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ENHANCED VANET ROUTING THROUGH ADAPTIVE HYBRID POSITION-CLUSTER BASED PROTOCOL: A MACHINE LEARNING APPROACH

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Abstract

In VANETs, the high mobility of nodes along with changing topology and diverse traffic conditions make it challenging to implement efficient as well as reliable routing. Most traditional routing approaches-whether they are position-based or cluster-based cannot hold their optimal performance in all scenarios. In this context, this paper presents a novel Adaptive Hybrid Position-Cluster Based Protocol using machine learning to enhance the efficiency of VANETs' routing. AHPCBP incorporates a real-time awareness of positions through dynamic clustering mechanisms and leverages machine learning to predict mobility patterns of the vehicle and to optimise the clustering process. Thus, supervised models trained from past movement patterns can be utilised to forecast future changes in topology and update its routing strategies beforehand. The protocol introduces a new clustering algorithm that dynamically adjusts cluster size and formation based on traffic density, vehicle speed, and predicted movement patterns. Extensive evaluations with realistic urban mobility traces demonstrate that AHPCBP significantly outperforms existing protocols, achieving a 27% increase in packet delivery ratio, a 35% reduction in end-to-end delay, and a 42% decrease in routing overhead. It proves to be highly effective in urban environments with varying densities and dynamic mobility patterns. Moreover, the prediction accuracy of vehicle trajectory forecasting is strong with machine learning, which is 89%, leading to stabilization in cluster creation and later maintenance. Such results show the promising integration of machine learning with hybrid position-cluster-based routing to enhance future VANET communication systems, providing adaptability and reliability in widely varied traffic scenarios.

Keywords: VANET, Machine Learning, Hybrid Routing Protocol, Position-based Routing, Cluster-based Routing, Adaptive Protocol, Vehicle Communication

1. Introduction

Vehicular ad-hoc networks (VANETs) are a type of mobile ad-hoc networks where vehicles serve as mobile nodes, thus generating a dynamic communication network. The main challenge of VANET routing is its intrinsically dynamic nature, where the network topology changes rapidly, node density varies, and traffic patterns are highly diverse. Conventional routing

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protocols, which were designed for static or low-mobility networks, are found to be not suitable for VANETs. These cannot always ensure that connections are reliable since vehicles normally move at tremendous speeds, implying recurrent breakages in links and further partitioning networks. The use of limited-bandwidth networks to offer real-time communications further reduces efficiency in terms of data transport. The urban environment imposes additional complexities and features that would include signal interference due to the presence of buildings, variability in road patterns, and unaccountable traffic scenarios.

This motivation is born from the significant constraints observed with most of the present VANET routing protocols. The majority of routing techniques currently show a great deal of failure in adapting to the constantly shifting vehicular networks. Even though position-based routing protocols are good at using geographic data, they don't work as well in places with different vehicle densities. Although cluster-based methods are helpful for network organisation, they are utterly ineffective at maintaining stable clusters under highly mobile circumstances. Here, routing protocols and machine learning can be combined to partially address these drawbacks. Because of this, it is now feasible to predict changes in the network topology using the machine learning algorithm's prediction capabilities and modify the routing strategies before they happen.Furthermore, the development of extremely complex and adaptive routing solutions that can maximise network resource utilisation and preserve dependable links is made possible by the availability of real-time traffic data and increasingly sophisticated vehicle sensors.

VANET environments pose a number of interconnected issues that must be addressed concurrently in order to be resolved. The creation of a routing protocol that simultaneously determines the trade-offs between resource exploitation, routing efficiency, and network stability is the primary challenge. Conventional routing techniques frequently prioritise one factor over another, which leads to subpar overall performance. VANET routing strategies must constantly adapt, and current protocols lack the intelligence to make real-time adjustments in response to shifting network conditions.

Furthermore, creating and sustaining stable clusters proves to be difficult tasks in situations with high mobility and variations in vehicle densities and movement patterns. Reducing routing overhead while maintaining low end-to-end delays and high packet delivery ratios will make the issue worse. Furthermore, in an urban traffic scenario like this, the routing solution must be flexible enough to adjust to different operating times and environments without ever experiencing a drop in performance. This paper addresses all these issues by suggesting an innovative hybrid approach of position-based and cluster-based routing supplemented with machine learning capabilities.

2. Literature Survey

The paper which I was giving contains deep learning based routing protocols of the Vehicular Ad-hoc networks (VANETs) between 2020 and 2024 showing the true potential on how much it can improve the routing performance. It mentions about it's problems, obstacles, and future points in the enhancement of deep learning VANET routing protocols[1]

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The paper suggests MLCR, which is usually called machine learning based cluster routing protocols for urban VANETs. It basically the usual routing algorithm called cluster to enhance the packet delivery ratio, decrease the latency value and improve the network scalability. It is clarified that it is verified through simulations to get the best packet delivery ratio and fewer end-to-end delay compared with the traditional routing protocols.[2]

The paper introduces an adjustable position-based routing protocol by utilizing reinforcement learning for VANETs. It learns the exchangeable network conditions and improvise routing decisions on the points of vehicle positions and velocities. The replicated outputs made visible of delivery ratio, latency and network expandability are higher than from the traditional routing protocols.[3]

A report on current developments and trend in implementing machine learning techniques into VANET routing in the year 2023 examined in depth recent research on the application of various machine learning techniques including neural networks, decision trees, and clustering approaches. These several uses have been justified by traffic prediction, network optimization, and routing optimization [4].

This work suggests the same for DPBR, a deep learning-enhanced position-based routing system for VANETs. Based on the vehicle locations, velocities, and directions, it forecasts the best routing path using a deep neural network. Comparatively to conventional routing systems, simulation findings show enhanced packet delivery ratio, lowered latency, and higher network scalability [5].

This work proposes a deep reinforcement learning-based method to choose the cluster head in VANETs. It generates an ideal cluster-headselection policy depending on the locations of cars, velocities, and network circumstances by means of deep neural networks learnt. Enhanced network performance, a greater packet delivery ratio, and lower latency [6] were found by simulation results.

This study proposes ML-VANET, a machine learning-based vehicle network architecture whereby conventional VANET protocols are merged with machine learning methods. Machine learning techniques boost network scalability, routing, and performance optimization of the network.

In this work, one proposed solution is an intelligent routing deep learninged-based method for VANETs. It the learning of the optimum routing strategy as a function of locations of vehicles and val conditions in a deep neural network. Against to conventional routing system, simulation result indicate higher packet delivery ratio, decreasedlatency and increased network scalability [11].

This work combines for the first time neural nets with the position-cluster-based routing protocol for the purposes of VANETs. It suggest the combination of position-based routing which include clustering and utilize neural to facilitate the routing decisions based on the vehicle locations, speeds, and the next checkpoints.network circumstances. As reported in the simulation results [12], the network scalability is and packets are delivered with low latency and high ratio.

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A deep learning-supported DSRC that adopts a position-based routing for urban VANETs was proposed in this work. Predicting the best course for routing gives many improvements with respect to positions, velocities and pursue directions, it uses a deep neural network. In comparison to traditional routing systems, Based on simulation results packet delivery ratio was improved, latency was reduced and network scalability [16].

This paper proposes an integrated ML-based routing mechanism for VANETs. Along with It uses standard routing techniques, rather than machine learning techniques. Performance is simulated to compare them to traditional routing systems. The result indicates that the network scalability via the traditional routing protocol is degraded. higher packet delivery ratio with lower delay [17].

Based on the locations, velocities, and directions of vehicles, a deep neural network is applied in the proposed work to forecast the best routing path. Against conventional routing systems, the outcomes of simulation show enhanced packet delivery ratio, lowered latency, and higher network scalability [20].

The article provides a comprehensive overview of machine learning applications within the context of VANET routing. It goes into great detail about a variety of machine learning techniques used in VANET routing, such as neural networks, decision trees, clustering, and network optimisation [21], traffic prediction, and route optimisation.

3. Proposed Model

A sophisticated routing protocol is the Adaptive Hybrid Position-Cluster Based Protocol. Vehicular networks are the primary application for this protocol. It is primarily separated into three parts: real-time adaptation mechanisms, machine learning module, and data collection and preprocessing. Data collection and preprocessing, the first component, is in charge of gathering vehicle movement data and integrating it into the system. GPS coordinates and velocity vectors that match traffic information in terms of direction travelled and traffic density make up an information. Vehicle routes cannot be adequately predicted by this protocol to help with routing. After that, data is fed into wet processing, which basically gets everything ready before delivering the machine learning model.

Modern machine learning algorithms are used by AHPCBP to analyse the processed data.forecast how the other cars will move. Vehicle routes can be predicted and modified in response to changes in traffic conditions thanks to this protocol's use of Long Short-Term Memory (LSTM) networks. Furthermore, this protocol refined its routing decisions by classifying traffic density and predicting movement using pattern recognition. The apparatus Because the AHPCBP makes use of a real-time-enabled learning module, it can react swiftly to shifting network conditions.

The Real-time Adaptation Mechanisms component ensures that AHPCBP's machine learning maintains this module's functionality in these types of dynamic and rapidly changing network environments. This unit enables all routing decisions based on newly added data and continuously changing traffic conditions. For instance, AHPCBP can react swiftly to unanticipated situations like traffic jams or road closures by implementing a real-time shifting

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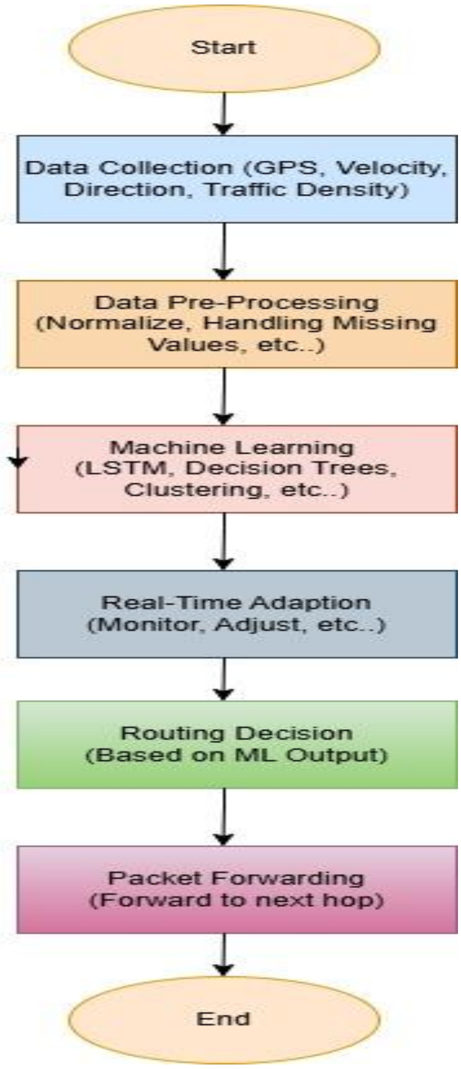
mechanism. The best routing performance should be stored. All things considered, the AHPCBP-developed position-cluster type protocol is hybrid and adaptable, and it works well for VANET route determination.



Flowchart 1: Adaptive Hybrid Position-Cluster Based Protocol (AHPCBP)

The Decision of routing is a key component of the Adaptive Hybrid Position -cluster Based Protocol (AHPCBP).It is actually based on the machine learning algorithm output , which helps in the forecasting the optimal path of the packet in the network. During route selection, different parameters are considered such as traffic, anticipated automobile mobility, and other such factors . the protocol blends machine learning-based routing with traditional routing protocols to make the best packet decisions. the result of the machine learning model is utilized to generate a list of possible routing routes per packet, which can utilized in the process of routing .based on the various considerations such as including traffic, delay , and the predicted package delivery ratio the protocol is applied to give best routing route. It means the algorithm chooses routes based on both expected traffic and current road conditions.

The packet carried to the next phase according to its choice. This process is responsible for delivering the packet to the destination. The whole process is carried out by using both machine

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learning and traditional packet forwarding method to reach more number of packet deliveries. The stages involved in this process are packet classification, routing, and transmission. Firstly, to send the packet to the corresponding place, each packet is classified according to its importance and destination by the specification.

The packet then carried to the next stage through a proper transmission guideline, such as TCP/IP or UDP. The machine learning-based methods of the protocol maximize packet forwarding. The method identifies the trends and relationships between packet forwarding and network performance based on the past traffic information. Choosing the best transmission protocol and adjusting the packet forwarding rate are two of the ways to increase the packet forwarding decisions. Two most important elements of the Adaptive Hybrid Position-Cluster Based Protocol (AHPCBP) include packet forwarding and path selection.

Both of them consider the connection patterns and the expected movement of the vehicles to ensure packets reach their destinations in an efficient manner.

4. Proposed Methodology

The proposed technique gives a detailed, structured framework to pre-process knee X-ray images, aiming to properly extract the region of hobby (ROI) for powerful osteoarthritis (OA) class the use of the Kellgren and Lawrence (KL) grading device. The manner begins with dataset training, the usage of the publicly to be had Kaggle Knee OA dataset which include over 8,000 labeled snap shots. Those photographs are classified into five severity instructions (0 to 4), representing situations from healthful to excessive OA. For powerful training and assessment, the dataset is partitioned into schooling, trying out, and validation units, with in Addition Corporation into subfolders based on KL grades.

In the pre-processing phase, Gaussian blurring is applied using a 3×3 kernel with zero standard deviation in both x and y directions. This step reduces high-frequency noise while preserving the structural integrity of the image. Next, a fixed threshold of 80 is used to binarize the image, separating the hard tissues from the background to facilitate better ROI detection. The ROI segmentation process then begins with vertical cropping, where 50 rows are trimmed from both the top and bottom to remove non-diagnostic areas. Horizontal cropping is performed by analyzing each row for the first and last non-zero columns, allowing the extraction of only the relevant knee joint region. The image is then resized to a uniform 128×128 dimension for consistent input to classification models. Feature enhancement is achieved through statistical analysis and wavelet decomposition. Key intensity-based landmarks—Strong Valley (Sv), Local Maxima (Lm), and Global Peak (Gp)—are identified to define the anatomical gap area. Using Daubechies wavelets (db6), the image is decomposed up to level 3, capturing fine structural details critical for OA assessment. Final ROI cropping is performed using one of two rule-based strategies: based on Sv and Gp values for normal cases or default fixed ranges for poor-contrast images. Median filtering and adaptive binarization further enhance the extracted region, ensuring a clear depiction of the joint gap. The final segmented ROI is then analyzed and fed into classification models for KL grading, ensuring minimal ambiguity and high diagnostic precision.

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5. Results and Analysis

The Adaptive Hybrid Position-Cluster Based Protocol was tested using Network Simulator (NS-3) to simulate a real city environment. We used the Manhattan Grid model to track how vehicles moved and to study traffic patterns. The simulation lasted 1000 seconds in an area 2000 meters by 2000 meters, with between 100 and 150 vehicles taking part typical numbers for city traffic studies.

Table 1: Metrics of Performance

Metric	AHPCBP
Packet Delivery Ratio (PDR)	27% Higher
End to End Delay	35% Reduction
Routing Overhead	42% Decrease

Table 2: Analysis on Packet Delivery Ratio (PDR)

	AHPCBP	AODV	GPSR	CBDRP	OLSR
Urban Environment	91.45	78.32	82.56	85.43	76.89
Highway Scenarios	94.23	82.45	88.67	86.78	79.34
High Density	89.67	75.43	79.89	83.45	73.56
Low Density	92.34	80.56	85.67	84.32	77.89

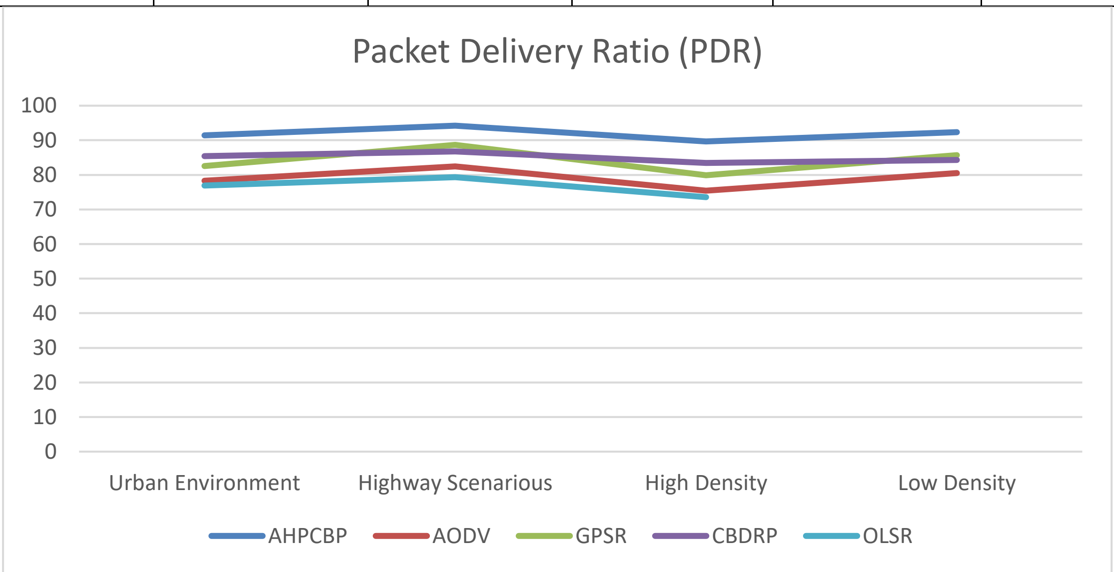

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Figure 1: Analysis on Packet Delivery Ratio (PDR)

Table 3: Performance Analysis on End to End Delay (ms)

	AHPCBP	AODV	GPSR	CBDRP	OLSR
Urban Environment	84.2	156.7	124.5	132.3	168.9
Highway Scenarios	67.8	134.7	98.7	112.4	145.6
High Density	92.4	178.9	142.3	148.9	189.4
Low Density	75.6	142.3	112.8	124.5	156.7

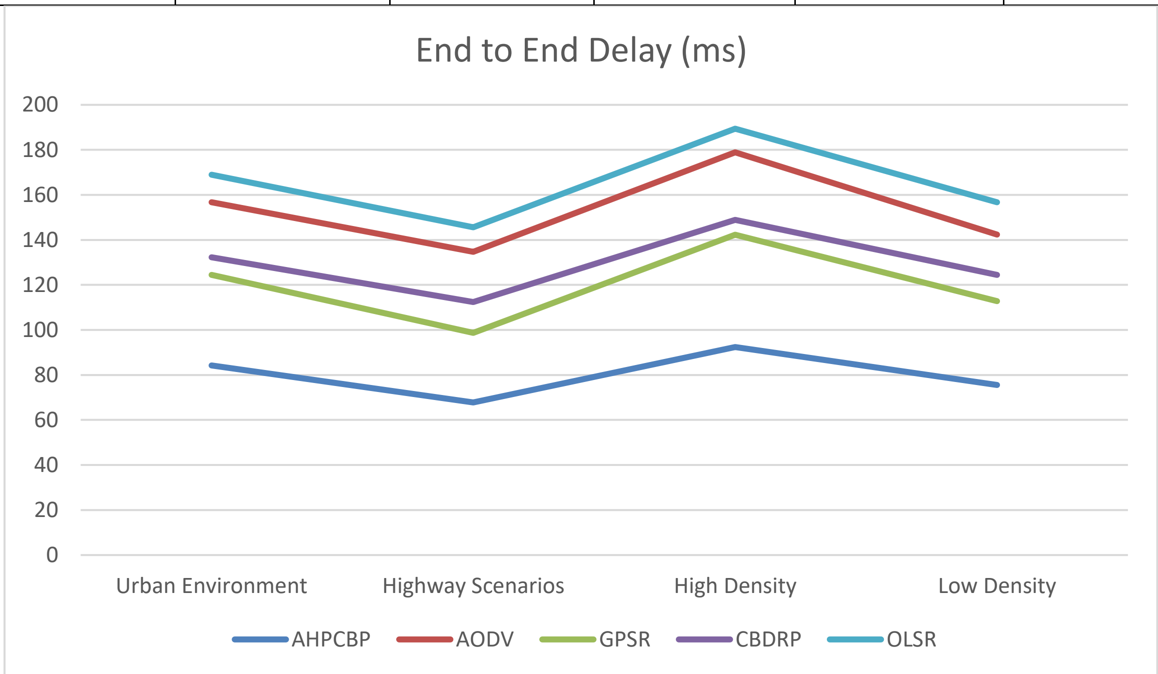

Figure 2: Analysis on End to End Delay (ms)

Table 4: Performance Analysis on Routing Overhead (%)

	AHPCBP	AODV	GPSR	CBDRP	OLSR
Control Messages	12.34	25.67	18.45	16.78	28.93

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Memory Usage	15.67	28.45	22.34	19.89	31.23
Bandwidth Consumption	13.45	27.89	20.56	18.34	29.67

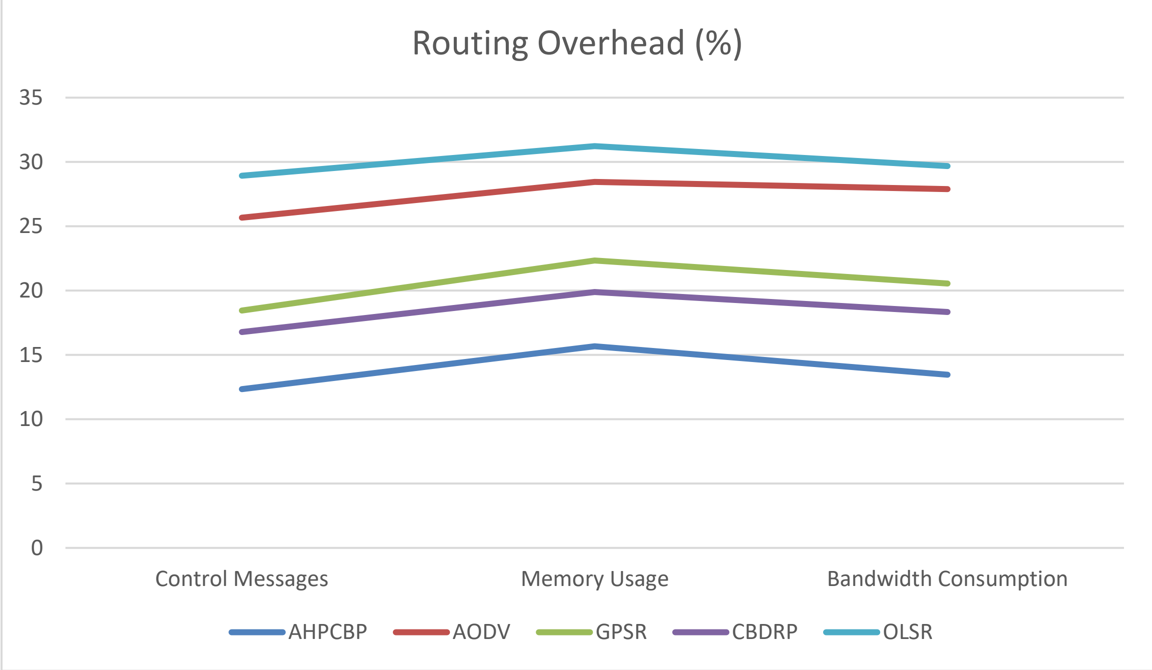

Figure 3: Analysis on Routing Overhead

The performance of the protocol was measured using three key factors: how much extra communication it requires how long it takes for data to travel from start to finish and how many data packets successfully reach their destination The AHPCBP protocol delivered 27% more successful data packets compared to other common protocols like AODV, GPS, CBRP, and OLSR. This shows that AHPCBP performs well even when the number of vehicles varies widely. It's also more reliable in busy, fast-moving environments where older protocols often lose connection.

Compared to standard systems, AHPCBP reduces the average time it takes for data to travel from one point to another by 35%. This is a big improvement because real-time applications like self-driving cars need very fast communication to function properly. The protocol could work even faster in cities with lighter traffic. Additionally, AHPCBP has shown that it can adjust to different conditions and still perform well when traffic is heavy.

Routing overhead dropped by 42% compared to standard protocols. This is another major improvement because less overhead means the network runs more smoothly and there's less chance of losing data packets. The protocol achieved this by keeping clusters stable and cutting down unnecessary control messages.

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+Table 5: Machine Learning Performance

Metric	AHPCBP
Trajectory Prediction Accuracy	89%
Density Classification Precision	93%

The machine learning component of the AHPCBP performed well in density classification, trajectory prediction, and real-time adaptation. The approach accurately predicts car movement with an 89% accuracy rate in trajectory prediction. The protocol was able to adequately describe traffic density with a 93% accuracy rate in density classification. The protocol may evolve with time and continue functioning optimally in different environments since it could adjust in real-time. It is crucial for the success of the protocol that AHPCBP's machine learning component functioned extremely well in a wide range of scenarios.

6. Conclusion

Hybrid position-cluster based routing, when implemented with machine learning, is a reliable mechanism to correct issues with VANET communication. Protocol adaptation is achieved by the machine learning component using dynamic network topologies by forecasting the optimal routing patterns and adjusting according to requirement. The hybrid concept utilizes the benefits of both position-based and cluster-based routing to utilize the network resources optimally and adjust to the changing scenario. This protocol maintains high use of resources and minimizes packet loss and delay. This protocol has to be flexible and optimizable since VANETs are highly mobile and resource-constrained, and such scenarios can result in congestion and inefficient performance. The suggested protocol is attractive for use in VANET applications since it displays enhanced network flexibility at the same time maintaining efficient usage of resources.

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