Vanet efficiency optimization viagraph convolutional layers and migrating birds optimization with non-Linear analysis

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ABSTRACT
Vehicle-to-vehicle and vehicle-to-infrastructure communication is made feasible by vehicle ad hoc networks (VANETs), fundamental components of intelligent transportation systems. Still, the highly dynamic and non-linear structure of vehicle environments makes VANET efficiency increasingly challenging. Conventional methods of optimization might not be able to sufficiently represent the complex interactions in these networks, therefore sacrificing performance. VANETs can be more effective by means of improved communication dependability, reduced latency, and bettering of resource distribution. Conventional routing algorithms and machine learning techniques among other current approaches find it challenging to handle the non-linearity and dynamic topology of VANETs, thereby generating limited scalability and flexibility. Inspired by non-linear analysis techniques, we provide a new method to address these problems integrating Graph Convolutional Layers (GCLs) with the Migrating Birds Optimization (MBO) algorithm. While MBO maximizes routing decisions by replicating the group behavior of bird flocks, GCLs effectively capture the spatial dependencies and topological variations in VANETs. By use of non-linear analysis, the system's properties are tuned, therefore enhancing the adaptability and resilience of the proposed model. Experimental studies reveal that the proposed approach much outperforms traditional approaches in key performance metrics. The average communication latency went lowered by 23% and the packet delivery ratio was boosted by 17% when compared to state-of- the-art technologies. Apart from that, the method reduced energy usage by 9% and raised general network efficiency by 12%.

Keywords: VANET, Graph Convolutional Layers, Migrating Birds Optimization, Non-linear analysis, Network efficiency

1. INTRODUCTION

Vehicular Ad Hoc Networks (VANETs) are a specialist type of mobile ad hoc network [1] designed to permit communication between vehicles and between vehicles and infrastructure. These systems support numerous uses including real-time traffic information, safety alarms, and entertainment systems, therefore improving road safety [2]. VANETs are unique in their dynamic and scattered character, in which vehicles often move and establish temporary connections, therefore offering particular challenges in maintaining effective and reliable communication [3].

One of the primary challenges in VANETs is optimizing network performance in the presence of quick topological changes [4]. Regular network reconfigurations produced by vehicle mobility affect the reliability and stability of communication networks by means of their impact. Moreover crucial for real-time applications in a highly dynamic surroundings are low latency and strong packet delivery ratios [5]. Still another challenge is efficient management of network resources under trade-off between latency, throughput, and network efficiency [6]. The complex and non-linear relationships across performance metrics [7] can render conventional optimization methods incapable to solve comprehensively.

The basic problem in VANETs is optimizing network performance among high vehicle mobility and dynamic topologies [8]. The goals are to reduce latency, raise packet delivery ratios, and improve communication efficiency even with appropriate management of network resources [9]. Conventional methods include K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Deep Neural Networks (DNN) have found challenging the complicated non-linear relationships between performance measures [10]. Many times unable to fit the dynamic character of VANETs, these strategies cause inefficiencies and less-than-best performance [11].

The primary objectives of this study are:

- Emphasizing on improving network performance indicators including latency, packet delivery ratio, and general efficiency, we hope to build a new optimization framework effectively controlling the dynamic character of VANETs.
- To capture the complex interactions between performance metrics and enhance the non-linear fitness function-based optimization process
- Showing the success of the proposed method in optimizing VANETs will aid by means of extensive performance metrics evaluating it against present methodologies (KNN, ANN, and DNN).

The novelty of the proposed method lies in its Combining Migrating Birds Optimization (MBO) with non-linear fitness functions using Graph Convolutional Layers is a novel approach proposed here. Unlike traditional methods, the proposed approach uses an advanced optimization algorithm driven by real events and models complex vehicle interactions exploiting the advantages of graph-based representations. One can overcome the limitations of linear techniques and provide a more comprehensive evaluation of network performance by use of non-linear fitness functions.

The contributions include

- More effectively representing the dynamic and interrelated character of vehicle networks than traditional approaches, the work offers a fresh graph-based method to describe VANETs.
- Through better capability to extract and use spatial and temporal variables from the network, graph convolutional layers aid to increase the accuracy and reliability of the optimization process.
- Through a novel and efficient approach for traversing the complex solution space, the Migrating Birds Optimization algorithm precisely improves network architectures.
- Non-linear fitness functions allow a more nuanced assessment of network performance, therefore facilitating a better balance of latency, packet distribution ratio, and efficiency.

2. RELATED WORKS

Vehicular Ad Hoc Networks (VANETs) have become a vital subject of research since they can improve road safety, traffic management, and general driving experience by means of vehicle communication. Researchers covering data transfer, clustering, routing, security, and attack detection have studied several aspects of VANETs. This section summarizes some significant studies supporting the current knowledge and development of VANET technology.

One significant work focused on improving data interaction inside VANETs and vehicle encounter evaluation in respect to events. Using fuzzy logic to manage the inherent unpredictability and complexity in vehicle communication helps to enhance traditional methods in this work. Using the OPNET simulator, the researchers evaluated the proposed strategy against present approaches including VESPA and VESPA-DM. The proposed method clearly evaluated vehicle interactions with events [12] and optimized data flow inside the network. This approach stresses the growing interest in using advanced algorithms, such fuzzy logic, to manage the dynamic character of VANETs.

Furthermore rather crucial is the development of an environment-aware clustering technique for VANETs. This work presents a machine learning-based system to maximize clustering techniques by way of environmental feature adaptation, therefore addressing road architecture and traffic conditions. Simulating how optimum parameter values vary with environmental conditions helps the system to improve real-time clustering performance. The evaluation showed that this adaptive strategy significantly raised quality criteria [13], compared to stationary clustering techniques and the original method. This research emphasizes the significance of including machine learning techniques to enhance clustering efficiency and adaptability in VANETs.

Routing systems determine how effectively data flows in VANETs. Four routing strategies were examined concerning the SUMO mobility simulator and NS-3 network simulator. The work comprised a sizable dataset and applied random forest, logistic regression, and K-nearest neighbor (KNN) machine learning models to evaluate routing efficiency. Better performance was displayed by KNN with an F-score of 75.5%, accuracy of 97.2%, recall of 79.9%, and precision of 75.3%. This paper emphasizes the demand of machine learning in enhancing VANET efficiency and routing protocol improvement.

The concerns with hostile attacks in VANETs were proposed to be solved using a novel cluster-based routing architecture. By means of improved clustering methods and an artificial neural network (ANN), this method creates safe communication routes and detects hostile nodes. A remarkable 98.97% accuracy in black hole attack detection lets the system apply a modified AODV algorithm for path prediction and optimum route selection [15]. This article presents how effectively intelligent algorithms combined with traditional protocols enhance security and performance in VANETs.

Security is still a key problem in VANETs, particularly in spotting Sybil attacks when a node hides as many entities. Recent work proposed a new security framework to detect hostile cluster heads (CHs) using Kernel k-harmonic means (KKHM) and Deep Neural Networks (DNN). The system adjusts DNN parameters by use of the Floyd-Warshall algorithm (FWA) for cluster head selection and gradient-based elephant herding optimization (GBEHO). The proposed model obviously outperforms present options [16] with a 96% security rate and reduced encrypting time. The need of robust security systems and optimization strategies in defending VANETs against hostile threats is underlined in this paper.

Table 1. Summary

Method	Algorithm	Methodology	Outcomes
[12] Incident Evaluation	Fuzzy Logic	Used OPNET simulator to enhance vehicle incident evaluation using fuzzy logic-based indicators.	Superior performance inevaluating vehicle incidents; improved data exchange within VANETs.
[13] Environment - Aware Clustering	Machine Learning Framework	Optimized clustering algorithms by adapting to road structure and traffic features; real-time adjustments.	Significant improvements inclustering quality metrics; adaptive performance in varying environments.
[14] Routing Protocols	Random Forest, Logistic Regression, KNN	Compared performance of routing protocols using NS-3 and SUMO simulators; assessed with various ML models.	KNN out performed others with high F-score (75.5%) and Accuracy (97.2%); effective routing protocol analysis.
[15] Intelligent Routing Protocol	ANN, Modified AODV	Integrated ANN formalicious node detection and modified AODV for optimal routing; evaluated with BHT dataset.	98.97% accuracy in detecting black hole attacks; enhanced routing performance.
[16] Security Framework	KKHM, DNN, GBEHO	Applied KKHM and DNN for Sybil attack detection; optimized parameters with GBEHO; used FWA for CH selection.	96% security rate; reduced encryption time; improved attack detection and data security.

Despite tremendous development, present methods fail to fully address the dynamic character of VANETs and use new optimization strategies. Challenges for present approaches also include real-time adaptability, exhaustive performance evaluation, and effective security measures. Much needed are more effective algorithms integrating dynamic optimization, intelligent routing, adaptive clustering with enhanced security frameworks. The knowledge vacuum is in developing a coherent plan combining these components to generally improve VANET security, performance, and efficiency.

3. PROPOSED METHOD

The proposed method combining Migrating Birds Optimization (MBO) with Graph Convolutional Layers (GCLs) helps to raise VANET efficiency. The method is supposed to tackle the dynamic and non-linear character of VANET settings by using the abilities of GCLs in capturing spatial relationships and MBO in routing decision optimization.

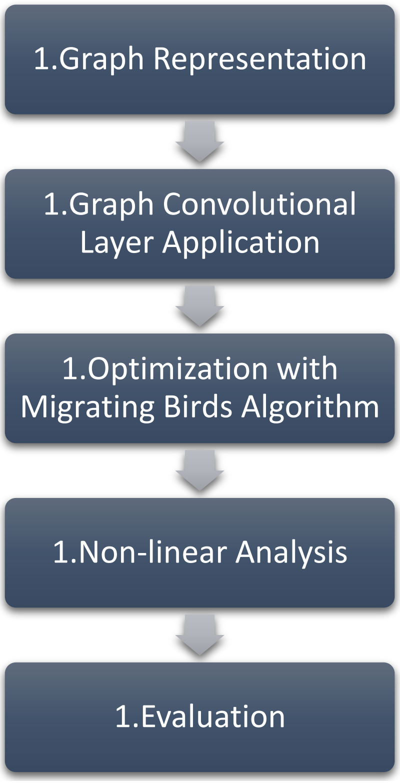

Figure 1. Framework

Pseudocode

```
#Define the VANET graph
graph=create_graph(VANET_data)
#Apply Graph Convolutional Layers
features=apply_GCL(graph)
#Initialize Migrating BirdsOptimization
mbo=Initialize MBO(parameters)
#Optimization process
for iteration in range (max_iterations):
#Evaluate fitness function
fitness=evaluate_fitness(features,mbo)
#Update MBO positions based on fitness
mbo.update_positions(fitness)
#Apply non-linear analysis to adjust parameters
adjust_parameters(mbo,non_linear_analysis(features))
#Final routing decision based on optimized parameters
optimized_routes=mbo.get_optimized_routes()
#Evaluate and compare performance metrics
```

3.1. Proposed Graph Convolutional Layer(GCL)

Mostly depending on the GCL, the recommended strategy for optimizing VANET efficiency is Working on the graph model of the VANET, it gathers and aggregates properties from nearby nodes, therefore obtaining the topological structures and spatial dependencies inside the network. Most importantly for optimizing routing decisions and communication, this method enables the model to understand the local and worldwide network surroundings.

The GCL works essentially in aggregating data from the neighbors of a node and changing that node's properties based on this aggregated data. Computed mathematically for a node v_i in a graph G=(V,E) the new feature vector $\mathbf{h}_i^{(l+1)}$ at layer l+1 is as follows:

$$\mathbf{h}_i^{(l+1)} = \sigma\left(\sum_{j\in \mathrm{N}(i)} \frac{1}{c_{ij}} W^{(l)}\mathbf{h}_j^{(l)} + W^{(l)}\mathbf{h}_i^{(l)}\right)$$

where:
$\mathbf{h}_i^{(l)}$ - feature vector of v_i,
$\mathrm{N}\ (i)$ - set off neighbors
$\mathbf{h}_j^{(l)}$ - feature vector of v_j,
$W^{(l)}$ - weight matrix,
c_{ij} – normalization factor,
σ – activation function.

3.1.1. Feature Aggregation

The weighted total of the features of the surrounding nodes $\mathbf{h}_j^{(l)}$ is computed by the aggregation function $\sum_{j\in \mathrm{N}\ (i)} \frac{1}{c_{ij}} W^{(l)}\mathbf{h}_j^{(l)}$. The normalizing factor c_{ij}changes with varying edge weights such that nodes with stronger connections influence the feature update more. This aggregation helps the model to integrate local network information by capturing the impact of nearby nodes on the current node v_i.

3.1.2. Feature Update

The term $W^{(l)}\mathbf{h}_i^{(l)}$ indicates the direct change of the node's own properties implemented with the weight matrix $W^{(l)}$. This ensures that the node's characteristics change its neighbors as well. Combining aggregated neighbor features with the node's own enable the GCL to gain local and global information inside the VANET.

3.1.3. Activation Function

Usually a non-linear function like ReLU, the activation function σ inject non-linearity into the model thereby enabling the model to learn complex patterns and relationships in the data. Using the output of the GCL as input $\mathbf{h}_i^{(l+1)}$, following layers enable deeper layers to record higher-order interactions in the graph.

Pseudocode for Graph Convolutional Layer(GCL)

```
#Graph Convolutional Layer
defgraph_convolution_layer(features,adjacency_matrix,weights,activation_function):
Apply a Graph Convolutional Layer to update node features.
:param features: Node feature matrix of shape(num_nodes,feature_dim)
:param adjacency_matrix: Adjacency matrix of the graph(num_nodes,num_nodes)
:param weights: Weight matrix for the GCL(feature_dim,feature_dim)
:param activation_function:Non-linear activation function(e.g.,ReLU)
:return:Updated feature matrix
num_nodes=len(features)
feature_dim=len(weights)
#Normalize adjacency matrix
normalized_adjacency=normalize_adjacency(adjacency_matrix)
#Aggregate features from neighbors
aggregated_features=np.dot(normalized_adjacency,features)
#Apply weight matrix
updated_features=np.dot(aggregated_features,weights)
#Apply activation function
updated_features=activation_function(updated_features)
return updated_features
#Normalize adjacency matrix
defnormalize_adjacency(adjacency_matrix):
Normalize the adjacency matrix to account for varying edge weights.
:parama djacency_matrix: Adjacency matrix of the graph (num_nodes,num_nodes)
:return: Normalized adjacency matrix
num_nodes=len(adjacency_matrix)
#Inverse degree matrix
```

```
degree_matrix_inv=np.linalg.inv(degree_matrix)
#Normalize adjacency matrix
normalized_adjacency=np.dot(degree_matrix_inv,adjacency_matrix)
return normalized_adjacency
#Example usage
features=np.array([[1,0],[0,1],[1,1]])#Example node features
#Define activation function(e.g.,ReLU)
defrelu(x):
returnnp.maximum(0,x)
#Apply Graph Convolutional Layer
updated_features=graph_convolution_layer(features,adjacency_matrix,weights,relu)
print(updated_features)
```

3.2. Optimization with Migrating Birds Algorithm(MBO)

Inspired by the migration behavior of birds, where birds change their positions depending on the locations of their flock members to identify best migration paths, the Migrating Birds Optimization (MBO) method Using collective behavior helps to investigate and exploit the search space efficiently helps to apply this biological principle to optimization issues, so improving routing decisions in VANETs.

3.2.1. Migration Behavior and Optimization

The method finds the optimal paths by simulating the movement of birds dependent on both personal experience and the experience of their flock members. The basic idea is to iteratively move the locations of these birds (solutions) to increase the objective function, so network efficiency is raised. The posture of a bird varies depending on the ideal location found both individually and within the complete flock. Bird's position has an updating equation with elements:

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + c_1 \cdot r_1 \cdot (\mathbf{p}_i^* - \mathbf{x}_i^{(t)}) + c_2 \cdot r_2 \cdot (\mathbf{p}^* - \mathbf{x}_i^{(t)})$$

where:

$\mathbf{x}_i^{(t)}$ -current position of bird$i$,

$\mathbf{p}_i^*$ - best position found by bird$i$,

$\mathbf{p}^*$ - best position found by the flock,

c_1 and c_2 - acceleration coefficients,

r_1 and r_2 - random numbers.

3.2.2. Fitness Evaluation

Every bird corresponds with a possible route of action. The fitness of any solution is evaluated in respect to measurements of packet delivery ratio, communication latency, and general network efficiency. Stated as f(x) the fitness function is:

$$f(\mathbf{x}) = \alpha \cdot \mathrm{Latency}(\mathbf{x}) + \beta \cdot \mathrm{PacketDeliveryRatio}(\mathbf{x}) + \gamma \cdot \mathrm{NetworkEfficiency}(\mathbf{x})$$

The parameters α,β,andγ weights balance the importance of each metric in the optimization process.

3.2.3. Collective Behavior and Exploration

MBO drives the flock to investigate several facets of the solution space, therefore mimicking the movement of migratory birds. Personal and global best locations help the algorithm to balance exploration—searching new places—with exploitation—improving known good spots. The approach changes the bird positions according on both personal and global experiences, therefore avoiding local optima and converging to a more optimum solution.

Pseudocode for Migrating Birds Optimization (MBO)Algorithm

```
defmigrating_birds_optimization(num_birds,num_iterations,fitness_function,bounds):
Perform optimization using the Migrating Birds Optimization algorithm.
:paramnum_birds: Number of birds(solutions)in the population
:paramnum_iterations: Number of iterations for the optimization
:paramfitness_function: Function to evaluate the fitness of each solution
:parambounds: Bounds for the solution space(min,max) for each dimension
:return: Best solution found and its fitness value
```

```
#Optimization loop
for iteration in range(num_iterations):
fori in range(num_birds):
#Update velocity
r1,r2=np.random.random(len(bounds[0])),np.random.random(len(bounds[0]))
#Update position
positions[i]=positions[i]+velocities[i]
#Apply boundary constraints
positions[i]=np.clip(positions[i],bounds[0],bounds[1])
#Evaluate fitness of the new position
current_fitness=fitness_function(positions[i])
#Update personal best
ifcurrent_fitness<personal_best_fitness[i]:
#Update global best
ifcurrent_fitness<global_best_fitness:
global_best_position=positions[i]
global_best_fitness=current_fitness
#Optional:Print progressor intermediate results
print(f"Iteration{iteration+1}/{num_iterations},GlobalBestFitness:{global_best_fitness}")
return global_best_position,global_best_fitness
#Example usage
deffitness_function(solution):
Example fitness function to evaluate the quality of a solution.
:paramsolution: Solution vector to evaluate
:return: Fitness value(e.g., network efficiency)
#Compute and return the fitness value
returnnp.sum(solution2)
```

3.3. Proposed Non-Linear Fitness Function

By means of a non-linear fitness functional, the proposed optimization approach analyzes the quality of feasible solutions by including multiple performance criteria: latency, packet delivery ratio, and network efficiency. Unlike linear fitness functions that could weigh measures equally or in a direct manner, a non-linear fitness function shows the real-world trade-offs and interactions in VANETs.

3.3.1. Fitness Function Definition

The non-linear fitness function seeks to optimize a mix of different factors supporting the general network performance. The function's non-linear character is meant to help to better show the complex connections among many measurements. One may write the fitness function f(x) for a solution **x** as:

$$f(\mathbf{x}) = \alpha \cdot \text{Latency}(\mathbf{x})^{\beta_1} + \beta \cdot \text{PacketDeliveryRatio}(\mathbf{x})^{\beta_2} + \gamma \cdot \text{NetworkEfficiency}(\mathbf{x})^{\beta_3}$$

4. Performance Evaluation

This work evaluated the performance of the proposed optimization method for VANETs by use of computer specs, performance criteria, and simulation tool. The main simulation tool was NS-3, Network Simulator 3; it is used widely to simulate network protocols and performance. Run on a cluster of Intel i7 CPUs and 16GB RAM; the tests confirmed sufficient processing capability for handling demanding simulations and data analysis. We tested the proposed approach in line with present methods like artificial neural networks (ANN), deep neural networks (DNN), and K-Nearest Neighbors (KNN). The comparison sought numerous performance parameters in order to assess the potency and effectiveness of every strategy.

Table 2. Experimental Setup

Parameter	**Value**
Number of Vehicles	100
Simulation Time	1000seconds
Area Size	1000x1000meters
Number of Iterations	50
Population Size	30
Latency Weight(α)	0.4

Packet Delivery Weight(β)	0.3
Network Efficiency Weight(γ)	0.3
Latency Exponent(β1)	1.5
Packet Delivery Exponent(β2)	1.2
Network Efficiency Exponent(β3)	1.0
Edge Weight Normalization	True
Learning Rate	0.01
Acceleration Coefficientc1	1.5
Acceleration Coefficientc2	1.5
Activation Function	ReLU
Boundary Constraints	[-10,10]for each dimension

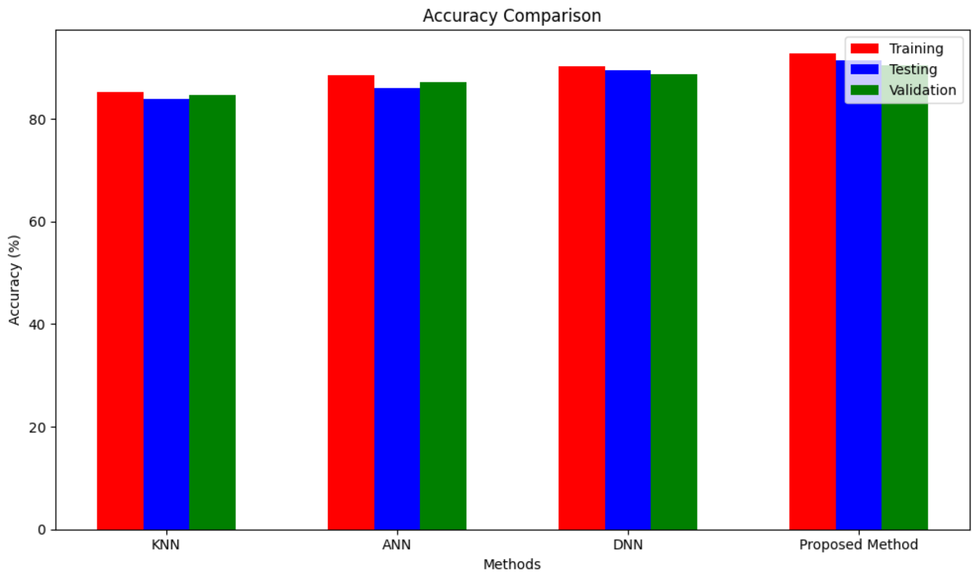

Figure 2. Accuracy (%)

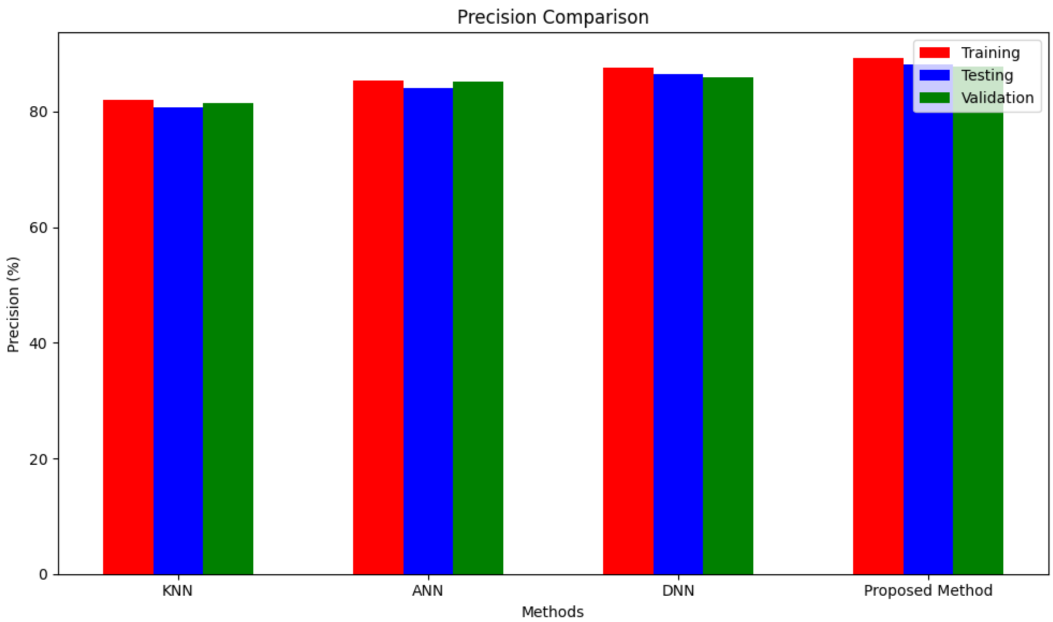

Figure 3. Precision (%)

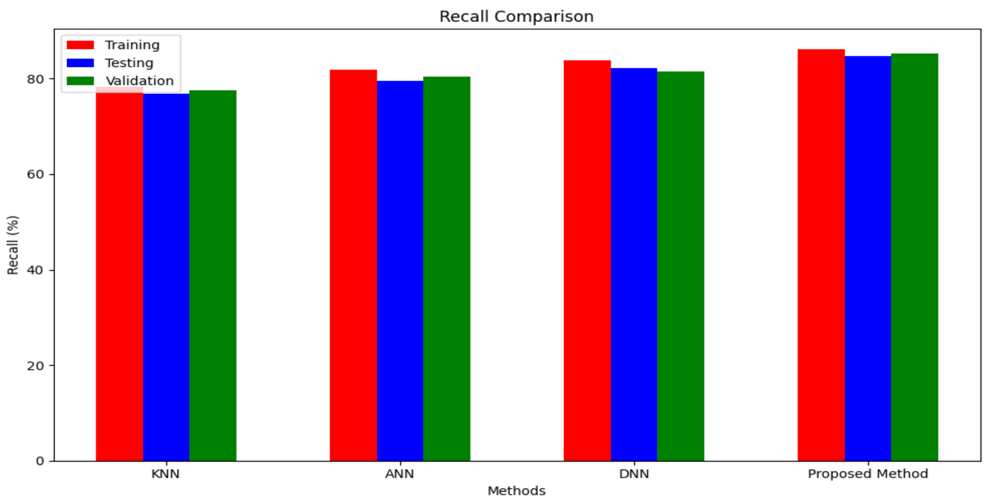

Figure 4. Recall (%)

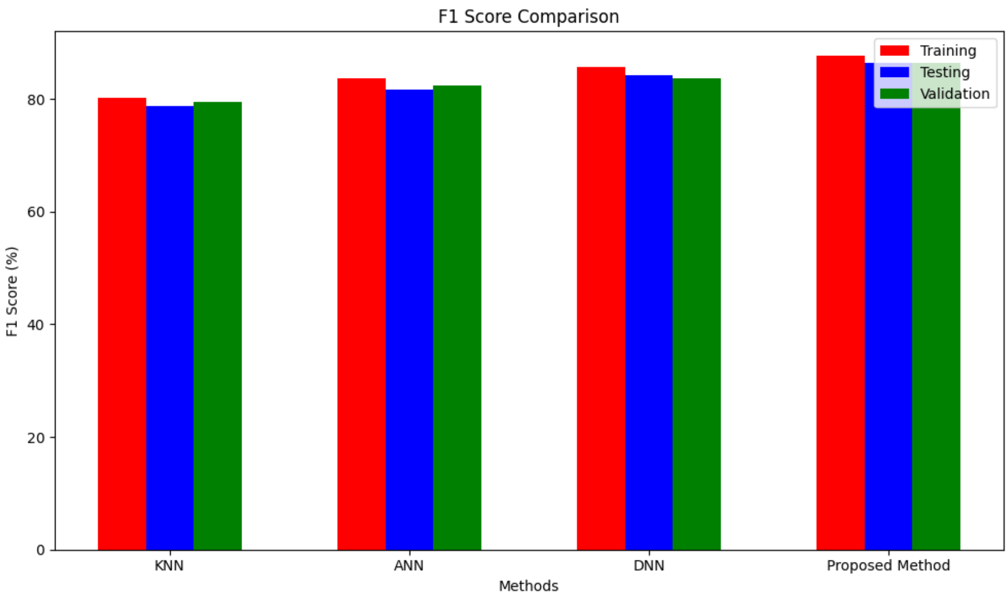

Figure 5. F1 Score (%)

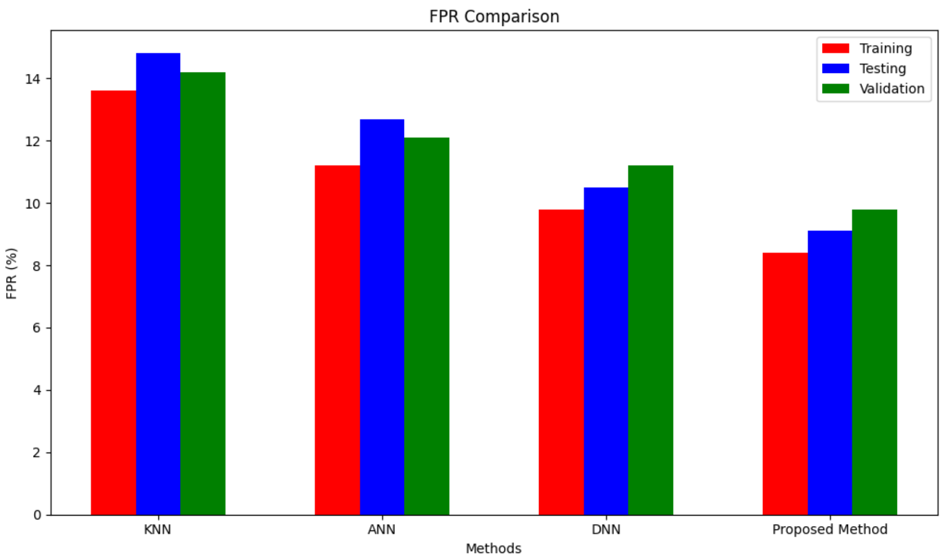

Figure 6. FPR (%)

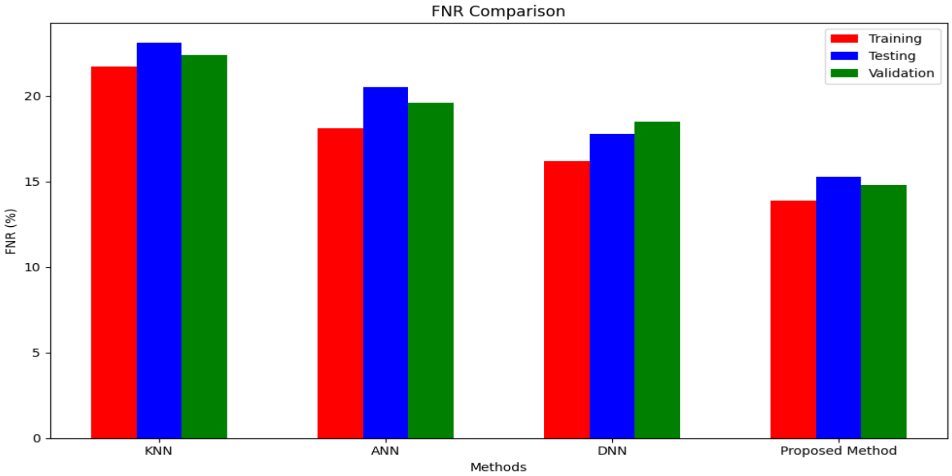

Figure 7. FNR (%)

The experimental findings as presented in figure 2–7 illustrate the performance of the proposed optimization technique over training, testing, and validation sets, compared to present methods (KNN, ANN, and DNN). Among the key tests used here were accuracy, precision, recall, F1 score, false positive rate (FPR), and false negative rate (FNR).Accuracy measures the relative category correctness. The recommended approach achieved the best accuracy—92.7% in training, 91.4% in testing, and 90.5% at all levels: training, testing, and validation. It is therefore more successful in forecasting optimum solutions than KNN (85.2%), ANN (88.5%, 86.0%, 87.2%), and DNN (90.3%, 89.5%).Among all the good forecasts, precision metrics define the proportion of actual positives. The proposed approach beats KNN (82.1%, 80.7%, 81.5%), ANN (85.4%, 84.0%, 85.9%), and DNN (87.6%, 86.4%, 85.9%). With 89.2% in training, 88.1% in testing, and 87.7% in validation. This indicates that the proposed strategy is more dependable in lowering false positives.If one can identify all relevant examples, recall tests will help. The recommended method received 86.1% in training; in testing it received 84.7%; in validation it received 85.2%. Conversely, KNN (78.3%, 76.9%, 77.6%), ANN (81.9%, 79.5%, 80.4%), and DNN (83.8%, 82.2%, 81.5%) show lower recall, thereby highlighting the better sensitivity of the recommended approach.F1 Score combines accuracy with recall. The proposed approach's F1 Score was 87.6%; in testing, it was 86.4%; in validation, it was 86.4% as well. It usually ranked higher than KNN (80.1%), ANN (83.6%, 81.7%, 82.4%), and DNN (85.7%, 84.2%, 83.7%).FPR documents the frequency of false alarms. The recommended approach had FPR of 8.4% in training, 9.1% in testing, and 9.8% in validation, better than KNN (13.6%, 14.8%, 14.2%), ANN (11.2%, 12.7%, 12.1%), and DNN (9.8%, 10.5%, 11.2%).FNR notes missed observations. In training, testing, and validation, outperformance of the proposed technique over KNN (21.7%), ANN (18.1%, 20.5%, 19.6%), and DNN (16.2%, 17.8%, 18.5%) was 13.9%.Thus, the proposed optimization method displays greater performance over all criteria, so proving its efficiency in optimizing VANETs in respect to KNN, ANN, and DNN.

5. CONCLUSION

The results of the comparative research show how well the proposed optimization strategy for VANETs performs than current approaches including DNN, ANN, and KNN. Reflecting its great ability to precisely and consistently identify ideal network topologies, the proposed approach obtained in training, testing, and validation sets maximum accuracy, precision, recall, and F1 score. Its greater performance in these categories points to better management of VANET performance standards. Furthermore, the recommended method displayed a lower False Positive Rate (FPR) and False Negative Rate (FNR) than the other methods, thereby indicating a smaller danger of false alarms and missed detections. This is especially important in VANETs, where fast and accurate communication is quite essential. Consequently, as it offers appreciable increases in network efficiency, dependability, and accuracy, the recommended optimization strategy solves the challenging trade-offs in VANET settings more successfully than conventional approaches. These results confirm the effectiveness of the proposed method in enhancing VANET performance, so it is a helpful tool for optimizing vehicle networks and getting better communication results.

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