International Journal of Artificial Intelligence and Machine Learning
Publisher's Home Page: https://www.svedbergopen.com/
Research Paper Open Access

A Distributed Multi-Agent Intelligence Framework For Autonomous Traffic Coordination In Smart Transportation Systems

Sumithra Salla[1], Rakesh Arya[2], Gagan Tiwari[3], Mahesh Kurulekar[4], Uday Chandrakant Patkar[5], Shalini E[6], Antonibiya S[7], Dr. Ravi Kumar Sharma[8]

[1] Assistant Professor, Department of Biotechnology, Chaitanya Bharati Institute of Technology, Hyderabad, Telangana, India. ORCID: 0000-0003-3265-4001
[2] Assistant Professor, Department of Computer Application, Dev Bhoomi Uttarakhand University, Dehradun, Uttarakhand, India. Email: pc.mtech.mca@dbuu.ac.in ORCID: 0000-0003-2436-3060
[3] Professor, Department of Computer Sciences, Noida International University, Greater Noida, Uttar Pradesh, India. Email: gagan.tiwari@niu.edu.in
[4] Assistant Professor, Department of Civil Engineering, Vishwakarma Institute of Technology, Pune, Maharashtra 411037, India. Email: mahesh.kurulekar@vit.edu
[5] Department of Computer Engineering, Bharati Vidyapeeth's College of Engineering, Lavale, Pune, Maharashtra, India. Email: patkarudayc@gmail.com
[6] Assistant Professor, Department of Computer Science, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: shalini@maher.ac.in
[7] Assistant Professor, Department of Mathematics, Meenakshi College of Arts and Science, Meenakshi Academy of Higher Education and Research, India. Email: antonibiya@maher.ac.in
[8] Dr. Ravi Kumar Sharma M.M. Institute of Computer Technology & Business Management, Maharishi Markandeshwar (Deemed to be University), Mullana – 133207, Haryana, India.

Abstract
Rapid urbanization and increasing vehicle density have made efficient traffic management a critical challenge in modern smart cities. Traditional centralized traffic control systems often suffer from poor scalability and delayed responsiveness under dynamic and uncertain traffic conditions. This research proposes Multi-Agent Traffic Signal Coordination Network (MATSC-Net), a distributed multi-agent intelligence framework for autonomous traffic coordination in smart transportation systems. The framework employs a decentralized architecture, where agents representing vehicles and traffic control units make decisions based on local observations while collaboratively optimizing global traffic flow. Smart Transportation Traffic Coordination Dataset of 4,000 is carried out describing traffic conditions, vehicle movement characteristics, road infrastructure attributes, intelligent transportation indicators, and traffic coordination factors. Min–max normalization is applied to scale traffic features into a uniform range and reduce variability across different data sources. A convolutional neural network (CNN)-based extraction method is utilized to effectively capture spatial traffic patterns such as vehicle density, lane occupancy, and road connectivity. The decision-making process of each agent is driven by a Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm, which enables efficient learning in continuous action spaces. Furthermore, an Intelligent Artificial Bee Colony (IABC) optimization technique is integrated to enhance policy optimization, improve convergence speed, and avoid local optima. Experimental results demonstrate that the 98.34% accuracy, 98.12% Precision, and 97.95% recall using python 3.10 and the proposed framework significantly enhances traffic throughput, reduces congestion, and making it a scalable solution for intelligent transportation systems.

Keywords: Vehicle density, Intelligent transportation systems, Multi-Agent, Optimization, Distributed Multi-Agent Intelligence.

1. Introduction

Smart transportation technologies for self-driving vehicles are developing quickly to enhance the security, efficiency, and comfort of road transportation. Nevertheless, current technologies encounter difficulties in sensor precision, weather resistance, and error-free decision-making [1]. Smart cities aspire to enhance urban environments using intelligent transportation and parking systems, and don't continue to encounter problems like traffic jam, parking inefficiency, loss of time, wastage of resources, and security problems [2]. Management of traffic congestion plays an important role in smart cities. Vehicle overcrowding, poorly developed infrastructure, traffic congestions, environmental pollution, and traffic management problems persist in modern urban transportation systems [3]. Due to rapid Urbanization and increased numbers of vehicles, there is a need to address certain transportation problems within contemporary cities. The existing transportation system faces several problems such as congestion, ineffective signaling, accidents, pollution, insufficient infrastructure, and poor traffic management [4]. The Software-Defined Networking (SDN) concept offers flexibility and centralized control in current communication systems. Yet, there are issues that continue to influence the efficiency of SDNs, like complex networks, security, traffic control, scalability, and reliability among others [5]. Sensing and edge intelligence using a data-centric approach were already contributing to better decision-making for transportation management within an intelligent transportation environment. The most important problems that exist include computational constraints, delays, unreliable communications, scalability, energy conservation, and heterogeneity [6]. The Intelligent Transport System (ITS) had developed to improve mobility and safety through information management. However, ITS was still plagued by problems like congestion, infrastructure, and accident risk in urban road systems [7].

1.1 Problem Statement: The Coordination of autonomous traffic systems can be problematic owing to dynamic traffic situations, non-linearity, multiple agents' involvement, and lack of scalable intelligent models for traffic optimization in smart transportation systems. To address these encounters, this research develops a framework for autonomous traffic system coordination named Multi-Agent Traffic Signal Coordination Network (MATSC-Net).

2. Related work

Current intelligent traffic management techniques enhance traffic prediction, signal optimization, and congestion mitigation for transportation settings yet suffer from constraints, such as poor scalability, slow convergence, communication cost, and difficulties with adaptation under dynamic traffic environment conditions, as shown in table 1 below.

Table 1: Effectiveness of intelligent traffic coordination and optimization approaches

Ref	Objective	Method	Result	Limitations
[8]	Detection of accidents in smart cities using vision-based analysis	Inflated 3D Convolutional Long Short-Term Memory (I3D-CONVLSTM2D) for Red Green Blue (RGB) image sequences and Optical Flow.	Achieved 87% Mean Average Precision (mAP) in accident detection	Performance affected by imbalanced datasets
[9]	Prediction of traffic flow levels accurately in smart city environments	Hierarchical Extreme Learning Machine (HELM) model used for layered feature learning.	Provided high prediction accuracy in complex traffic conditions	Higher computational complexity due to hierarchical structure
[10]	Prediction of short-term traffic flow and speed for Intelligent Transportation Systems (ITS)	Transformer-based Deep learning (DL) model for capturing long-range temporal dependencies.	Achieved 94.2% accuracy in traffic flow and 92.1% in speed prediction.	Poor generalization to unseen traffic conditions.
[11]	Enhancement of intersection performance using autonomous and connected vehicles.	Particle Swarm Optimization (PSO) for optimizing synchronization points based on local traffic conditions	Achieved throughput above 2.1 and delay below 0.03	Limited scalability and simulation-only validation.
[12]	Improvement of vehicle audio perception for accident detection and safety enhancement.	Transformer-based audio classification model for detecting accident-related sound patterns using multimodal Machine Learning (ML).	High detection accuracy with low false alarms and fast response time	High computational cost in extremely noisy environments

[13]	Forecast electric vehicle charging energy consumption using synthetic data.	Temporal Charge Generative Adversarial Network (TCGAN) for generating improved predictions using ensemble learning	Delivered accurate energy consumption forecasts using synthetic datasets.	Limited dataset scope was restricted to a specific geographic region.

2.1 Research Gap

existing traffic management systems based on intelligent transportation suffer from low scalability, inefficiency of decentralization, delays in decision making, simulation-based verification methods, challenges in managing computationally demanding traffic scenarios, and deterioration of performance due to imbalance in datasets [8-13]. To address these challenges, the proposed MATSC-Net framework integrates Multi-Agent Deep Deterministic Policy Gradient (MADDPG)-based multi-agent decision-making, and Intelligent Artificial Bee Colony (IABC)-based policy optimization to enhance traffic signal coordination, reduce congestion, accelerate convergence, and improve overall traffic flow efficiency for autonomous traffic coordination.

3. Multi-Agent Traffic Signal Coordination Network (MATSC-Net) Framework

The purpose of the proposed MATSC-Net is to enable intelligent traffic management and efficient signal control by effectively learning dynamic traffic patterns from heterogeneous transportation data. The entire process of the proposed system is illustrated in Figure 1. Smart Transportation Traffic Coordination data is collected and are preprocessed then Convolutional Neural Network (CNN)-based feature extraction, while MADDPG is employed for multi-agent decision-making and IABC is applied for policy optimization to improve convergence performance and enhance traffic coordination efficiency.

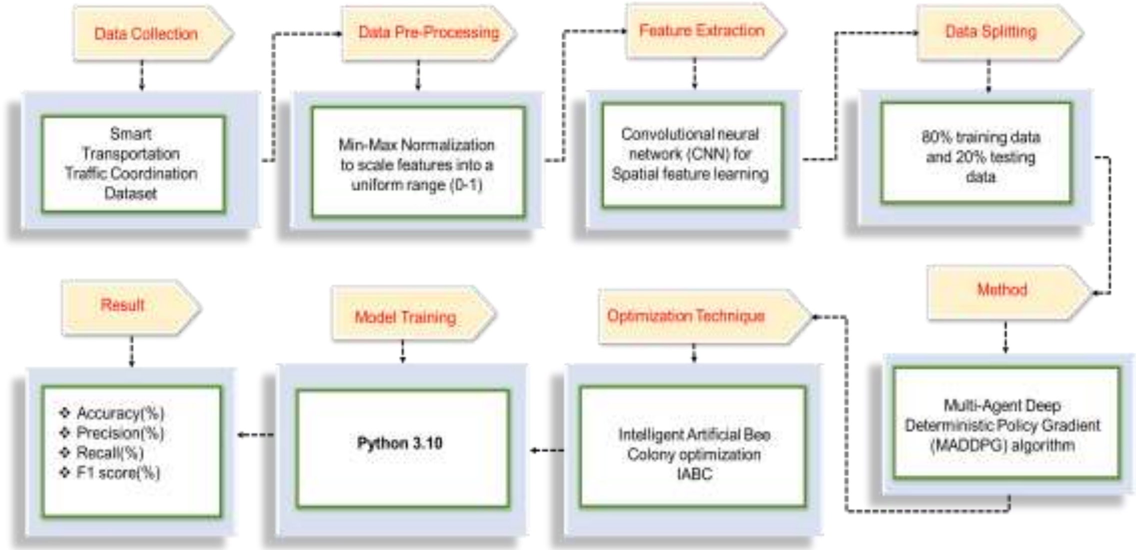

Figure 1: Workflow Diagram of the Proposed Traffic Intelligence Framework

3.1 Data Collection

The Smart Transportation Traffic Coordination Dataset contains 4,000 records and 32 columns describing traffic conditions, It includes vehicle movement features, road infrastructure features, intelligent transportation system indicators, and traffic coordination features. The database captures different scenarios that exist in urban transportation environments, which include vehicle density, traffic flow, lanes used, road capacity, traffic signaling infrastructure, coordination of agents, environmental conditions, and traffic incidents. The dataset is suitable for studying traffic behavior, congestion patterns, transportation network performance, and intelligent traffic management systems. Each record captures a unique traffic state characterized by operational and environmental attributes that influence overall traffic movement and road efficiency. For experimental evaluation, the dataset is divided into an 80:20 ratio, where 80% as training and 20% as testing. Source: https://www.kaggle.com/datasets/zara2099/smart-transportation-traffic-coordination-dataset/data.

3.2 Data preprocessing

Preprocessing plays an important role in improving the quality of the Raw Smart Transportation Traffic Coordination for intelligent traffic analysis by employing Min–Max normalization and missing value imputation.

- **Missing Value Imputation for Reliable Traffic Analysis:** Traffic observations that was missed due to malfunctioning of sensors, delay in communications, or insufficient vehicle data are detected and replaced using traffic information from nearby temporal and spatial locations. It is used to identify and replace incomplete traffic observations to maintain data integrity, reduce information loss, and improve the reliability of feature extraction and learning processes.
- **Min-Max normalization:** It scales the traffic and environmental characteristics, which are different in nature, like vehicular density, speed, queue length, lane occupancy, and traffic volume. The Min-Max method used to minimize feature scale differences, avoid numerical imbalance and increase the convergence rate by preventing the dominating behavior of the higher valued features.

$$\psi_{ij} = \frac{T_{ij} - T_j^{min}}{T_j^{max} - T_j^{min}} \times R \quad (1)$$

In equation (1), ψ_{ij} denotes the normalized traffic coordination feature value of the i^{th} traffic instance and j^{th} traffic attribute. T_{ij} represents the original traffic-related feature. T_j^{min} indicates the minimum observed value of the j^{th} traffic coordination attribute. T_j^{max} represents the maximum observed value of the j^{th} traffic coordination attribute. R denotes the scaling interval. However, Min-Max normalization normalized all feature space with a consistently distributed magnitude and increased stability in terms of convergent behavior.

3.3 CNN-Based Spatial Traffic Feature Extraction

After completing the data preprocessing step, the processed data moves to the next feature extraction by using CNN for extracting useful features from the transportation data for efficient traffic coordination. CNN employs convolution, ReLU activation, pooling, and full connection for efficient spatial traffic feature extraction for intelligent traffic analysis and coordination.

- **Input Layer:** It receives pre-processed traffic features including vehicle density, lane occupancy, queue length, traffic flow, road connectivity information.
- **Convolutional Layer:** The convolution layer receives the feature map from the input layer in terms of traffic characteristics. This layer extracts traffic features like clustering of vehicles, areas of traffic congestion, usage of lanes, and traffic spatial distribution through convolution filters.

  $$Feature\ Vector = \sum((Input_{m\times n} * Weight_{m\times n}) + Bias) \quad (2)$$

  Equation (2) shows $Feature\ Vector$ denotes extracted spatial traffic feature map, m represents the height of the local traffic region, n represents the width of the same local traffic region. $Input_{m\times n}$ represents the Local traffic region capturing vehicle lane status. $Weight_{m\times n}$ shows learnable filter used to detect traffic patterns. $Bias$ denotes the Adjustment term that stabilizes feature extraction.
- **Activation Layer (ReLU):** Feature maps obtained after feature extraction are transferred to the ReLU activation layer, where non-linearity is achieved through the preservation of positive values while ignoring the negative values.

  $$\sigma(Z) = max(0, Z) \quad (3)$$

  In equation (3), $\sigma(Z)$ represents an activated traffic feature, Z denotes the Raw convolution output of traffic pattern strength. max means the function selects the greater value between 0 and Z.
- **Max-Pooling Layer:** It helps reduce the dimensions of the feature maps using dominant values of features within certain areas. This technique not only helps reduce computation but also helps retain important properties of the traffic data, including traffic congestion.
- **Fully Connected Layer:** The fully connected layer is responsible for carrying out feature integration at the higher levels and converts deep representations of the spatial traffic information to decision features.

  $$Y_{(p\times 1)} = Weight_{(p\times j)} Z_{(j\times 1)} + Bias_{(p\times 1)} \quad (4)$$

  Equation (4) shows $Y_{(p\times 1)}$ denotes the final decision feature vector of size p outputs ×1, representing traffic signal coordination outputs. $Weight_{(p\times j)}$ shows Learnable mapping matrix of size p decision units × j feature inputs that transforms deep traffic features into control decisions. $Z_{(j\times 1)}$ represents the Flattened feature vector of size j × 1 capturing learned spatial traffic patterns. $Bias_{(p\times 1)}$ denotes the Offset vector of size p × 1 that adjusts outputs to improve stability in dynamic traffic conditions.
- **Output layer:** The CNN generates high-level spatial traffic feature representations capturing congestion patterns, vehicle interactions, and network dependencies effectively. Figure 2 shows the CNN architecture.

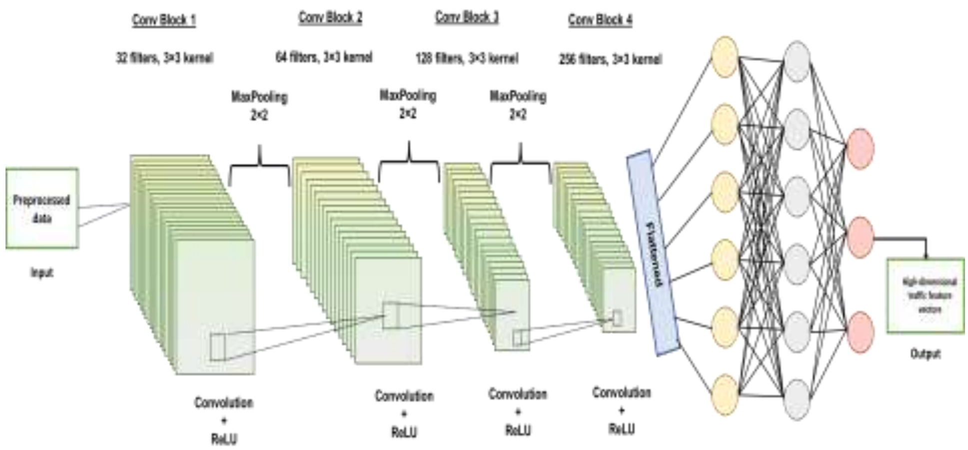

Figure 2: CNN Architecture for Spatial Feature Extraction

3.4 Distributed Multi-Agent Traffic Environment Modeling and Formulation

A distributed multi-agent traffic environment is developed to model actual interaction between vehicles, signal-controlled intersections, road sections, and the corresponding vehicle to vehicle communication networks using the decentralized architecture. There are two types of agent architectures in the suggested traffic environment, including traffic signal agents responsible for controlling signal phase, allocating green time, adjusting cycle length, and coordinating signals, and vehicle agents handling route selection. In the suggested traffic environment, vehicle density, queue size, traffic volume, average vehicle speed, signal phase, and congestion level were taken into account as states, and signal timing adjustment, phase switching, routing and speed control. This environment enables MADDPG agents to learn scalable and coordinated traffic control policies under dynamic transportation conditions.

3.5 Multi-Agent Learning Using MADDPG

The MADDPG model uses normalized observation of multiple autonomous agents that include vehicle density, lane occupancy, status of traffic signals, trajectory of vehicles, and road connectivity features through the CNN of the intelligent transportation system. This technique is utilized for the training of traffic agents in such a way that they collectively learn optimal traffic control policies, which helps to minimize waiting time, and improve decision-making in smart transportation systems.

$$L(\phi_a) = \mathbb{E}_D[(y_a - Q^{\mu_a}(s, u_1, u_2, \dots, u_n; \phi_a))^2] \quad (5)$$

In equation (5), $L(\phi_a)$denotes the critic network loss function of agent a, $\phi_a$represents the critic network parameters of agent a. $E_D$denotes the expectation over experiences sampled from the replay memory D. y_a represents the target Q-value used for critic learning. Q^{μ_a} denotes the action-value function that estimates the expected cumulative reward. s represents the global traffic state comprising vehicle density, lane occupancy, traffic signal status, vehicle trajectories, and road connectivity information. $u_1, u_2, \dots, u_n$denote the actions executed by all traffic agents. n represents the interacting agents in the transportation environment.

$$\nabla_{\theta_i} J(\mu_i) = \mathbb{E}_M\left[\nabla_{\theta_i}\mu_i(\tau_i)\nabla_{c_i}Q^{\mu_i}(X, c_1, c_2, \dots, c_N)\ |_{c_i=\mu_i(\tau_i)}\right] \quad (6)$$

Equation (6) shows $\nabla_{\theta_i} J(\mu_i)$ denotes the policy gradient of agent i. $J(\mu_i)$represents the objective function of the actor network. θ_i denotes the learnable parameters of the actor network. E_M represents the expectation over sampled experiences from memory M. $\mu_i(\tau_i)$denotes the policy function that generates actions for agent i. $\tau_i$represents the local observation of agent i, including traffic density, queue length, vehicle movement, and signal-state information. Q^{μ_i} denotes the centralized critic function used to evaluate joint actions. X represents the global traffic state information. $c_1, c_2, \dots, c_N$denote the actions of all participating agents. Nrepresents the total number of agents in the system. $c_i = \mu_i(\tau_i)$ indicates that the action of agent $i$is the generated by its policy network. However, the MADDPG framework produces the most optimal multi-agent traffic control strategies that include adaptive traffic light timings, coordination of movements for vehicles, and dynamic routing through reinforcement learning in a distributed intelligent transportation environment.

3.6 IABC for Traffic Signal Policy Optimization

The Artificial Bee Colony (ABC) algorithm is an optimization approach that was developed based on the collective behaviors of honeybees. Three types of virtual bee populations are utilized by the algorithm, including those of the employed, onlookers, and scouts, for finding the best possible solutions. Despite having a high degree of exploration and strong global searching abilities, the traditional ABC algorithm is associated with the problems of low convergence rate and poor exploitation capabilities near optimum regions. The IABC algorithm attempts to address these shortcomings through improved exploitation and solution update schemes.

IABC: The IABC includes traffic state characteristics, actions from agents, rewards, parameter policies, and potential solutions that were created through the multi-agent learning process. The IABC technique is utilized to improve the policy parameter values through intelligent search of the solution space for finding high-quality solutions in traffic coordination. It provides a better exploration versus exploitation trade-off, faster convergence, avoids premature convergence to local optima, and fine-tunes the agents' decisions.

$$u_{pq} = y_{pq} + \varphi_{pq}(y_{mq} - y_{nq}) \quad (7)$$

$$u_{pq} = y_{best,q} + \phi_{pq}(x_{pq} - x_{nq}) \quad (8)$$

$$u_{pq} = best,_{q} + \varphi_{pq}(y_{mq} - y_{nq}) \quad (9)$$

$$u_{pq} = s_1 y_{pq} + (1 - s_1) y_{mq} + \varphi_{pq}[s_1(y_{pq} - y_{nq}) + (1 - s_1)(y_{mq} - y_{nq})] \quad (10)$$

$$u_{pq} = best_q + \varphi_{pq}[s_2(y_{pq} - y_{nq}) + (1 - s_2)(y_{mq} - y_{nq})] \quad (11)$$

In equations (7-11) u_{pq}denotes the updated candidate traffic signal policy solution generated by the IABC optimization process, y_{pq}represents the current policy solution, $y_{mq}$and y_{nq}denote the neighboring policy solutions selected from the solution population, and $y_{best,q}$represents the globally best traffic coordination policy identified during the optimization process. The index $p$denotes the p^{th}candidate solution in the population, while $q$denotes the q^{th}dimension or parameter of the policy solution vector. The indices m and n represent randomly selected neighboring solutions that are different from the current solution p. The parameter ϕ_{pq}denotes a random search coefficient typically generated within the range $[-1,1]$, which controls the direction and magnitude of the solution update, thereby enhancing exploration of the search space. The adaptive factors $s_1$and $s_2$are binary selection parameters. However, the outcome is an optimized solution for the policy with faster convergence, increased coordination between the traffic systems, reduced congestion, and effective traffic signals.

3.7 Decentralized Multi-Agent Intelligence for Autonomous Traffic Coordination

In MATSC-Net autonomous traffic coordination was feasible through decentralized actions, which include the application of optimal policies by learning from the traffic signal agent and the vehicle agent. The traffic signal agent manages to change the phase and time to green through parameters such as the number of queues and vehicles. On its part, the vehicle agent makes decisions concerning adaptive routing, vehicle velocity control, and lane selection through the traffic context. The interactions are made to optimize global traffic conditions through the minimization of congestion propagation.

4. Results

The distributed multi-agent intelligence framework for autonomous traffic coordination in smart transportation systems was efficiently offered by MATSC-Net. The experiments were conducted on a workstation equipped with an Intel Core i9-13900K processor, 64 GB RAM, and NVIDIA RTX 4090 GPU (24 GB VRAM). The proposed MATSC-Net framework was implemented using Python 3.11 with TensorFlow 2.16, Keras, NumPy, Pandas, and Scikit-learn libraries. This section offers the findings of MATSC-Net performance, experimental analysis, Class-wise Traffic State Prediction Analysis, and comparative analysis.

4.1 Evaluation Metrics

Queue Length: Number of vehicles waiting in queues, Traffic Flow Rate: Vehicle flow rate per unit time, Average Travel Time (min): Average travel duration, Coordination Score: Coordination effectiveness indicator, Policy Reward: Traffic control performance indicator, Agent Cooperation Index: Degree of agent collaboration, Action Efficiency: Operational efficiency score, Convergence Iteration: Iteration count until convergence, Congestion Index: Traffic congestion severity measure, Measures the predicted traffic states out of total predictions (%), Precision (%): Indicates the proportion of correctly identified positive traffic predictions among all predicted positives (%), Recall (%) : Measures the traffic states from all true cases (%), F1-Score (%):representing balanced classification performance (%).

4.2 Experimental analysis

The analysis of relationships between feature variables and distributions of traffic states gives us valuable information about traffic dynamics, independence of feature variables, and coordinated behavior. Figure 3(a) demonstrates the independence of traffic features by revealing very low correlations between them with coefficients of −0.03 to 0.01, whereas Figure 3(b) illustrates the Free Flow, Moderate, Heavy, and Severe traffic states with the use of traffic indicator such as Traffic Flow Rate (1.0, 0.0) and Average Speed (0.3, 0.96).

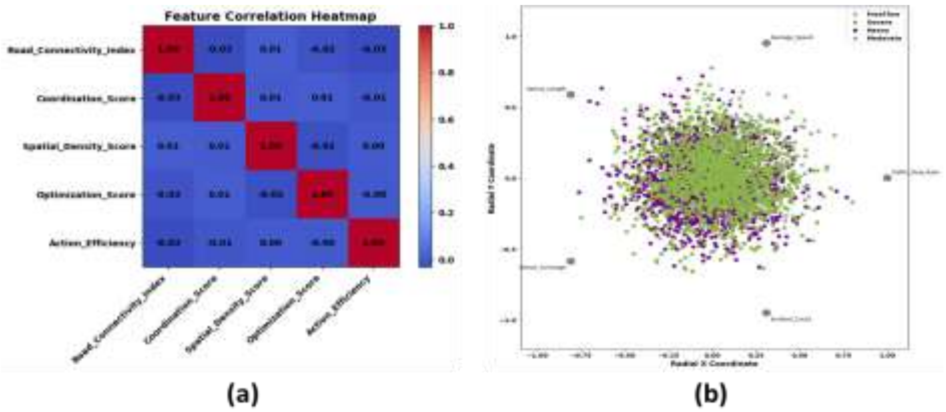

Figure 3: Graphical illustration of (a) Feature Correlation Heatmap and (b) Traffic State Distribution Visualization.

Evaluation of the efficiency of optimization and convergence allows for gaining an understanding of learning stability, solution quality, and consistency of optimization. Figure 4(a): The optimization score fluctuates between 46.1 and 56.0 with maximum achieved during the 13th hour and minimum at hour 12, showing consistent optimization performance. Figure 4(b): The number of convergence iterations changes between 20 and 500, reaching its maximum occurrence at 190 times.

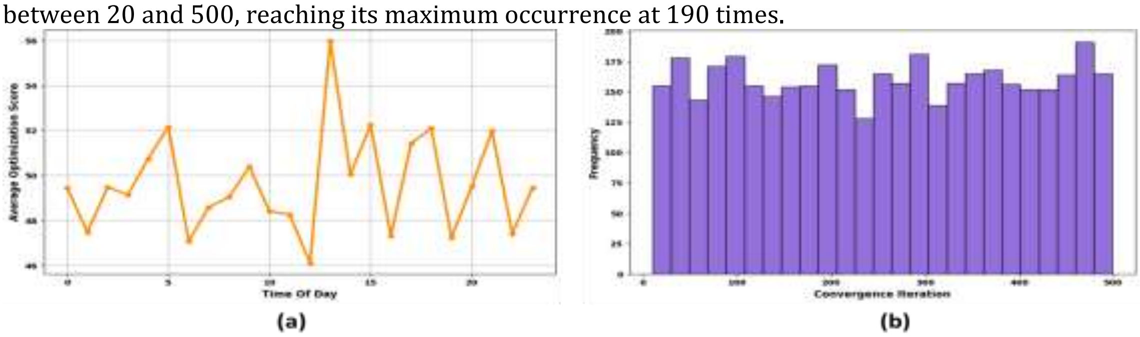

Figure 4: Graphs of (a) Scores Against Hours of the Day and (b) Convergence Iterations Distributions.

4.3 Class-wise Traffic State Prediction Analysis

The reliability of the proposed model in different traffic conditions was assessed based on the model's prediction accuracy with class-wise evaluation. As illustrated in Table 2 below, the MATSC-Net performed exceptionally well in all cases, with 98.12% accuracy, 97.95% recall rate, and 98.03% F1 score. The highest F1 score was obtained in the Severe traffic condition.

Table 2: Class-wise Performance Analysis

Traffic State	Precision (%)	Recall (%)	F1-Score (%)
Free Flow	98.72	98.31	98.51
Moderate	97.86	97.41	97.63
Heavy	97.54	97.18	97.36
Severe	98.37	98.92	98.64
Average	98.12	97.95	98.03

4.4 Comparative Analysis

The comparative analysis of the proposed MATSC-Net framework is conducted by comparing its performance with existing approaches, including Intelligent Adaptive Advantage Actor Critic (IA2C) [14], Multi-Agent Adaptive Advantage Actor Critic (MAA2C) [14], Multi-Agent Advantage Actor Critic (MA2C) [15], and conventional Multi-Agent Reinforcement Learning (MARL) [16] techniques. For this comparison, all models were trained and evaluated using the Smart Transportation Traffic Coordination Dataset with same splits and process. Table 3 presents the comparative evaluation of traffic optimization and Figure 3 illustrates the performance comparison between the existing approaches and the proposed MATSC-Net framework. Better performance was achieved by the proposed model with 98.34% accuracy, 98.12%

precision, and 97.95% recall, demonstrating enhanced traffic coordination, faster convergence, and efficient intelligent transportation management.

Table 3: Traffic State Classification Performance

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
IA2C	89.84	89.32	88.95	89.13
MAA2C	91.76	91.21	90.84	91.02
MA2C	94.28	93.87	93.45	93.66
MARL	96.13	95.84	95.51	95.67
MATSC-Net [Proposed]	98.34	98.12	97.95	98.03

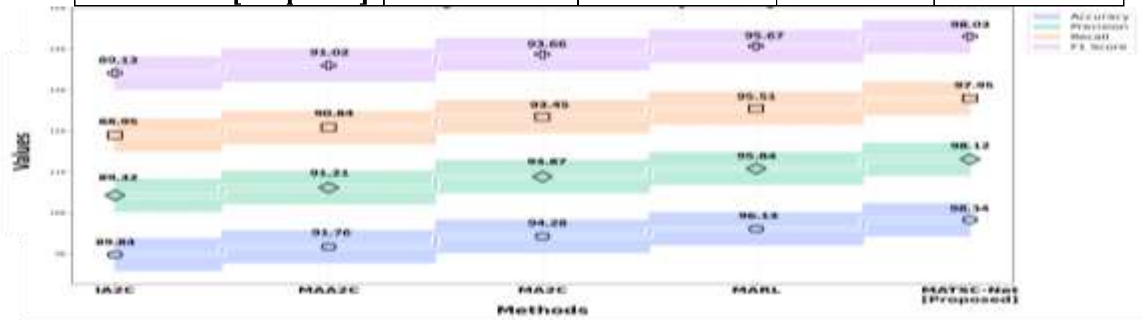

Figure 5: Traffic State Classification Performance Evaluation

4.5 Traffic Coordination and Multi-Agent Learning Performance Analysis

The effectiveness of the MATSC-Net architecture, traffic coordination efficiency, congestion reduction capacity, multi-agent collaboration efficiency, and learning convergence behavior were compared. Such comparisons were done based on the IA2C, MAA2C, MA2C, and MARL models by assessing the performance with respect to traffic flow, congestion levels, traffic coordination levels, and reinforcement learning performance. The results show that MATSC-Net performs better than other multi-agent traffic management strategies in Table 4.

Table 4: Traffic Coordination, Congestion Mitigation, Multi-Agent Collaboration, and Learning Convergence Performance

Method	Traffic Flow Rate	Average Travel Time (min)	Queue Length (Vehicles)	Congestion Index	Coordination Score	Agent Cooperation Index	Action Efficiency	Policy Reward	Convergence Iterations
IA2C	845	15.8	35.7	0.65	0.742	0.718	0.704	0.741	698
MAA2C	932	13.7	29.4	0.54	0.816	0.792	0.775	0.816	572
MA2C	1084	11.2	21.6	0.41	0.887	0.861	0.846	0.891	436
MARL	1169	9.6	17.9	0.33	0.921	0.902	0.889	0.926	368
MATSC-Net [Proposed]	1264	8.1	13.8	0.26	0.967	0.951	0.943	0.972	246

5. Discussion

The distributed multi-agent intelligence framework for autonomous traffic coordination in smart transportation systems was efficiently offered by MATSC-Net. Existing approaches, including IA2C [14] and MAA2C [14], MA2C [15], and MARL [16] were widely utilized for traffic signal control; however, their performance was limited by slower convergence, inefficient coordination, and reduced scalability in dynamic traffic environments. Furthermore, previous methods exhibited lower traffic throughput, higher congestion levels, and less effective decision-making capabilities. Therefore, this research proposes a

MATSC-Net framework that overcome these challenges and demonstrated better traffic coordination, enhanced learning efficiency, and improved optimization performance, while provides a robust and scalable solution for autonomous traffic management in intelligent transportation systems.

6. Conclusion

The MATSC-Net framework for autonomous traffic coordination in smart transportation systems was efficiently proposed by using MADDPG and IABC. It utilizes Smart Transportation Traffic Coordination Dataset, and pre-processing is performed through Min–Max normalization and CNN-based spatial feature extraction. The proposed MATSC-Net framework demonstrates enhanced performance in traffic flowrate, congestion reduction, convergence speed. The results shown 98.34% accuracy, 98.12% Precision, 97.95% recall and 98.03% F1-Score as compared to existing techniques. The framework is evaluated on a single dataset and future work will incorporate real-time traffic data, larger transportation networks, and advanced multi-agent coordination strategies.

References

1. Hasanujjaman, M., Chowdhury, M.Z. and Jang, Y.M., 2023. Sensor fusion in autonomous vehicle with traffic surveillance camera system: detection, localization, and AI networking. Sensors, 23(6), p.3335. https://doi.org/10.3390/s23063335
2. Abbas, Q., Ahmad, G., Alyas, T., Alghamdi, T., Alsaawy, Y. and Alzahrani, A., 2023. Revolutionizing urban mobility: IoT-enhanced autonomous parking solutions with transfer learning for smart cities. Sensors, 23(21), p.8753. https://doi.org/10.3390/s23218753
3. Saleem, M., Abbas, S., Ghazal, T.M., Khan, M.A., Sahawneh, N. and Ahmad, M., 2022. Smart cities: Fusion-based intelligent traffic congestion control system for vehicular networks using machine learning techniques. Egyptian Informatics Journal, 23(3), pp.417-426. https://doi.org/10.1016/j.eij.2022.03.003
4. Lilhore, U.K., Imoize, A.L., Li, C.T., Simaiya, S., Pani, S.K., Goyal, N., Kumar, A. and Lee, C.C., 2022. Design and implementation of an ML and IoT based adaptive traffic-management system for smart cities. Sensors, 22(8), p.2908. https://doi.org/10.3390/s22082908
5. Masood, F., Khan, W.U., Jan, S.U. and Ahmad, J., 2023. AI-enabled traffic control prioritization in software-defined IoT networks for smart agriculture. Sensors, 23(19), p.8218. https://doi.org/10.3390/s23198218
6. Hazarika, A., Choudhury, N., Nasralla, M.M., Khattak, S.B.A. and Rehman, I.U., 2024. Edge ML technique for smart traffic management in intelligent transportation systems. IEEE Access, 12, pp.25443-25458. https://doi.org/10.1109/ACCESS.2024.3365930
7. Khalil, R.A., Safelnasr, Z., Yemane, N., Kedir, M., Shafiqurrahman, A. and Saeed, N., 2024. Advanced learning technologies for intelligent transportation systems: Prospects and challenges. IEEE Open Journal of Vehicular Technology, 5, pp.397-427. https://doi.org/10.1109/OJVT.2024.3369691
8. Adewopo, V.A. and Elsayed, N., 2024. Smart city transportation: Deep learning ensemble approach for traffic accident detection. IEEE Access, 12, pp.59134-59147. https://doi.org/10.1109/ACCESS.2024.3387972
9. Alruban, A., Mengash, H.A., Eltahir, M.M., Almalki, N.S., Mahmud, A. and Assiri, M., 2024. Artificial hummingbird optimization algorithm with hierarchical deep learning for traffic management in intelligent transportation systems. IEEE access, 12, pp.17596-17603. https://doi.org/10.1109/ACCESS.2023.3349032
10. Samieiyan, B. and Awasthi, A., 2026. A Custom Transformer-Based Framework for Joint Traffic Flow and Speed Prediction in Autonomous Driving Contexts. Future Transportation, 6(1), p.15. https://doi.org/10.3390/futuretransp6010015
11. El-Qoraychy, F.Z., Du, W., Abbas-Turki, A., Dridi, M., Créput, J.C., Mualla, Y. and Koukam, A., 2026. Distributed PSO for dynamic intersection management: Enhancing traffic flow and safety in connected autonomous vehicles. Expert Systems with Applications, 303, p.130200. https://doi.org/10.1016/j.eswa.2025.130200
12. Balivada, S., Tanna, M.S., Dhedia, M.A., Wu, J. and Gao, J., 2026. Audio based Intelligence for Smart Autonomous Vehicles using Deep Reinforcement Learning. IEEE Access, 14, p. 61613- 61629. https://doi.org/10.1109/ACCESS.2026.3681929
13. Mohanty, P.K., Reddy, K.H.K., Panigrahy, S.K. and Roy, D.S., 2024. Leveraging generative and explainable AI for electric vehicle energy toward sustainable, consumer-centric transportation. IEEE Access, 12, pp.143721-143732. https://doi.org/10.1109/ACCESS.2024.3405959

14. Mushtaq, A., Haq, I.U., Sarwar, M.A., Khan, A., Khalil, W. and Mughal, M.A., 2023. Multi-agent reinforcement learning for traffic flow management of autonomous vehicles. Sensors, 23(5), p.2373. https://doi.org/10.3390/s23052373
15. Louati, A., Louati, H., Kariri, E., Neifar, W., Hassan, M.K., Khairi, M.H., Farahat, M.A. and El-Hoseny, H.M., 2024. Sustainable smart cities through multi-agent reinforcement learning-based cooperative autonomous vehicles. Sustainability, 16(5), p.1779. https://doi.org/10.3390/su16051779
16. Olusanya, O.O., Owosho, Y., Daniyan, I., Elegbede, A.W., Sodipo, Q.B., Adeodu, A., Phuluwa, H.S., Ramasu, T.K. and Kana-Kana Katumba, M.G., 2025. Multi-agent reinforcement learning framework for autonomous traffic signal control in smart cities. Frontiers in Mechanical Engineering, 11, p.1650918. https://doi.org/10.3389/fmech.2025.1650918