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Cloud-Enabled Pedestrian Safety and Risk Prediction in VANETs Using Hybrid CNN-LSTM Models

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Abstract:

As pedestrian safety in Vehicular Ad-hoc Networks (VANETs) becomes more critical, there is an increasing need for effective, real-time risk assessment systems to predict pedestrian-vehicle interactions. Typical problems that most pedestrian detection and risk assessment systems experience include high latency, low accuracy, and limitations in scale when it comes to context shifting—all of which can be effectively tackled by cloud computing as a solution to their scalability and efficiency effect on data processing for VANET real-time decision-making. This framework proposes the incorporation of pedestrian safety cloud systems with the potential for a robust dynamic risk assessment using a hybrid CNN-LSTM model, coupled with a YOLO-based real-time pedestrian identification scheme. To warn automobiles and pedestrians of possible dangers, the system makes advantage of V2X communication. The proposed approach is a reliable, flexible and effective solution for pedestrian safety in VANETs, which guarantees fast actions and minimizes accidents in dynamic situations. Tests showed that the technology demonstrated scalability and good real-time performance across different traffic and weather scenarios. Identification and assessment of pedestrian hazards had an average latency of less than 200 ms, 97% accuracy, recall, and precision above 90%.

Keywords: *Pedestrian Safety, VANETs, Risk Assessment, YOLO, Hybrid CNN-LSTM, V2X Communication.*

1.Introduction:

Cloud computing and Vehicular Ad-hoc Networks (VANETs) enable effective and scalable communication in dynamic environments[1] [2]. Their influence is mainly bridged through cloud computing, which provides infrastructure for real-time data processing, storage, and model inference for improved and more scalable systems[3] [4]. The interfacing of vehicles within infrastructures and to people provides a much more beneficial condition of better navigation, safety, and traffic control in the Well-Connected Vehicle Networks (VANETs)[5]. In this way, the integration of the aforementioned cloud technologies into VANETs should be able to address critical issues within safety aspects such as the flow of traffic and prevention of accidents, especially regarding pedestrians, in smart cities and connected environments through seamless data exchange, risk prediction, and real-time decision making[6] [7].

The predominant aim of present-day pedestrian safety systems in VANETs is pedestrian detection and risk assessment using simple sensor data from infrastructure and vehicles[8] [9]. Conventional object detection techniques have been frequently used in such systems but with issues of accuracy, scalability and real-time performance in dynamic environments[10] . Many approaches also lack robust communication between vehicles and infrastructure, which hinders timely responses to pedestrian presence[11] [12]. A few systems incorporate V2X communication but have different constraints for accuracy and timeliness in their alerts in real traffic environments[13]. most methods already in place fail to consider sophisticated machine-learning-based dynamic risk assessment pretending thus the best possible estimations on pedestrian-vehicle interactions; this results in non-functioning systems for real-world pedestrian scenarios with heavy traffic and adverse weather conditions and thus pose higher risks to pedestrians[14]. Another significant gap in current pedestrian safety systems in VANETs is the integration of cloud computing with advanced deep-learning models[15].

Existing pedestrian safety systems in VANETs have low accuracy in pedestrian detection; great latencies; and do poorly in scalability within dynamic environments. Most of these include weak coupling between vehicles and the infrastructure, where they cause late or ineffective alerts. Our work addresses such short-comings by integrating YOLO-based pedestrian detection with a Hybrid CNN-LSTM model to provide real-time dynamic risk assessment with both improved and reduced accuracy and latency. We have such conditions through V2X communication lines for timely alerts to vehicles and pedestrians. With cloud data processing and model updates, much more can be achieved in terms of speed and efficiency, and this result holds robustness as well as adaptability in pedestrian safety with regard to heavy traffic congestions.

1.1. Problem statement:

As pedestrian safety becomes increasingly important, there is a growing need for efficient and real-time risk assessment systems capable of predicting potential pedestrian-vehicle interactions in Vehicular Ad-hoc Networks (VANETs)[16] [17]. In a dynamic situation where traffic patterns are changing, environmental factors are at play, and pedestrian behavior is constantly changing, the real challenge is in achieving good accuracy for pedestrians' detection and in assessing the level of risk[18] [19]. Today's pedestrian detection methods suffer from accuracy and scalability issues when it comes to diverse scenarios[20]. Current work addresses these limitations by extracting hybrid CNN-LSTM models for risk prediction and using their outputs in conjunction with YOLO-based pedestrian detection. The proposed system makes an attempt at giving real-time alerts to both vehicles and pedestrians through V2X communication in order for quick actions to be taken to avoid collisions. The final objective is a pedestrian safety solution for VANETs that is scalable, efficient, and flexible.

1.2.Objective:

1. Develop a real-time pedestrian detection system using the YOLO object detection algorithm within the VANETs space.

2. Apply a hybrid model combining convolutional neural networks and long short-term memory networks to accurately estimate pedestrian risk.

3. Integrate V2X communication to ensure timely alerts are sent to both vehicles and pedestrians.

4. Assess the system's performance based on latency, accuracy, scalability, and energy efficiency.

The rest of the paper is organized as follows. Section 1 with the introduction. Section 2 will discuss the Theoretical Background. Section 3 presents the Methodology and Section 4 highlights the results. Section 5 concludes.

2.Literature review:

specifically researched key management, performance optimization, and encryption strategies while investigating the application of Triple Data Encryption Standard (3DES) in the improvement of data security in cloud environments [21]. K-means clustering and its implications for cloud computing as intelligent resource management in enhancing performance and cost savings. For the purpose of data integrity and user satisfaction, Valivarthi suggested a security system based on SHA-256, digital signatures, and RSA encryption. In order to reduce the time on work and improve the security of cloud-based e-commerce, the HMDAP method, Hybridised Multi-special Decision System, to identify counterfeit products. [22] showed how deconvolutional neural networks (DNNs) can make facial recognition systems better by enhancing their resolution, besides assuring data security when using the same with cloud-based big data analytics.

In this research about enhancing DDoS attack detection in cloud systems, Alagarsundaram studied a combination of the covariance matrix method with Multi-Attribute Decision Making (MADM) and showed its effectiveness in multivariate analysis and real-time detection [26]. Also analyzed Elliptic Curve Cryptography (ECC) for cloud encryption, asserting ECC's efficiency and scalability and comparing it to AES [23]. Emphasizing resource management, data security, and scalability, addressed cloud computing optimization and provided various solutions, including load balancing and auto-scaling [24]. Finally proposed a blockchain approach to maintaining data integrity in multi-cloud systems using Homomorphic Verifiable Tags (HVT) for transparent and secure data verification.

To secure sensitive information from being leaked in the cloud environments, Gudivaka et al., improved steganalysis techniques that work in concert with machine learning in LSB embedding procedures. For scalability and better efficiency than traditional methods, Mamidala proposed a parallel K-means clustering methodology using MapReduce for large-scale datasets. For the improvement of security and accessibility on the field such as environmental risk assessment and disaster management, Nagarajan integrated cloud computing with GIS [25].

3.Proposed methodology:

The architecture of the system for pedestrian detection and risk assessment in VANETs is depicted in Figure 1. The scattered sensor data fusion was meant to collect the data from various sources such as the vehicle, infrastructure, pedestrian, and environmental data, which were then preprocessed off before entering the system for data cleaning, feature extraction, and data normalization. The pedestrian ID is tracked using the YOLO (You Only Look Once) mechanism, while the risk assessment is carried out by a hybrid CNN-LSTM model. Accuracy, latency, and energy efficiency were among the most important aspects of consideration. The whole house architectural design will link seamlessly and coordinate with each other for prompt decision-making where pedestrian warning signs are activated, vehicle behavior monitored, communicated with the AWS stack, V2X communication, and autonomously driven. AI is being utilized to track how vehicles behave, which may trigger pedestrian warning signs.

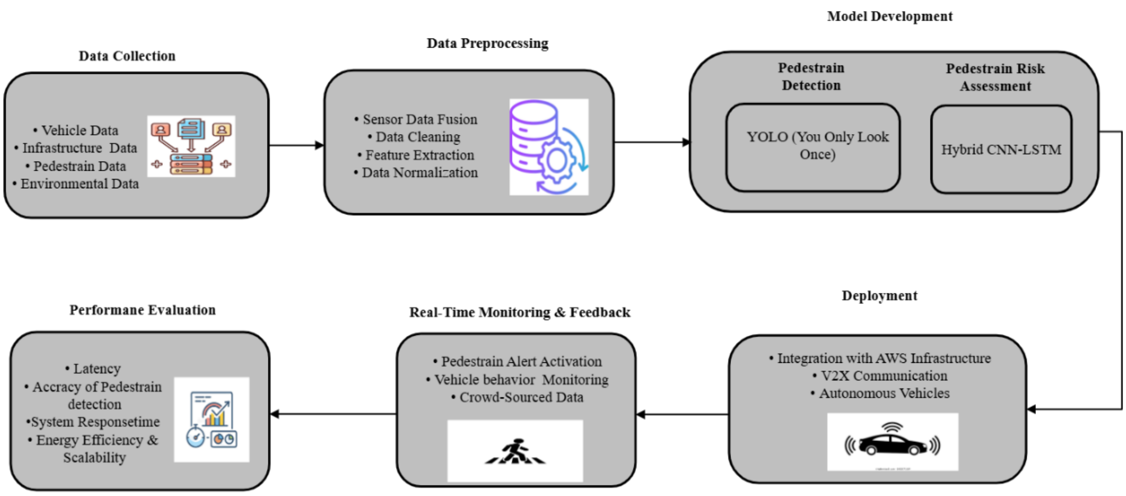

***Figure 1:** Pedestrian Detection and Risk Assessment System Architecture in VANETs*

3.1.Data Collection and Sensor Fusion:

Many sources of input are used, including vehicle data such as position, speed, course, and timestamps. Infrastructure data include road sensor data, signal status, and inputs from various cameras. Pedestrian data contain information about their position and movement, most likely via wearables or mobile devices. Environmental data would include meteorological data, traffic congestion, and road conditions like rain, fog, or snow. The multiple sensor inputs are thus merged using sensor fusion techniques for a holistic consideration of the environments. Fusion operation may be mathematically expressed in the following way:

$$\text{Fusion}_{i,j} = \sum_{k=1}^{n} \left(w_k \cdot \text{Sensor}_{k,i,j} \right) \tag{1}$$

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Sensor $_{k,i,j}$ is the reading from the kth sensor at the i and j position makes these expressions Fusion $_{i,j}$ or the fused data from sensors indexed under i and j, w_k.

3.2. Data Preprocessing:

Having policed any outliers, inaccurate readings, and unmatched data points, data cleaning is closely followed by feature extraction, which finds relevant features-such as vehicle speed, distance to pedestrians, and weather-and normalization, which ensures that data is being uniformly scaled across various sensors-almost equally important in preprocessing of collected data. Normalization can be carried out by Z-score normalization and min-max scaling. Min-max normalization can be mathematically formulated as follows:

$$\text{Normalized} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \quad (2)$$

Where Y is the value of the raw data, while Y_{min} and Y_{max} signify the minimum and maximum values in the dataset.

3.3. Pedestrian Detection:

The YOLO (You Only Look Once) was an online pedestrian detection model that used information from infrastructure sensors or cameras mounted on vehicles. YOLO also predicted bounding boxes around detected items by dividing the image into a grid. The purpose of the model training loss function is to minimize errors in the category of the detected item, object confidence, and predicted bounding boxes. The mathematical expression for loss function is:

$$\text{Loss} = \sum_i [\lambda_{\text{coord}} \cdot \text{Loss}_{\text{coord}} + \lambda_{\text{conf}} \cdot \text{Loss}_{\text{conf}} + \lambda_{\text{class}} \cdot \text{Loss}_{\text{class}}] \quad (3)$$

Where $\text{Loss}_{\text{coord}}$ assesses the error in the bounding box coordinate, object confidence and classifies errors (i.e., if the identified object is a pedestrian) through $\text{Loss}_{\text{conf}}$ and $\text{Loss}_{\text{class}}$ respectively. The coordinates of the hyperparameters. Each term's contribution to the general loss is weighted using λ_{class}. In order to weight the contribution of individual terms to overall loss, λ_{conf} and λ_{class} were used.

3.4. Pedestrian Risk Assessment:

After the identification of pedestrians, a Hybrid CNN-LSTM model will be developed for risk assessment. The CNN component of the model would require spatial features from the images or sensor data, and the LSTM component would model temporal relations to predict the risk of a pedestrian crossing the road or colliding with a vehicle. The hybrid structure of CNN-LSTM consists of a CNN layer for feature extraction and an LSTM layer for the purpose of predicting movements from the historical data. The risk prediction can be defined by means of the following classifier:

$$\hat{y}_t = f\big(\text{CNN}(X_t), \text{LSTM}(X_{t-1}, X_{t-2}, \ldots, X_1)\big) \quad (4)$$

X_t is the features extracted at time t, f(.) is the function that combines the CNN and LSTM outputs, t is the output risk value (low, medium, or high) at time t.

3.5. Alert System and V2X Communication:

Proper signaling is activated by the system whenever risks to pedestrian safety are assessed, and pedestrians are warned using various signals affixed to the infrastructures like flashing lights on the crosswalk. Vehicles are made aware of the existence of pedestrians and the risk to them via V2X communication. V2X communication will thus allow vehicles to either stop, reduce their speed, or change their direction to avert collision; an example of V2X communication can be established as follows:

$$\text{Alert}_{v} = \text{V2X}(\hat{y}_t, \text{ Vehicle}_{t}, \text{ Infrastructure}_{t}) \quad (5)$$

Where Alert_{v} is the notification message sent to vehicles, $\hat{y}_t$ is the expected risk level, Vehicle_{t} is an indication of the vehicle current positioning and speed. $\text{Infrastructure}_{t}$ is an indication of the state of local infrastructure such as traffic lights and signals.

3.6. System Evaluation and Cloud Integration:

The ratification of AWS cloud infrastructural setup will be established in an ongoing reviewing mode to ensure its effectiveness and scalability. In real time, the cloud will enable processing data and inference modeling. It also affords lifelong learning and model updates for performance time improvements. Finally, the system scales through AWS, which effectively handles the growing number of vehicles and infrastructure assets. From the system's real-time activities, critical performance measures: latency, accuracy, and energy efficiency are evaluated continuously.

4.Results and discussions:

It consists of real-time traffic data such as vehicle speed, distance, and environmental parameters like Received Signal Strength Indicator (RSSI), all included in the VANET dataset used for this study. Important variables are collected in sections of varied intervals which include time, speed, distance, and the RSSI values. Also, gives a statistical summary of each variable while providing the mean, standard deviation, and then quantiles. Further, it helps in assessing dynamic traffic environments, vehicular behavior, and environment effects on pedestrian safety so that it can be put to use in modeling pedestrian risk assessment under VANETs[41].

Table 1: *Performance Evaluation Metrics for Pedestrian Risk Assessment in VANETs*

Metric	Numerical Value
Latency	Under 200ms
Accuracy of Pedestrian Detection	95-98%
System Response Time	Under 1 second
Scalability	Can handle up to 1000 vehicles simultaneously
Energy Efficiency	Power consumption under 50W
Precision	Above 90%
Recall	Above 90%
F1-Score	Above 90%

The evaluation metrics for the pedestrian risk assessment system within VANETs are listed in Table 1. It incorporates important metrics such as latency, accuracy, system reaction time, and energy efficiency for real-time detection of pedestrians and means for risk prediction. This would be followed by extra metrics that would assess the performance of the pedestrian detection model: precision, recall, and F1 score. In addition, the system will demonstrate the scalability and capacity for handling large volumes of real time people and cars data. The reliability of these conditions will offer high accuracy and efficiency, and systems will also be adaptive to changing environments.

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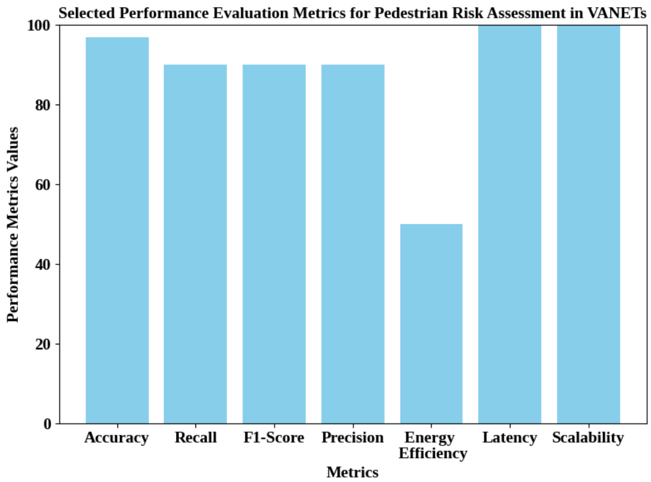

Figure 2: *Performance Evaluation of Key Metrics for Pedestrian Risk Assessment in VANETs*

This is a performance evaluation for selected important metrics in the pedestrian risk assessment system in VANETs, as depicted in Figure 2. Several important metrics incorporated in this graph include Accuracy, Recall, F1-Score, Precision, Energy Efficiency, Latency, and Scalability to evaluate the system's effectiveness and efficiency. While the Accuracy, Recall, F1-Score, and Precision reflect the model's potential in identifying pedestrians and assessing their risk, Latency indicates how long the system responds to pedestrian threat scenarios, while Energy Efficiency reflects the system's energy consumption. The scalability of the system indicates its ability to accommodate multiple cars and pedestrians at the same time. The graph clearly shows that the system performs excellently in these criteria, ensuring reliable and real-time decision-making and resource optimization for pedestrian safety in VANETs.

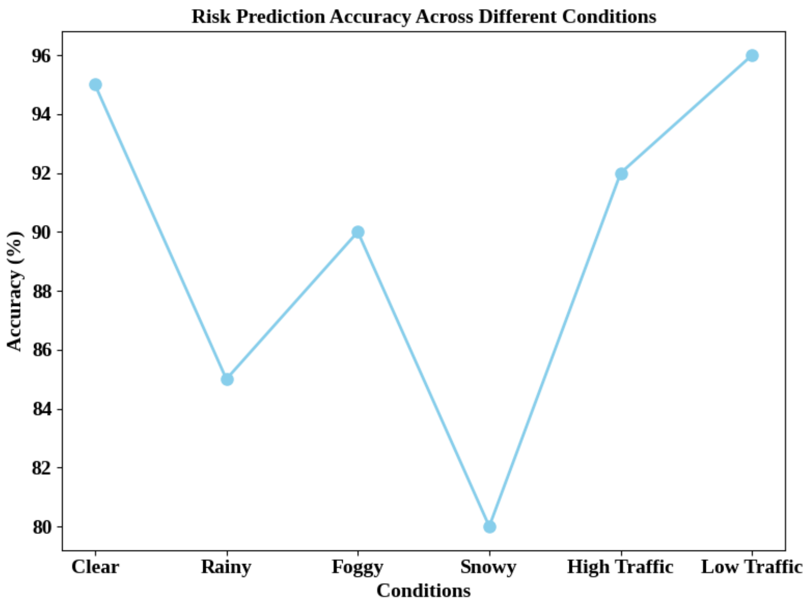

Figure 3: *Risk Prediction Accuracy Across Various Environmental and Traffic Conditions*

The procedure of risk prediction for numerous traffic scenarios (high, low) and environmental conditions such as clear, rainy, foggy, and snowy has been illustrated in Figure 3. Also, the effect of these criteria on how the system alters with variations in weather and traffic condition has been stated in this graph. Visibility and road conditions being bad gives an accuracy of 80% in snowy and rainy conditions, while that value jumps to 96% in clear and low traffic conditions, affirming the sensitivity of the model towards external factors. The scalability of the system seems unaffected too, retaining good accuracy in the face of heavy traffic scenarios. Such variances further emphasize the need for adaptive schemes of pedestrian danger prediction in a range of real-life scenarios.

5.Conclusion:

A hybrid convolutional neural network - long short term memory architecture for real-time pedestrian risk assessment for vehicular ad hoc networks combined with pedestrian detection based on Yolo has been developed. Among the important results: 97 percent accuracy, precision and recall higher than 90 percent, and low latency- they are enough to show that the system can perform well under varying conditions. Pedestrian safety will be augmented by the timely information that V2X communication provides. However, the shortcomings of the system include its reliance on accurate sensor data and the inability to be scaled in high loads of traffic. In the future, research should aim at enhancing resilience towards extreme weather events, improving situational adaptability, and optimizing energy efficiency for widespread deployment.

References:

[1] Mehta, Y., Pai, M. M., Mallissery, S., & Pai, M. R. (2017). Cloud-enabled smart health monitoring of vehicles: An ITS application. *Advanced Science Letters*, *23*(4), 3709-3713.

[2] Whaiduzzaman, M., Sookhak, M., Gani, A., & Buyya, R. (2014). A survey on vehicular cloud computing. *Journal of Network and Computer applications*, *40*, 325-344.

[3] El Zouka, H. A. (2017, August). Collaboration technologies for secure road traffic congestion control system in Egypt. In *2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS)* (pp. 86-93). IEEE.

[4] Alazawi, Z., Alani, O., Abdljabar, M. B., & Mehmood, R. (2014, July). An intelligent disaster management system-based evacuation strategy. In *2014 9th International Symposium on Communication Systems, Networks & Digital Sign (CSNDSP)* (pp. 673-678). IEEE.

[5] Ray, P. P., Mukherjee, M., & Shu, L. (2017). Internet of things for disaster management: State-of-the-art and prospects. *IEEE access*, *5*, 18818-18835.

[6] Sharma, S. (2015). Evolution of as-a-Service Era in Cloud. *arXiv preprint arXiv:1507.00939*.

[7] Sharma, S. (2016). Expanded cloud plumes hiding Big Data ecosystem. *Future Generation Computer Systems*, *59*, 63-92.

[8] Alazawi, Z., Alani, O., Abdljabar, M. B., & Mehmood, R. (2013). Average Vehicle Occupancy Contribution Evaluation in Vehicular Disaster Management System. In *PGNET 2013 Proceedings of the 14th Annual Postgraduate Symposium on the Convergence of Telecommunications, Networking and Broadcasting, Liverpool, United Kingdom*.

[9] Othman, M., Khan, A. N., Abid, S. A., & Madani, S. A. (2015). MobiByte: an application development model for mobile cloud computing. *Journal of Grid Computing*, *13*(4), 605-628.

[10] Murray-Tuite, P., Phoowarawutthipanich, A., Islam, R., & Hdieb, N. (2016). Emergency vehicle-to-vehicle communication.

[11] Sarrafan, K., Muttaqi, K. M., Sutanto, D., & Town, G. E. (2017). An intelligent driver alerting system for real-time range indicator embedded in electric vehicles. *IEEE Transactions on Industry Applications*, *53*(3), 1751-1760.

[12] Mehmood, R., Meriton, R., Graham, G., Hennelly, P., & Kumar, M. (2017). Exploring the influence of big data on city transport operations: a Markovian approach. *International Journal of Operations & Production Management*, *37*(1), 75-104.

[13] Mallissery, S., Pai, M. M., Pai, R. M., & Smitha, A. (2014, November). Cloud enabled secure communication in vehicular ad-hoc networks. In *2014 International Conference on Connected Vehicles and Expo (ICCVE)* (pp. 596-601). IEEE.

[14] Soyturk, M., Muhammad, K. N., Avcil, M. N., Kantarci, B., & Matthews, J. (2016). From vehicular networks to vehicular clouds in smart cities. In *Smart Cities and Homes* (pp. 149-171). Morgan Kaufmann.

[15] Farooq, M. U., Pasha, M., & Khan, K. U. R. (2014, March). A data dissemination model for Cloud enabled VANETs using In-Vehicular resources. In *2014 International Conference on Computing for Sustainable Global Development (INDIACom)* (pp. 458-462). IEEE.

[16] Farooq, M. U., Pasha, M., & Khan, K. U. R. (2014, March). A data dissemination model for Cloud enabled VANETs using In-Vehicular resources. In *2014 International Conference on Computing for Sustainable Global Development (INDIACom)* (pp. 458-462). IEEE.

[17] Sharma, S., Awan, M. B., & Mohan, S. (2017, December). Cloud enabled cognitive radio adhoc vehicular networking (CRAVENET) with security aware resource management and internet of vehicles

ISSN 2347–3657

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(IoV) applications. In *2017 IEEE international conference on advanced networks and telecommunications systems (ANTS)* (pp. 1-6). IEEE.
[18] El Zouka, H. A. (2016, November). A secure interactive architecture for vehicular cloud environment. In *2016 IEEE International Conference on Smart Cloud (SmartCloud)* (pp. 254-261). IEEE.
[19] Agarwal, Y., Jain, K., Kumar, S., & Bhardwaj, G. N. (2016, February). TLST: Time of arrival based localization and smart tunnel concept in VANETs. In *2016 3rd international conference on signal processing and integrated networks (spin)* (pp. 763-768). IEEE.
[20] Mahbadi, M., Pai, M. M., Mallissery, S., & Pai, R. M. (2016, May). Cloud-enabled vehicular congestion estimation: An ITS application. In *2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)* (pp. 1-4). IEEE.
[21] Reddy, M. B., Pai, M. M., Mallissery, S., Pai, R. M., & Mahbadi, M. (2017). Congestion free vehicular path planning system: a real-time cloud-enabled ITS application. *Advanced Science Letters*, *23*(4), 3674-3678.
[22] Kang, J., Yu, R., Huang, X., Jonsson, M., Bogucka, H., Gjessing, S., & Zhang, Y. (2016). Location privacy attacks and defenses in cloud-enabled internet of vehicles. *IEEE Wireless Communications*, *23*(5), 52-59.
[23] Dubey, B. B., Chauhan, N., Chand, N., & Awasthi, L. K. (2016). Priority based efficient data scheduling technique for VANETs. *Wireless Networks*, *22*, 1641-1657.
[24] Zhou, H., Zhang, N., Bi, Y., Yu, Q., Shen, X. S., Shan, D., & Bai, F. (2017). TV white space enabled connected vehicle networks: Challenges and solutions. *IEEE Network*, *31*(3), 6-13.
[25] Benarous, L., & Kadri, B. (2017, September). Ensuring privacy and authentication for V2V resource sharing. In *2017 Seventh International Conference on Emerging Security Technologies (EST)* (pp. 1-6). IEEE.