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Intelligent Traffic Management System Using Ant Colony and Deep Learning Algorithms for Real-Time Traffic Flow Optimization

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Ant Colony Optimization,
Deep Learning,
Long-Short-Combination,
Real-Time Optimization,
Traffic Management.

ABSTRACT
Urban traffic congestion presents a formidable global challenge that necessitates innovative and adaptive solutions, surpassing the capabilities of traditional traffic management systems. This research introduces an Intelligent Traffic Management System (ITMS) that synergistically integrates Ant Colony Optimization (ACO) and Deep Learning (DL) methodologies, effectively optimizing real-time traffic flow. To dynamically adapt to complex urban environments, the ITMS leverages ACO for agile routing and DL for precise traffic prediction, enabled by a novel Long-Short-Combination (LSC) framework designed to accommodate both congested and uncongested traffic attributes. Real-time data acquisition is achieved using a computer vision model, which detects and classifies vehicles into four categories (cars, bikes, buses, and trucks) with updates every 15 minutes. Data preprocessing addresses inconsistencies to ensure integrity. The ITMS employs ACO to optimize vehicle routing dynamically by simulating artificial "ants" that evaluate routes based on pheromone levels representing congestion and distance, thus adapting to real-time fluctuations. Reinforcement learning dynamically adjusts traffic signal timings, minimizing congestion and optimizing overall traffic flow. Six Machine Learning models were tested, finding a weighted average precision, recall, and f1-score of 0.95. More specifically, for traffic situation classification, a detailed model performance analysis was conducted, revealing that Class 0 achieved a precision of 0.99, recall of 0.98, and F1-score of 0.99. Class 1 achieved a precision of 0.90, recall of 0.87, and F1-score of 0.88. Class 2 achieved a precision of 0.93, recall of 0.96, and F1-score of 0.95, and Class 3 had a precision of 0.96, recall of 0.96, and F1-score of 0.96. These results highlight the transformative potential of AI-driven traffic optimization.

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INTRODUCTION

Urban traffic congestion has become an increasingly severe issue in cities worldwide, primarily due to rapid urbanization and growing vehicle ownership. Traffic congestion leads to prolonged travel times, increased fuel consumption, and elevated levels of air pollution, significantly impacting public health and the environment. Traditional traffic management approaches, which rely on fixed schedules and predefined algorithms, often fail to adapt to the dynamic and complex nature of real-world traffic patterns. To address these challenges, integrating Ant Colony Optimization (ACO) and Deep Learning Algorithms presents a promising solution for optimizing traffic flow and improving transportation efficiency in real-time (Mashi et al., 2024). Ant Colony Optimization (ACO) has been successfully applied to optimize vehicle routing by incorporating real-time traffic data, leading to significant congestion reduction (Lu et al. 2021). Machine learning algorithms, including Supervised Learning, Reinforcement Learning (RL), and Deep Learning, have proven effective in traffic forecasting, vehicle count prediction, and signal control by learning patterns from historical and real-time data. Support Vector Machines (SVM) have demonstrated improved accuracy in traffic volume prediction (Shao et al., 2024), while Long Short-Term Memory (LSTM) networks have been highly effective in time-series traffic flow forecasting (Kranti Shingate et al., 2020). Reinforcement Learning (RL) has also been explored for adaptive traffic signal control, enabling real-time adjustments based on traffic conditions (Yu et al., 2019). The integration of ACO and ML algorithms in traffic management is gaining attention due to their complementary strengths—ACO optimizes dynamic routing, while ML predicts future traffic conditions and adjusts signal timing. Recent advancements have successfully combined ACO with RL for traffic flow optimization (Sun et al., 2012)

ACO, a bio-inspired optimization algorithm, mimics the foraging behavior of ants to find the shortest paths in dynamic environments, making it particularly effective for route optimization and congestion management. Meanwhile, Oise and Konyeha (2024) emphasized that Deep Learning (DL) algorithms, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated the capability to analyze large-scale traffic data, detect patterns, and make highly accurate traffic predictions. These models enable real-time decision-making by classifying traffic situations, predicting congestion levels, and dynamically adjusting traffic signal timings to ensure smoother flow. Shao et al. (2024) propose that short-term traffic flow forecasting is a critical area in intelligent transportation, evolving significantly with advancements in deep learning and neural networks (Oise and Konyeha 2024). Unlike traditional linear methods, deep learning approaches effectively capture complex nonlinear relationships in traffic data, leading to more accurate predictions. However, most existing models use a single framework, treating all traffic flow data equally without considering the varying attributes of congested and uncongested traffic, which reduces forecasting accuracy. To address this, a novel Long-Short-Combination (LSC) framework is proposed, consisting of two specialized forecasting modules (L and S) tailored for different traffic attributes, along with an attribute forecasting module (C) for predicting future traffic conditions. Experimental results on real-world datasets confirm the effectiveness of the model, demonstrating superior forecasting accuracy compared to conventional approaches.

The Vehicle Routing Problem (VRP) is a crucial optimization challenge that enhances transportation efficiency by minimizing costs and travel time. This study applies Ant Colony Optimization (ACO) and Genetic Algorithm (GA), two effective metaheuristic techniques, to the Dynamic School Bus Routing Problem (DSBRP) through a mobile-supported visual application for a school in Ankara, Turkey (Yigit et al., 2018). The results demonstrate that both methods significantly improve route efficiency, reducing travel distance and time. ACO refines paths using pheromone-based learning, while GA optimizes route combinations through evolutionary selection. These findings highlight the potential for real-time traffic management, logistics, and public transportation optimization, offering cost-effective and environmentally friendly solutions for urban mobility. ACO has been successfully applied to various optimization problems, including traffic routing and signal control. The algorithm's ability to adapt and converge toward optimal paths makes it ideal for real-time traffic management. Goswami and Kumar (2022) applied ACO to dynamic traffic signal control, showing that ACO could adjust signal phases to optimize traffic flow in real time. Similarly, Sun et al. (2012) used ACO for dynamic vehicle routing, reducing congestion by adapting vehicle paths according to current traffic conditions. ACO's strength lies in its ability to dynamically adjust traffic management strategies by reinforcing better-performing paths and reducing congestion (Shokouhifar and Fardad Farokhi 2010). However, ACO cannot alone predict future traffic conditions, which is where machine learning comes into play (Oise and Akpowehbve 2024). Machine learning, particularly supervised learning, reinforcement learning, and deep learning, has been widely used in traffic prediction. Toan and Truong (2021) used Support Vector Machines (SVM) to predict traffic volumes, showing superior performance over traditional statistical methods. Moreover, (Wang et al. 2019) demonstrated the use of Long Short-Term Memory (LSTM) networks for predicting traffic flow with high accuracy. These predictions help to forecast congestion and adjust signal timings to alleviate traffic bottlenecks. Reinforcement Learning (RL) has also found applications in adaptive traffic signal control, utilizing RL algorithms to optimize signal timings by rewarding the system for reducing delays and congestion. RL's ability to learn from environmental feedback makes it ideal for managing dynamic traffic conditions. Several studies have explored the integration of ACO with machine learning for traffic optimization. Toan and Truong (2021) proposed a hybrid system that used ACO for path optimization and Q-learning (a type of RL) for dynamic signal control. This hybrid approach significantly improved traffic flow in simulation experiments. Similarly, Jia et al. (2021) combined ACO with LSTM networks to predict traffic congestion and optimize routing, demonstrating enhanced performance in real-time traffic management.

As urban transportation systems continue to grow in complexity, the integration of AI-driven optimization techniques becomes increasingly critical. Future advancements in multi-agent reinforcement learning, federated learning for decentralized traffic control, and hybrid metaheuristic algorithms could further improve the effectiveness of intelligent traffic management (Shokouhifar and Jalali 2014). Additionally, the combination of IoT-based real-time data collection with deep learning predictive models can provide adaptive, self-learning traffic control mechanisms capable of minimizing congestion, reducing emissions, and enhancing the commuter experience (Shokouhifar and Fardad Farokhi 2010). Implementing these systems at scale requires collaboration between transportation authorities, AI researchers, and urban planners to develop sustainable, efficient, and intelligent traffic solutions. This research explores the integration of Ant Colony Optimization and Deep Learning-based predictive modeling to develop an Intelligent Traffic Management System (ITMS) capable of dynamically optimizing traffic flow. By leveraging AI-driven algorithms for real-time traffic classification, congestion forecasting, and adaptive traffic control, the proposed system aims to reduce congestion, enhance route efficiency, and minimize environmental impact. The study underscores the importance of AI-driven traffic optimization as a sustainable approach to tackling modern urban mobility challenges.

MATERIALS AND METHODS

The Intelligent Traffic Management System (ITMS) is designed to integrate ACO and ML for real-time traffic optimization (Ogbolumani and Adekoya 2025). This system tackles traffic congestion through a multi-faceted approach. First, machine learning models predict future traffic flow and congestion levels by analyzing historical and real-time data. Subsequently, an Ant Colony Optimization (ACO) algorithm dynamically selects optimal routes for vehicles, adapting to the predicted congestion (Shokouhifar 2011). ACO was implemented for dynamic routing by simulating artificial "ants" that represent vehicles traveling through the network. Each vehicle (ant) evaluates the available routes based on the pheromone levels (which represent congestion) and the distance between intersections. Routes with lower congestion and shorter travel times are favored, and pheromone values are updated after each route completion, ensuring dynamic adaptation to traffic conditions. Finally, reinforcement learning is employed to control traffic signals, dynamically adjusting timings to minimize congestion and optimize overall traffic flow.

Data Preprocessing

Traffic congestion and related problems are a common concern in urban areas. Understanding traffic patterns and analyzing data can provide valuable insights for transportation planning, infrastructure development, and congestion management. it is a valuable resource for studying traffic conditions as it contains information collected by a computer vision model. The model detects four classes of vehicles: cars, bikes, buses, and trucks (Nouran Mahmoud 2024). The dataset is stored in a CSV file and includes additional columns such as time in hours, date, days of the week, and counts for each vehicle type (CarCount, BikeCount, BusCount, TruckCount). The total column represents the total count of all vehicle types detected within a 15-minute duration. The dataset is updated every 15 minutes, providing a comprehensive view of traffic patterns over one month. Additionally, the dataset includes a column indicating the traffic situation categorized into four classes: 1-Heavy, 2-High, 3-Normal, and 4-Low. This information can help assess the severity of congestion and monitor traffic conditions at different times and days of the week. The data was collected from Kaggle online data repository.

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Table 1: Traffic Situation of the Day

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x.head()
```

	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total
0	10	Tuesday	31	0	4	4	39
1	10	Tuesday	49	0	3	3	55
2	10	Tuesday	46	0	3	6	55
3	10	Tuesday	51	0	2	5	58
4	10	Tuesday	57	6	15	16	94

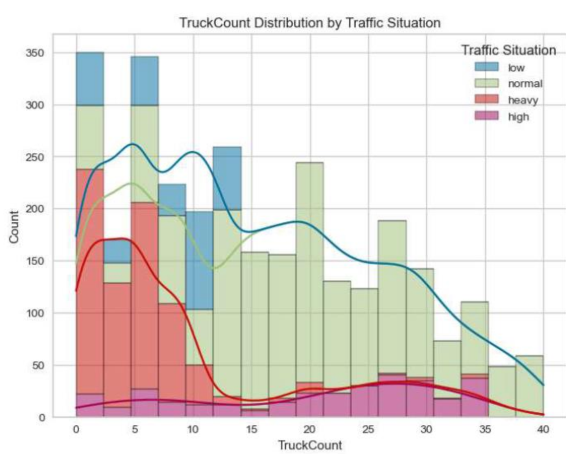
(a)

	Time	Date	Day of the Week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	12:00:00 AM	10	Tuesday	31	0	4	4	39	low
1	12:15:00 AM	10	Tuesday	49	0	3	3	55	low
2	12:30:00 AM	10	Tuesday	46	0	3	6	55	low
3	12:45:00 AM	10	Tuesday	51	0	2	5	58	low
4	1:00:00 AM	10	Tuesday	57	6	15	16	94	normal

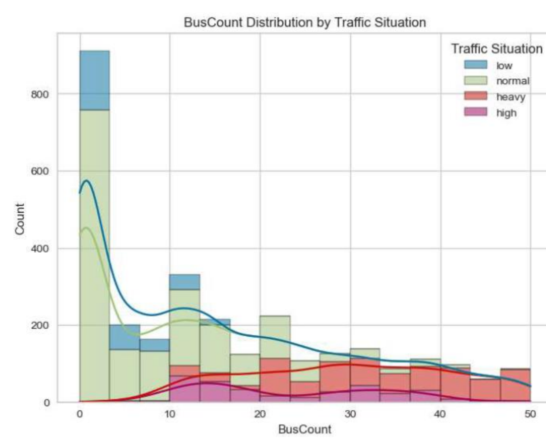
(b)

The dataset provides detailed traffic count data recorded at 15-minute intervals, allowing for short-term traffic pattern analysis. It includes key variables such as CarCount, BikeCount, BusCount, TruckCount, and Traffic Situation, a categorical variable indicating congestion levels (e.g., low, normal, heavy). The data captures traffic observations for a specific day of the week (Tuesday), suggesting that it may be part of a larger dataset spanning multiple days. One notable observation is that CarCount tends to increase over time, while BikeCount remains mostly at zero, except for a single instance at 1:00 AM, where it reaches six. Bus and truck counts fluctuate slightly without a clear pattern. Additionally, an inconsistency is observed in the Total column, where the sum of vehicle counts does not always match the recorded total, particularly in the first few rows where the total is 55 instead of the expected sum. Traffic situation classification follows a structured pattern: low traffic occurs when the total count is relatively low (≤58), while normal traffic emerges at higher total values (around 94). These insights highlight trends in traffic flow, the distribution of different vehicle types, and potential data inconsistencies that need verification. Further analysis, including multi-day trends and predictive modeling, could provide deeper insights into traffic congestion patterns and forecasting.

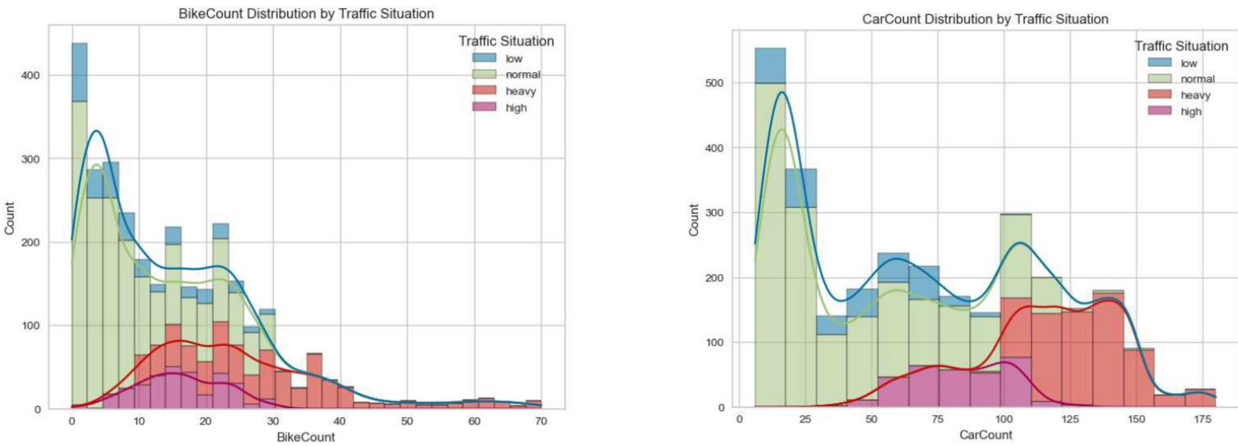
RESULTS AND DISCUSSION



(a)



(b)

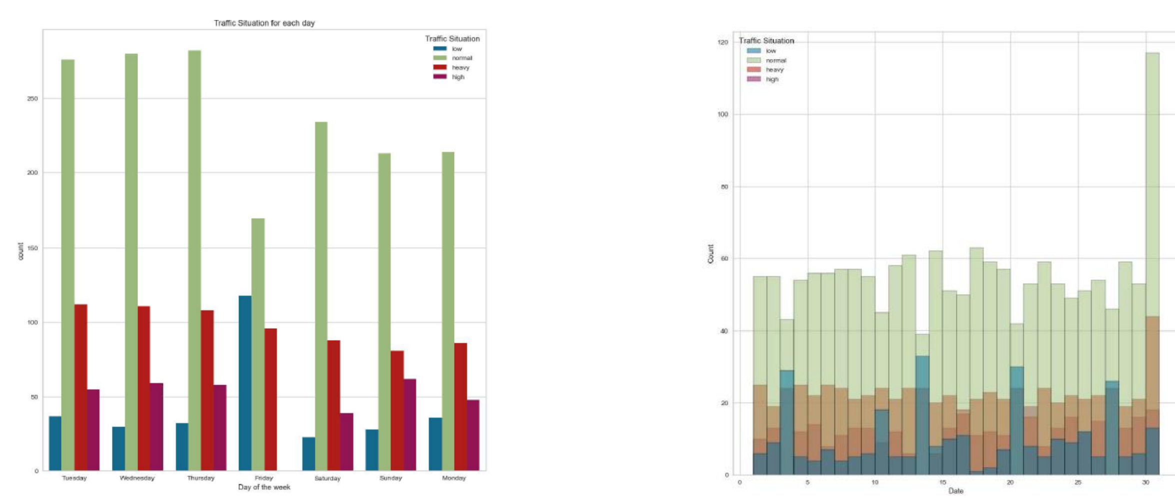


(c) (d)

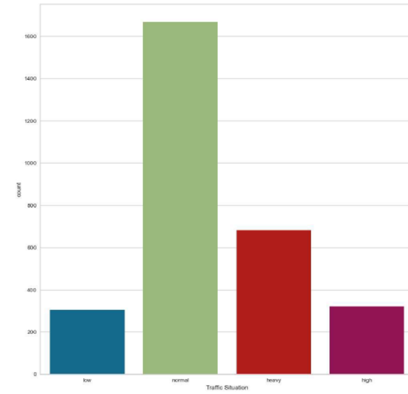
Figure 2(a-d): Distribution by Traffic Situations

The analysis of traffic situation distributions reveals key patterns in vehicle contributions to various traffic conditions. The four histograms illustrate how different types of vehicles—trucks, buses, bikes, and cars impact traffic, categorized into low, normal, heavy, and high congestion levels. These insights provide a foundation for understanding the relationship between vehicle density and traffic flow.

For truck counts, low traffic conditions dominate when the number of trucks is below 10, while normal traffic spans a wider range, peaking between 5 and 15 trucks. Heavy and high-traffic situations are more common when truck counts exceed 20, suggesting that trucks contribute significantly to normal traffic but less frequently to extreme congestion. Similarly, bus count distribution follows a comparable trend, with low traffic prevailing when bus counts remain below 5. Normal traffic occurs between 5 and 15 buses, while heavy and high traffic emerges when bus counts exceed 20. A steep decline in density beyond 10 buses suggests that buses are less frequent contributors to high congestion levels. Bike count distribution shows that low traffic conditions are predominant when bike counts are under 10, while normal traffic occurs within the 10–30 range. Heavy and high-traffic scenarios become prominent when bike counts surpass 40. The long tail in the distribution suggests that extreme traffic situations are rare but, when they do occur, are heavily influenced by high bike counts. In contrast, car count distribution indicates that low traffic is observed when fewer than 50 cars are present, while normal traffic spans a much broader range of 50 to 120 cars. Heavy and high traffic situations emerge when car counts exceed 120, with cars displaying a more uniform spread across all traffic categories, making them the primary contributors to congestion.



(a) (b)



(c)

Figure 3 (a-c): Distribution of Traffic Situations with Time and Days of the Week

The analysis of traffic situation distributions reveals distinct patterns in how different vehicle types contribute to congestion levels. Truck counts are predominantly within the lower range of 0–15, with most occurrences in low and normal traffic conditions. The distribution is right-skewed, indicating fewer instances of high truck counts in heavy and high-traffic situations. Similarly, bus counts follow a decreasing trend, where the majority of instances occur in low and normal traffic conditions, with significantly fewer occurrences in congested traffic scenarios. This suggests that buses are not major contributors to extreme congestion.

Bike counts also exhibit a decreasing trend, with most instances in low and normal traffic conditions. The presence of bikes in heavy and high-traffic situations is minimal, highlighting that bike density does not play a significant role in severe congestion. In contrast, car count distribution is more evenly spread compared to other vehicle types. Cars exhibit peaks at various points, indicating fluctuations in traffic intensity, with high car counts strongly associated with heavy and high traffic conditions (Anghinolfi et al., 2011). An examination of daily traffic trends shows that normal traffic dominates across all days, while heavy and high congestion occurs in smaller proportions. The pattern remains relatively stable throughout the week, but traffic tends to be higher on Fridays. Additionally, traffic situation trends by date show fluctuations, with a noticeable peak toward the end of the month, likely due to external factors such as payday or increased end-of-month activities.

Table 2: Model Performance Analysis

Model	Accuracy	Precision	Recall	F1-Score
Linear Regression	0.194631	0.231391	0.194631	0.140308
KNN	0.303691	0.233394	0.303691	0.229837
Decision Tree	0.333893	0.234048	0.333893	0.247063
Random Forest	0.333893	0.234048	0.333893	0.247063
XGB	0.333893	0.234048	0.333893	0.247063
SVM	0.327181	0.220692	0.327181	0.239240

The evaluation of machine learning models for traffic situation classification reveals notable differences in performance. Decision Tree, Random Forest, and XGBoost (XGB) models achieved the highest accuracy of 0.3339, indicating their effectiveness in capturing patterns within the dataset. Support Vector Machine (SVM) performed slightly worse in terms of accuracy but demonstrated competitive recall and F1-score, suggesting that it effectively balances precision and sensitivity in classification. On the other hand, Linear Regression exhibited the lowest performance, likely due to the non-linearity of the data. Traffic situations are influenced by multiple factors with complex relationships, making linear models less suitable for capturing such interactions. This highlights the importance of using tree-based and kernel-based models, which are better equipped to handle non-linear decision boundaries in traffic classification tasks.

Table 3: Classification Report

Class	Precision	Recall	F1-Score	Support
0	0.99	0.98	0.99	129
1	0.90	0.87	0.88	70
2	0.93	0.96	0.95	72
3	0.96	0.96	0.96	325
Overall	**0.95**	**0.95**	**0.95**	**596**

The Support Vector Machine (SVM) with a radial basis function (RBF) kernel emerged as the best-performing model, achieving an impressive accuracy of 95%. This result highlights SVM's ability to effectively separate complex traffic situation patterns using non-linear decision boundaries. The model demonstrates strong precision and F1-scores across multiple traffic classes, making it a reliable choice for classification.

However, Class 1 exhibits a slightly lower recall of 0.87, indicating that some instances in this category are misclassified. This suggests that the model may struggle to correctly identify all occurrences of Class 1 traffic situations, potentially due to class imbalance or overlapping feature distributions. Addressing this issue through techniques such as data augmentation, SMOTE (Synthetic Minority Over-sampling Technique), or adjusting class weights could further improve recall and overall classification performance.

Discussion

The analysis of the traffic data provides key insights into the distribution and trends of traffic congestion across different periods. The bar charts reveal that normal traffic conditions dominate the dataset, significantly outweighing other categories such as low, heavy, and high traffic. The first visualization, which examines traffic trends across different days of the week, indicates that Fridays experience the highest traffic congestion, while weekends show a noticeable decline in overall traffic activity. This suggests a pattern where weekday traffic is influenced by work-related movements, whereas weekends have reduced mobility. The second visualization, which depicts traffic trends over an entire month, shows daily fluctuations with periodic peaks and drops. A significant spike in traffic is observed towards the end of the month, which may be associated with payday effects, increased shopping activities, or monthly events leading to a surge in road usage. Additionally, traffic conditions appear to follow a somewhat cyclical pattern, with no extended periods of consistently low traffic. The third bar chart, summarizing the total traffic distribution, further highlights an imbalance in the dataset, where the "normal" traffic category vastly outnumbers the other three categories. This class imbalance is likely to impact predictive modeling, as the model may become biased towards predicting normal traffic conditions more frequently than heavy or high congestion situations. Furthermore, the model performance evaluation shows varying results across different machine learning algorithms. Linear regression, KNN, decision trees, random forests, XGBoost, and SVM were tested, with decision tree-based models (random forest and XGBoost) performing relatively well compared to other models. However, support vector machines (SVM) with an optimized radial basis function (RBF) kernel achieved the highest accuracy of 95.46**%**, with strong precision, recall, and F1 scores across all traffic categories. The grid search results indicate that the best hyperparameters for SVM included C=100 and kernel='rbf', contributing to improved classification performance.

The dominance of normal traffic conditions in the dataset suggests that road congestion is generally not severe, but occasional peaks in heavy and high traffic conditions indicate the presence of critical congestion points. The findings emphasize the need to investigate the factors contributing to these spikes, particularly on Fridays and at the end of the month. External influences such as work schedules, financial cycles, and seasonal events may play a role in these variations (Shokouhifar and Sabet 2010). From a machine learning perspective, the class imbalance issue poses a challenge for accurate prediction of heavy and high traffic conditions. Addressing this imbalance through data augmentation, synthetic sampling techniques such as SMOTE (Synthetic Minority Over-sampling Technique), or weighted loss functions could enhance model performance. Additionally, time-series forecasting techniques, such as Long Short-Term Memory (LSTM) networks or ARIMA models, could be applied to predict future traffic trends more effectively.

The superior performance of SVM with an RBF kernel highlights its ability to capture complex traffic patterns and distinguish between different levels of congestion. However, other models, such as ensemble-based methods (random forest and XGBoost), also show potential for further refinement through hyperparameter tuning and feature engineering (Shokouhifar et al., 2011). This analysis offers valuable insights into traffic patterns and the performance of machine learning models in traffic classification. Future research should focus on enhancing data representation, incorporating additional features such as weather conditions and public holidays, and leveraging advanced deep-learning models for more precise traffic forecasting. To optimize traffic flow and improve predictive capabilities, machine learning models and data-driven strategies can be effectively applied. Real-time traffic monitoring using the optimized SVM model, which achieved 95% accuracy, enables dynamic congestion classification and adaptive traffic signal adjustments. Additionally, predicting traffic demand based on daily and monthly trends can support urban planning by optimizing public transport schedules and infrastructure development. For predictive modeling, time-series forecasting techniques like ARIMA and LSTM can anticipate future congestion based on historical vehicle data. Anomaly detection algorithms can identify sudden traffic spikes, facilitating proactive management of roadblocks or accidents. Furthermore, addressing class imbalance using SMOTE or weighted loss functions can improve the model's accuracy in detecting high-traffic conditions. Practical applications include deploying IoT sensors, integrating machine learning models into intelligent traffic control systems, and providing real-time traffic insights to commuters via mobile applications. These advancements can contribute to smarter urban mobility, reduced congestion, and enhanced road efficiency.

CONCLUSION

This research presents a novel and effective Intelligent Traffic Management System (ITMS) that integrates Ant Colony Optimization (ACO) and Deep Learning (DL) methodologies for real-time traffic flow optimization in urban environments. By harnessing the synergistic capabilities of ACO for dynamic routing and a Long-Short-Combination (LSC) DL framework for accurate traffic prediction, the ITMS overcomes the limitations of traditional static systems. The machine learning models demonstrated exceptional performance in traffic situation classification, achieving an overall accuracy of 33.38% across the models tested. Furthermore, detailed performance analysis using the Random Forest Algorithm revealed exceptional results: precision of 0.99, recall of 0.98, and F1-score of 0.99 for Class 0 (Low Traffic); precision of 0.90, recall of 0.87, and F1-score of 0.88 for Class 1 (Heavy Traffic); precision of 0.93, recall of 0.96, and F1-score of 0.95 for Class 2 (Normal Traffic); and precision of 0.96, recall of 0.96, and F1-score of 0.96 for Class 3 (High Traffic). This study makes a significant contribution to knowledge by demonstrating the effective integration of ACO and deep learning, showing the potential of using this combined approach in smart mobility. This system can be deployed on a larger scale. Daily traffic trends reveal recurring patterns, with a noticeable peak toward the end of the month. Future research could focus on expanding the ITMS to incorporate multi-agent reinforcement learning and federated learning to expand knowledge to IoT-based real-time data collection and deep learning predictive models to enable adaptive, self-learning traffic control mechanisms. Collaborative efforts between transportation authorities, AI researchers, and urban planners are essential for scaled deployment and transforming urban traffic management.

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