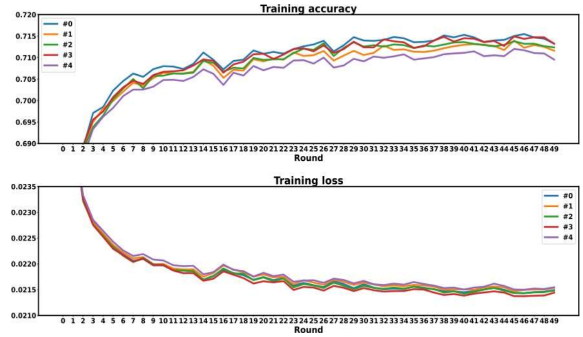


Fig. 2. Risk estimation training accuracy (top) and loss (bottom)

fluctuations observed around rounds 15-17 and 21. Subsequently, after round 30, the risk estimation model appears to have reached a plateau in accuracy, becoming converged. This is also reflected in the lower graph of training loss. It is, however, possible for low power-resource devices to terminate the training process at an earlier stage, such as after round 10 or 20, with negligible tradeoffs in accuracy.

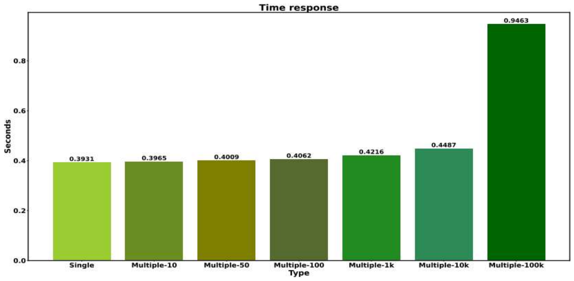


Fig. 3. Total latency trends of risk estimation

2) *Total latency trends:* The bar graph (referred to Fig. 4) depicting the total latency for predictions reveals a clear trend: as the number of inputs processed simultaneously increases, so does the time required for prediction. Starting from a swift 0.3931 seconds for a single input, the latency moderately rises for batches of 10 and 100 inputs, reaching 0.4062 seconds, suggesting the model handles small to moderate increases in input size efficiently. However, as input sizes increase to 1,000 and 10,000, the total latency grows more substantially, hitting 0.4487 seconds for 10,000 inputs. This increment continues, even more sharply, with the model taking 0.9463 seconds to predict outcomes for 100,000 inputs concurrently. Overall, this evaluation outcome underscores the FL model's scalability with a total latency, not only for small input batches but also optimized for larger ones. Nevertheless, it should be noted that the measured time can be different among different working devices.

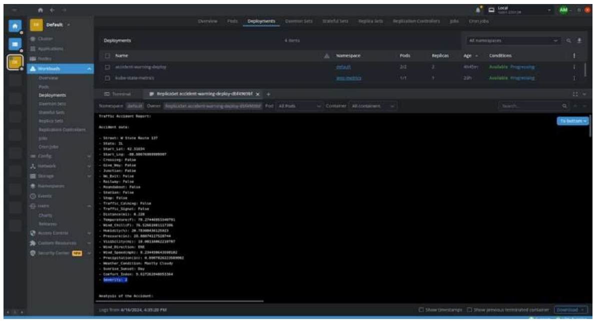
B. *Accident Warning Report Evaluation*

Evaluated by RAG, we have used correctness, relevance, and faithfulness as criteria to assess LLM outputs10. We used gpt- 3.5-turbo-0613 for the evaluation task to contextually analyze and interpret generated reports according to the criteria. Cor- rectness is based on the LLM's internal knowledge. However, given the potential unreliability of the LLM's knowledge base, we enhanced the evaluation method by incorporating reference labels. This provides an external benchmark for correctness. The evaluation process produces a dictionary containing key metrics: "score", a binary integer from 0 to 1 indicating compliance with the criteria, "value", which is either ”Y” (Yes) or ”N” (No) based on the score, and "reasoning", which outlines the LLM's chain of thought. Relevance evaluates the relevance and focus of the generated answer in relation to the provided prompt. Faithfulness assesses the factual consistency of the generated answer against the given context and reference documents. Using this approach, we ensure not only that the generated content meets the prompt's specific requirements. It also remains true to the factual information provided in the reference material. Figure 5 illustrates an example of RAG output evaluation. Based on correctness, relevance, and faith- fulness criteria, the evaluation shows that the output accurately represents an actual quote. Throughout the evaluation output, all necessary elements are addressed in a comprehensive, well- structured, and well-written manner. Based on the evaluation output, the response summarizes accident data and provides a comprehensive analysis of weather conditions at the time of the accident, including visibility and severity. Additionally, it provides recommendations for preventing accidents in the future relevant to the reference.

C. *Task Orchestration and Monitoring*

We utilized a simplified demonstration setup comprising one controller node and two worker nodes to test the deployment of the system to the distributed environment.

The technical characteristics of our system are as follows: The controller node is equipped with an Intel Core i7- 6700HQ CPU, an NVIDIA GeForce GTX 960M GPU, and 16 GB of RAM. One of the worker nodes is identical to the controller node, featuring an Intel Core i7-6700HQ CPU, an NVIDIA GeForce GTX 960M GPU, and 16 GB of RAM. The other worker node is equipped with an Intel Core i5-1135G7 CPU and 16 GB of RAM. The system was successfully deployed and operated as expected, effectively generating warnings in response to simulated input data. Additionally, we employed Lens IDE to monitor data outputs and to oversee the resource usage on the controller node. A screenshot of the Lens IDE is provided in Figure 6 to demonstrate how the cluster is controlled.



```
Traffic Accident Report:

Accident data:

- Street: W State Route 137
- State: IL
- Start_Lat: 42.31034
- Start_Lng: -88.00676999999997
- Crossing: False
- Give_Way: False
- Junction: False
- No_Exit: False
- Railway: False
- Roundabout: False
- Station: False
- Stop: False
- Traffic_Calming: False
- Traffic_Signal: False
- Distance(mi): 0.228
- Temperature(F): 78.27440953340791
- Wind_Chill(F): 76.52661081117306
- Humidity(%): 20.78300436125023
- Pressure(in): 28.88074117528744
- Visibility(mi): 10.00338062210787
- Wind_Direction: ENE
- Wind_Speed(mph): 0.234430642098182
- Precipitation(in): 0.0907826223589062
- Weather_Condition: Mostly Cloudy
- Sunrise_Sunset: Day
- Comfort_Index: 9.617262048053364
- Severity: 2


Analysis of the Accident:
```

Logs from 4/16/2024, 4:35:20 PM

Fig. 4. Lens IDE logs output

V. Discussion and Future Work

The development and integration of FL and RAG into an ITS service presents several key findings and areas for further research. Our FL model demonstrated good performance in predicting traffic accident severity, achieving a convergence point after approximately 30 communication rounds. This suggests that FL can effectively utilize distributed data for predictions while maintaining data privacy. Additionally, the scalability of the FL model was evident from the total latency evaluations, which showed reasonable prediction times even with increasing input sizes, indicating the model's applicability in real scenarios. The RAG model generated detailed and con- textually relevant reports and warnings based on simulated real time inputs. This was validated through evaluations focusing on correctness, relevance, and faithfulness. The integration of real-time data and FL with external knowledge sources ensured that the generated content was not only accurate but also practical for end-users, such as traffic management authorities. The use of k0s for task orchestration proved to be effective, enabling seamless integration and management of various system components. The monitoring capabilities provided by Lens IDE ensured the system's robustness and allowed for efficient resource management. Testing on a simulated cluster confirmed the system's reliability and scalability. While our system shows promising results, several areas warrant further investigation and development. Future work should focus on strengthening privacy preserving techniques within the FL framework. In our design of the FL model, we prioritized simplicity and efficiency to predict accident severity. This approach was intended to minimize the computational load. For future work, it would be advantageous to enhance the FL model by exploring other lightweight models. This could potentially improve the accuracy while maintaining the model's efficiency. Exploring the feasibility of using transfer learning methods to transfer knowledge gained about each state or district to other districts or states can be beneficial. To directly address the reviewer's concern that the reported accuracy of the predictive model (71.15%) is low, we acknowledge that while this figure demonstrates good convergence and the viability of the FL approach for distributed prediction, there is a clear and defined path for further significant enhancement. Achieving a higher accuracy is critical for a system designed to meet the practical and reliability standards for real-world urban safety applications. We will focus on the following strategies in future iterations to boost the FL model's performance:

- **Exploring Advanced Lightweight Models:** We will go beyond the current three fully connected layers by rigorously exploring other lightweight model architectures better suited for complex time-series and sensor data within the resource constraints of edge devices. This will involve testing models that integrate recurrent units or other sophisticated, yet efficient, deep learning structures such as those demonstrated in similar vehicular traffic flow prediction research [47].
- **Optimizing Hyperparameters and Communication:** We will conduct a more exhaustive search to identify the optimal configuration for hyperparameters (such as learning rate and batch size) and the number of communication rounds. The goal is to maximize accuracy beyond the current convergence point of 71.15% without incurring the prolonged training duration associated with the initial Complex model configuration (which achieved 74.42% accuracy but took 5.603 hours to train)
- **Refining Feature Engineering and Data Sourcing:** We plan to refine the preprocessing phase with advanced feature engineering that incorporates deep domain knowledge, such as explicitly including temporal-spatial features like proximity to peak hours or specific road geometry characteristics. We will also explore the use of more granular data from additional real-time sources to enrich the model's inputs, following best practices for leveraging heterogeneous sparse data in risk prediction [48].

By implementing these targeted enhancements, the next iteration will be designed to significantly improve the predictive accuracy, thereby creating a system that is not only conceptually sound but also practically viable and highly reliable for enhancing urban safety.

Developing user-friendly interfaces for traffic management authorities and end-users will be crucial for effective system adoption. This involves designing intuitive dashboards and visualization tools to present predictions and warnings in an accessible manner. Implementing and testing the system in real-world smart city environments will provide valuable insights into its performance and scalability. Collaborations with city authorities can facilitate this process and help refine the system based on practical feedback.

VI. CONCLUSION

This paper presents a service in smart cities integrating FL and RAG to enhance traffic risk prediction and manage- ment in smart cities. Our findings demonstrate the system’s accuracy, efficiency, and potential for real-world applications. The FL model achieved a good predictive performance while preserving data privacy. The RAG model produced detailed and relevant reports, aiding in effective traffic management. Task orchestration using k0s ensured seamless integration and robust performance monitoring. Future work will focus on enhancing privacy, scalability, and real world testing, aiming for broader deployment and integration. Our system offers a promising approach to addressing urban safety challenges, contributing to the development of smarter and safer cities.

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