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Intelligent route optimization for internet of vehicles using federated learning: promoting green and sustainable IoT networks

Desidi Narsimha Reddy[1], Swathi Buragadda[2], Janjhyam Venkata Naga Ramesh[3], Garapati Satyanarayana Murthy[4], Nallathambi Srija[5], Sarihaddu Kavitha[6]

[1]Data Consultant (Data Governance, Data Analytics, EPM: Enterprise Performance Management, AI & ML), Soniks Consulting LLC, Plano, United States
[2]Department of Computer Science and Engineering, Lakireddy Balireddy College of Engineering, Mylavaram, India
[3]Department of Computer Science and Engineering, Graphic Era Hill University, Dehradun, India
[3]Department of Computer Science and Engineering, Graphic Era Deemed to be University, Uttharakhand, India
[4]Department of Computer Science and Engineering, Aditya University, Andhra Pradesh, India
[5]Department of Information Technology, M. Kumarasamy College of Engineering, Tamil Nadu, India
[6]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, India

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ABSTRACT

As the internet of vehicles (IoV) continues to evolve, optimizing vehicle routing becomes increasingly important for enhancing traffic efficiency and minimizing environmental impact. This paper introduces an intelligent vehicle route optimization protocol leveraging federated learning (FL) to achieve green and sustainable IoV systems. By distributing the learning process across multiple edge devices, the proposed protocol minimizes the need for centralized data processing, reducing network congestion, and preserving user privacy. The system optimizes vehicle routes based on real-time traffic conditions, fuel efficiency, and carbon emissions, and promoting greener transportation practices. Simulations conducted in a dynamic IoV environment demonstrate significant improvements in route efficiency, fuel consumption, and carbon emissions. The results underscore the potential of FL in transforming IoV routing by balancing performance and sustainability, making it a promising solution for the future of connected transportation.

Corresponding Author:

Garapati Satyanarayana Murthy
Department of Computer Science and Engineering, Aditya University
Surampalem, Andhra Pradesh, India
Email: murthygsnm@yahoo.com

1. INTRODUCTION

The development of the internet of things (IoT) has led to the emergence of the internet of vehicles (IoV), which is crucial for the progression of contemporary intelligent transportation systems (ITS). The IoV facilitates ongoing data exchange between vehicles, roadside units (RSUs), and cloud platforms, which enhances traffic management, route planning, and overall mobility efficiency. The surge in connected vehicles has led to an escalating need for solutions that prioritize energy efficiency, environmental sustainability, and privacy considerations. In this context, federated learning (FL) is emerging as a promising strategy to enhance sustainable IoV frameworks, especially in the area of vehicle route optimization [1], [2]. Route optimization plays a vital role in the IoV, influencing travel time, fuel usage, traffic congestion, and carbon emissions significantly. Traditional centralized systems collect extensive data at central servers, leading to issues such as significant communication overhead, energy inefficiency, and possible privacy violations due to the transmission of sensitive driving and location information [3]. FL presents a decentralized approach to learning that contrasts with traditional centralized machine learning methods. In FL, model training occurs on edge devices like vehicles or RSUs while the raw data stays local. Exchanging solely model parameters or updates ensures the protection of user privacy while also greatly reducing the communication load. This decentralized approach enhances data confidentiality while simultaneously lowering the energy expenses linked to extensive centralized processing, positioning FL as a compelling option for sustainable IoV systems aimed at optimizing vehicle routing [4], [5].

This study focuses on developing an advanced vehicle routing protocol utilizing FL, incorporating elements like fuel consumption, traffic patterns, travel duration, and carbon output. The suggested protocol adjusts in real time by utilizing data gathered from IoV-enabled vehicles and RSUs, perpetually refining the routing model to mirror traffic dynamics and road conditions. In addition to sustainability, the FL-based strategy tackles challenges related to scalability, energy requirements, and the preservation of privacy. By assigning computation tasks to local devices, dependence on central servers is reduced, which in turn decreases overall energy consumption across the system. Furthermore, removing the necessity to centralize sensitive data boosts user trust and security, which is crucial for the widespread adoption of IoV [6], [7]. The IoV is recognized as a fundamental component of intelligent transportation systems, facilitating real-time interactions between vehicles and infrastructure to enhance traffic safety, routing, and flow management. While traditional routing methods have enhanced efficiency, there is a growing emphasis on approaches that integrate sustainability and privacy concurrently. The ongoing investigations in this field can be generally divided into three main categories: routing techniques based on the IoV, the significance of FL in IoT-driven frameworks, and environmentally friendly IoT approaches for sustainable transportation [3], [8].

Vehicle routing optimization has been thoroughly examined, utilizing algorithms like Dijkstra's algorithm, a search and genetic methods to identify routes while taking into account distance, congestion, and travel time. Innovative approaches utilizing real-time traffic updates have been developed. Nonetheless, these centralized solutions frequently demand substantial server resources and considerable communication bandwidth, which diminishes scalability as IoV networks grow [9], [10]. Contemporary IoV platforms utilize real-time data from vehicles and RSUs to facilitate dynamic routing, frequently leveraging cloud-based systems. Although these methods enhance adaptability, they are not without their limitations, including privacy concerns, data bottlenecks, and network congestion, which impede their long-term viability in extensive implementations [11]. FL has emerged as a decentralized approach to machine learning in the context of IoT. In contrast to centralized approaches that require the transfer of raw data, FL facilitates model training locally, sharing only parameter updates. This minimizes communication needs and enhances privacy protections [12].

Studies have shown FL's effectiveness in large-scale IoT and smart city contexts, including its application in wireless sensor networks and connected autonomous vehicles, where it facilitated distributed learning without the need to centralize sensitive data. Nonetheless, the utilization of FL for sustainable route optimization in the IoV is still significantly under-researched [4]. The implementation of FL in vehicular networks presents numerous advantages, such as enhanced scalability, improved privacy, and increased resilience. Decentralized FL systems enhance accuracy in route prediction and lessen reliance on centralized infrastructures by enabling vehicles and RSUs to collaboratively train models while keeping raw data private. Preliminary investigations indicate enhancements in routing efficiency via FL-based approaches; however, additional research is required to evaluate the environmental and energy-saving capabilities of these systems within green IoV frameworks [13].

The theme of sustainability has emerged as a critical focus in the realms of IoT and IoV, where the notion of "green IoT" highlights the importance of energy efficiency and environmentally conscious system design. The objective of green IoT is to reduce carbon emissions and enhance resource efficiency through the use of cutting-edge communication, sensing, and analytics technologies. In transportation, this results in decreased fuel consumption, reduced emissions, and less congestion [14].

Nonetheless, numerous eco-friendly IoV strategies continue to depend significantly on centralized architectures, potentially resulting in high energy consumption. In response to this challenge, decentralized designs have been suggested, including blockchain-enabled green IoT frameworks that allocate computation across edge devices, consequently lowering energy expenses. The incorporation of FL into green IoV systems for sustainable routing is still an area that requires further investigation [15]. In summary, current research underscores significant progress in algorithms for vehicle routing, IoT applications based on FL, and environmentally sustainable IoT frameworks. Nonetheless, the intersection of these three areas particularly, the application of FL to facilitate sustainable, and privacy-preserving vehicle routing in IoV has not been thoroughly explored. This study aims to close this gap by introducing a protocol for route optimization driven by FL, which tackles the intertwined issues of sustainability and privacy, while enhancing scalability and efficiency in IoV settings [16].

2. METHOD

The proposed architecture presents an innovative FL–based vehicle route optimization protocol aimed at enhancing the sustainability of the IoV. The integration of IoV, FL, and green IoT concepts significantly improves routing efficiency, lowers fuel consumption, reduces carbon emissions, and safeguards user privacy. The decentralized framework reallocates computational processes to edge devices, including vehicles and RSUs, which work together to train route optimization models instead of relying on centralized data centers [17]. In this context, vehicles and RSUs function as advanced edge nodes. Each gathers localized data including traffic conditions, fuel consumption, emission levels, and vehicle speed. Vehicles utilize this information to develop and enhance local models, whereas RSUs extend communication coverage and offer supplementary processing power for immediate routing decisions. A centralized server orchestrates the system by consolidating model updates sent from these nodes. The server employs algorithms like federated averaging to consolidate the updates into a global model, which is subsequently redistributed to the edge devices. It is crucial to note that raw data is not transmitted; only model parameters are shared, ensuring the protection of privacy. Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication protocols facilitate efficient and low-latency exchange of model updates, while secure communication layers incorporating encryption and authentication maintain the integrity and confidentiality of the shared data [18], [19]. FL serves as the foundation of the system, enabling decentralized model training across multiple devices while eliminating the need for centralized data storage. This approach effectively tackles challenges related to scalability, communication load, and privacy. The procedure initiates with every vehicle or RSU developing a localized model derived from its gathered data, enhancing metrics like travel duration, carbon output, and fuel efficacy. These localized models evolve continuously as vehicles navigate various traffic scenarios and road conditions. Rather than sending raw data, only the model parameters are shared with the global server, which consolidates them to enhance the global model. The model is subsequently distributed to the edge devices, where it integrates into local systems to enhance predictive accuracy. The cycle continues to repeat, allowing the system to adjust smoothly to variations in traffic patterns, road conditions, and environmental factors, all the while improving route efficiency progressively [20], [21].

The architecture fundamentally incorporates a route optimization algorithm that integrates real-time IoV data with FL to identify energy-efficient and sustainable travel paths. Vehicles collect data on traffic density, speed, fuel consumption, and emissions, whereas RSUs offer supplementary contextual information, including weather conditions and the quality of the road surface. The data streams contribute to local models that forecast the best routes, balancing the reduction of travel time with the goal of environmental sustainability. The algorithm effectively circumvents congested routes, minimizes idle time, and pinpoints energy-efficient alternatives. As conditions evolve such as an unforeseen rise in congestion the system adaptively recalibrates routes to ensure optimal efficiency. Through this approach, vehicles are consistently directed along routes that optimize energy conservation while maintaining punctual travel. During the FL cycle, vehicles gain advantages from collective insights within the network, where information acquired by one device enhances the route optimization abilities of all involved nodes [22], [23].

The system additionally integrates a mechanism for vehicle detection and communication. Figure 1 demonstrates the placement of a magnetic sensor, which is affixed to the underside of the vehicle chassis, positioned roughly 20 cm above the road surface. Upon the entry of vehicles into a 28-meter radius, magnetic flux values are identified and recorded in the onboard 4 GB memory of the intelligent vehicle. The measurements are analyzed alongside previously recorded datasets, facilitating precise identification of vehicle types. Figure 2 illustrates the workflow of the proposed system, in which the sensed magnitudes are evaluated against reference values to differentiate between vehicle categories in real time. The integration of vehicle detection with intelligent routing significantly bolsters situational awareness and improves decision-making, ultimately leading to enhanced system efficiency and sustainability.

The proposed architecture integrates green IoT principles by optimizing energy consumption and minimizing carbon emissions. Key green IoT features include: FL reduces communication overhead by transmitting model updates rather than raw data, saving energy in the data transmission process. The system optimizes routes based on fuel efficiency, directly reducing fuel consumption and associated energy costs. The route optimization algorithm selects paths that minimize stop-and-go traffic, avoiding high emission zones and congested areas to reduce carbon emissions. By adopting eco-friendly routes, the system contributes to reducing the overall carbon footprint of IoV networks. The decentralized FL system scales easily across large numbers of vehicles, ensuring that as more vehicles join the network, the system remains efficient without increasing the central server's load. Real-time learning enables the system to adapt to changing traffic patterns, making it resilient to fluctuations in road conditions [24], [25]. Privacy is a critical concern in IoV systems. The proposed FL-based architecture enhances privacy through its decentralized design. Key aspects include: vehicles and RSUs keep their raw data localized, sharing only model updates with the global server. This prevents sensitive data, such as vehicle location and driving behavior, from being exposed to external entities. Encrypted communication protocols are used to ensure that model updates transmitted between edge devices and the global server are protected against interception and tampering. Authentication mechanisms verify the integrity of data being transmitted, ensuring that only authorized vehicles and RSUs participate in the system. The decentralized nature of FL ensures that the system is robust against individual node failures. Even if some vehicles or RSUs drop out of the network, the system can continue to operate using model updates from other edge devices [26].

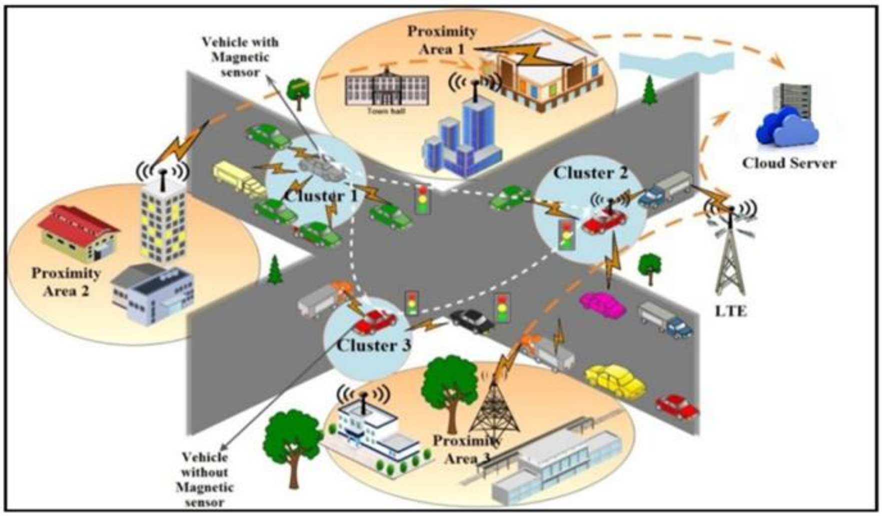

Figure 1. The process of detecting and communicating between IoT and IoV

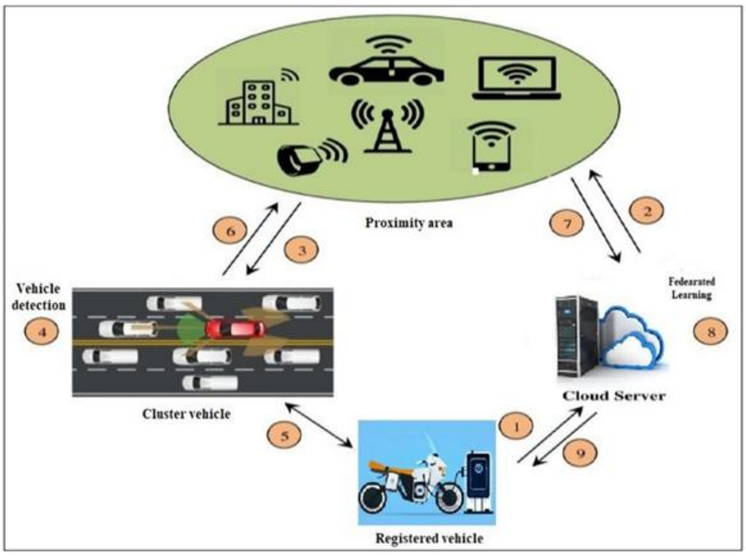

Figure 2. An operational view of an IoT connected IoV

3. RESULTS AND DISCUSSION

Simulations were conducted in a controlled IoV environment to evaluate the effectiveness of the proposed FL-based vehicle route optimization protocol. The main goals of these experiments were to assess the protocol's effectiveness in reducing fuel consumption, lowering carbon emissions, decreasing travel time, and enhancing overall energy efficiency, all while maintaining data privacy. The simulation design integrated mobility patterns inspired by real-world scenarios, concentrating on two particular urban areas chosen for their greater population density and consistently high vehicle demand during both weekdays and weekends. These locations were thus deemed representative for assessing scalability and practical applicability. The comprehensive historical dataset of vehicle activity was divided into two specific types of regions: active regions, defined by ongoing vehicular movement, and joint regions, where two active zones converge and share traffic flow. The patterns of behavior regarding mobility and vehicle requests in these regions were analyzed to establish operational boundaries for the simulation. The interaction between the two zones notably involved request overlaps to the cloud server, with neither surpassing a sixty-second update cycle. This guaranteed that the system functioned within practical time limitations. The cloud infrastructure efficiently handled incoming requests while simultaneously calculating the standard deviation of prediction errors. This capability enabled the model to enhance its performance by leveraging vehicle demand patterns identified over the preceding five weeks. The proposed framework exhibited significant proficiency in managing sequential data, especially in acquiring insights from lengthy historical sequences and adjusting them to meet real-time vehicular requirements.

The system's scalability was assessed under various conditions by juxtaposing its outcomes with those generated by both centralized and decentralized models across a range of scenarios. To enhance prediction accuracy, the suggested method integrated particular neighborhood-level characteristics in the estimation of local vehicle demand. This enhancement enabled the model to minimize errors that often occur when traditional approaches try to forecast overall vehicle demand in far-reaching or diverse areas. Conventional methods frequently encounter challenges in these situations, resulting in increased error rates and diminished reliability. The protocol based on FL demonstrated enhanced accuracy through the utilization of collaborative learning among vehicles and RSUs. The findings distinctly demonstrate the benefits of the proposed system. Figures 3 and 4 provide a detailed comparison of error rates between the baseline system and the FL-based protocol, demonstrating that the latter consistently resulted in lower prediction errors. Moreover, Figure 5 illustrates the increased scheduling efficiency of the proposed model, as it not only reduced errors but also showed improved adaptability to changing traffic conditions. The findings collectively demonstrate that the FL-based optimization protocol provides notable enhancements compared to current methods, resulting in improved efficiency, scalability, and sustainability within IoV environments.

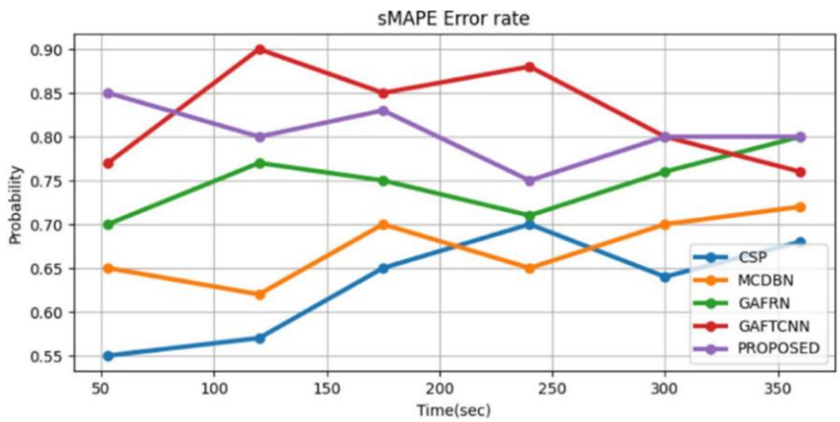

Figure 3. Symmetric mean absolute percentage error

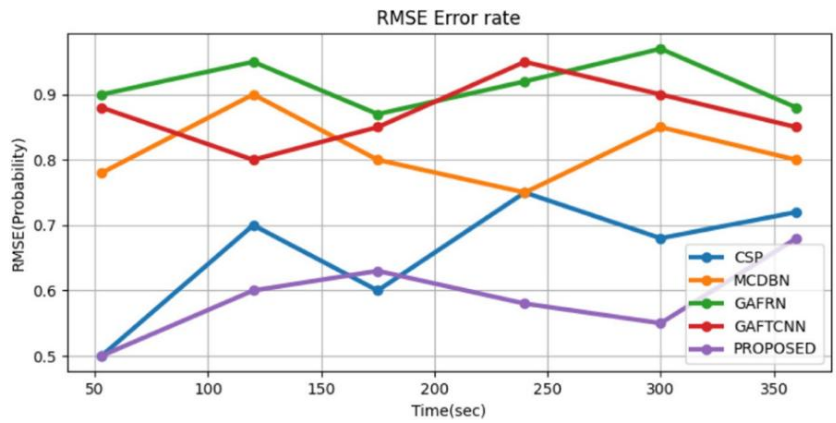

Figure 4. Root mean square error

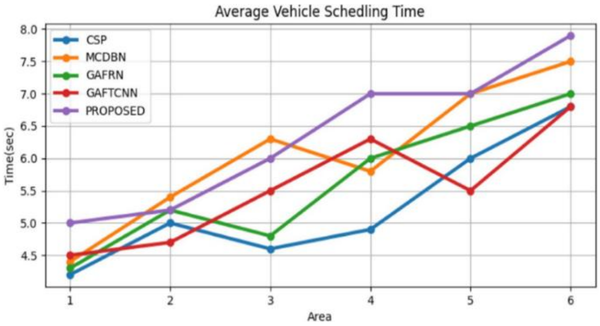

Figure 5. Mean vehicle scheduling rate

The utilization of intelligent scheduling allows this method to cut down on the typical amount of time that passengers have to wait. The waiting time for the proposed public transportation is significantly less than that of taxis. As a consequence of this, it is an excellent method for lowering the volume of vehicular traffic and easing congestion. When the number of public transportation vehicles (PTVs) for traffic optimization is increased from 500 to 1,100, the performance of the optimization process improves. As a consequence, there will be a decrease of 1,500 cars that are not required, which will have an effect on the total traffic congestion that is caused by the current utilization of PTVs. As can be seen in Figure 6, the model that was proposed has reached the peak in the top left corner. Figure 7 illustrates a comparison between the proposed system and the existing system (global positioning system (GPS)) in terms of the accuracy of its location. It is evident that the new system achieves a greater level of location accuracy than the existing system. The simulation results clearly demonstrate the advantages of using FL for vehicle route optimization in IoV systems. The proposed protocol successfully reduced fuel consumption and carbon emissions, making it an environmentally friendly solution for sustainable transportation. The decentralized nature of the FL framework also ensured that data privacy was preserved, addressing one of the major concerns in IoT systems. Although there was a slight increase in travel time, this was minimal compared to the significant benefits gained in energy savings and emissions reduction.

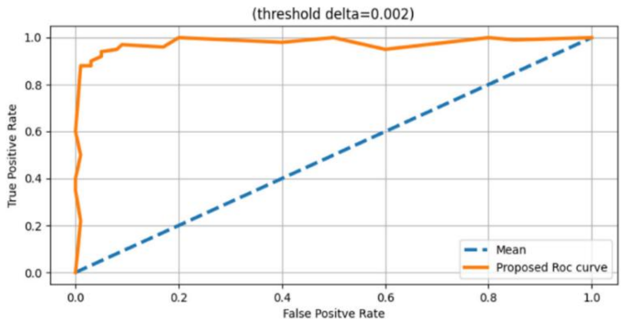

Figure 6. Intended receiver operating characteristic (ROC) curve

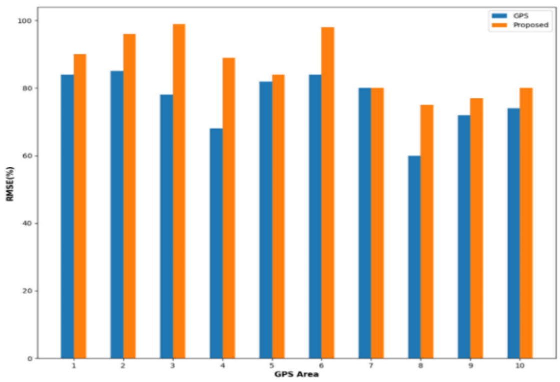

Figure 7. Comparison of GPS location accuracy with projected

4. CONCLUSION

In this paper, we proposed an intelligent FL-based vehicle route optimization protocol designed to support green and sustainable IoV systems. The architecture leverages FL to enable decentralized learning, preserving data privacy while optimizing vehicle routes for fuel efficiency, reduced emissions, and travel time. By integrating green IoT principles into the IoV, our approach contributes to the development of eco-friendly transportation networks that address the growing concerns of fuel consumption and carbon footprint in urban environments. The results suggest that the proposed FL-based protocol is a promising solution for optimizing vehicular routing in IoV, particularly in scenarios that demand data privacy and environmental sustainability. The decentralized nature of the system also ensures scalability, making it suitable for large-scale deployments in smart cities and beyond. However, further research is needed to explore more advanced optimization algorithms and to test the system in real-world IoV environments.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Desidi Narsimha Reddy	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Swathi Buragadda	✓	✓				✓		✓	✓	✓	✓	✓		
Janjhyam Venkata Naga Ramesh	✓		✓	✓			✓			✓	✓		✓	
Garapati Satyanarayana Murthy	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Nallathambi Srija	✓		✓	✓			✓			✓	✓		✓	
Sarihaddu Kavitha	✓		✓	✓			✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest regarding the publication of this paper. All authors have reviewed and approved the final version of the manuscript and confirm that there are no financial, personal, or professional relationships that could be construed as influencing the work reported in this study.

ETHICAL APPROVAL

This study does not involve any human participants, animals, or sensitive data requiring ethical approval. All procedures and analyses were conducted in accordance with standard academic and research integrity guidelines. Therefore, ethical approval was not required for this research work.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request. All datasets used in this research were obtained from publicly accessible sources or generated during the study in compliance with institutional and ethical standards.

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BIOGRAPHIES OF AUTHORS

Desidi Narsimha Reddy is a Data Consultant specializing in Data Governance and Data Analytics, including enterprise performance management and AI & ML. He holds a postgraduate degree in Machine Learning and AI from Purdue University, complemented by an MBA in Finance and Information Systems from MG University. Additionally, he has completed a program on 'Business analytics: from data to insights' from Wharton Management School and is a certified Project Management Professional (PMP) from the PMI Institute. His proficiency encompasses various domains, including financial reporting applications, data management, master data management, data governance, data science, and artificial intelligence and machine learning. He can be contacted at email: dn.narsimha@gmail.com.

Swathi Buragadda received the B.Tech. degree in Computer Science and Engineering from Nova College of Engineering, Jangareddygudem, India, in 2004 and the M.Tech. in Computer Science and Engineering with Computer Science specialisation from Vasavi College of Engineering, Jawaharlal Nehru Technological University Kakinada, Kakinda, India in 2010, respectively. Currently, she is an Assistant Professor at the Department of Computer Science and Engineering, Lakireddy Balireddy College of Engineering, Mylavaram, India. Her research interests include data mining, artificial intelligence, machine learning, and generative AI. She can be contacted at email: buragaddaswathi@gmail.com.

Janjhyam Venkata Naga Ramesh adjunct Professor working in the Department of CSE, Graphic Era Hill University and Graphic Era Deemed to Be University, Dehradun, Uttarakhand, India. He is having 20 years of experience in teaching for UG and PG engineering students. He has published more than 95 articles in IEEE/SCI/Scopus/WoS journals, conferences and also reviewer in various leading journals. He has authored six text books and ten book chapters. His research interests are wireless sensor networks, computer networks, deep learning, machine learning, and artificial intelligence. He can be contacted at email: jvnramesh@gmail.com.

Garapati Satyanarayana Murthy is working as a Professor of CSE in Aditya University, Surampalem. He completed his Ph.D. (CSE) in Rayalaseema University, Kurnool, India. He has 28+ years of teaching experience and 10+ years of research experience. He published various research articles in reputed international journals and conferences. He has several patents and book chapters also. He is reviewer for various Scopus indexed journals and editorial board member like research India Group of Journals. He acted as an advisor for several international conferences. He is the member for various professional bodies like IEEE, CSI, IAENG and CSTA. He is the BOS member for several professional colleges. His research work focuses on data mining, image processing, and cyber security. He can be contacted at email: murthygsnm@yahoo.com.

Nallathambi Srija received the B.E. degree in Computer Science and Engineering from Professional Group of Institution, Palladam, India, in 2017 and the M.E. degree in Computer Science and Engineering from Muthayammal Engineering College, Rasipuram, India, in 2019 and doing Ph.D. degree in Computer Science and Engineering with Deep learning specilization from M. Kumarasamy College of Engineering, Karur, India in 2024, respectively. Currently, she is an Assistant Professor at the Department of Information Technology, M. Kumarasamy College of Engineering, Karur, India. Her research interests include data science, image processing, internet of things, machine learning, and artificial intelligence. She can be contacted at email: srijanallathambi@gmail.com.

Sarihaddu Kavitha received the M.Tech. degree in Computer Science and Engineering from Bapatla Engineering College, Bapatla, India, in 2009 and submitted Ph.D. thesis in Computer Science Engineering with Speech Recognition in Natural Language Processing specialization in Acharya Nagarjuna University Guntur, India, respectively. Currently, she is an Assistant Professor at the Department of Computer Science and Engineering in Koneru Lakshmaiah Education Foundation, Guntur, India. Her research interests include cloud computing, real-time internet of things and intelligent route optimization for IoV using federated learning. She can be contacted at email: kavitha.sarihaddu@gmail.com.