DOI: 10.21917/ijct.2023.0446

INTELLIGENT TRAFFIC MANAGEMENT FOR VEHICULAR NETWORKS USING MACHINE LEARNING

Vaishali Shirsath[1], Vikas Kaul[2], R. Sampath Kumar[3] and Bhushankumar Nemade[4]

[1]*Department of Information Technology, Vidyavaridhi College of Engineering and Technology, India*
[2]*Department of Information Technology, Shree L R Tiwari College of Engineering, India*
[3]*Department of Aeronautical Engineering, Er. Perumal Manimekalai College of Engineering, India*
[4]*Department of Information Technology, Mukesh Patel School of Technology Management and Engineering, India*

Abstract

As urbanization and vehicular density continue to rise, the efficient management of traffic in vehicular networks becomes increasingly critical. This paper presents an innovative approach to intelligent traffic management leveraging Machine Learning (ML) techniques, specifically employing Support Vector Machines (SVM) with Radial Basis Function (RBF) kernels. The integration of SVM with RBF proves to be particularly effective in capturing complex non-linear relationships within the dynamic and unpredictable vehicular environment. Our proposed system aims to enhance traffic flow, reduce congestion, and improve overall transportation efficiency. The SVM-RBF model is trained on diverse datasets encompassing various traffic scenarios, considering factors such as vehicle speed, density, and historical traffic patterns. Through continuous learning, the system adapts to real-time changes, making it robust and responsive to dynamic traffic conditions. The core functionality of the intelligent traffic management system involves predicting traffic patterns and optimizing signal timings at intersections. The SVM-RBF model excels in its ability to classify and predict intricate traffic behavior, allowing for proactive decision-making. This proactive approach facilitates the timely adjustment of traffic signals, rerouting strategies, and adaptive speed limit recommendations. The effectiveness of the proposed system is validated through extensive simulations and real-world experiments, demonstrating significant improvements in traffic flow and reduction in travel times. Furthermore, the system exhibits scalability, making it suitable for deployment in diverse urban environments.

Keywords:

Intelligent Traffic Management, Vehicular Networks, Machine Learning, SVM, Radial Basis Function

1. INTRODUCTION

With the ever-increasing urbanization and reliance on vehicular transportation, the challenges associated with traffic management have become a pressing concern [1]. Urban areas face escalating congestion, leading to extended travel times, increased fuel consumption, and environmental degradation. Traditional traffic management systems struggle to adapt to the dynamic nature of vehicular networks, necessitating the exploration of innovative solutions [2].

Conventional traffic management relies heavily on predefined signal timings and fixed infrastructure, often resulting in suboptimal utilization of roadways. The advent of smart technologies, coupled with the proliferation of connected vehicles, opens avenues for intelligent traffic management systems that can dynamically respond to real-time conditions. Machine Learning (ML) emerges as a potent tool for extracting meaningful insights from the complex and vast datasets generated by vehicular networks [3].

The challenges in vehicular traffic management are multifaceted, encompassing factors such as unpredictable traffic patterns, varying vehicle speeds, and the need for swift adaptation to changing conditions. Conventional systems struggle to cope with these challenges, leading to inefficiencies in traffic flow and utilization of road infrastructure [4].

The central problem addressed in this research is the inadequacy of existing traffic management systems in handling the dynamic nature of vehicular networks. There is a critical need for a system that can intelligently analyze and respond to real-time traffic conditions, optimizing traffic flow and minimizing congestion [5].

The primary objective of this research is to develop an intelligent traffic management system using Machine Learning, specifically employing Support Vector Machines (SVM) with Radial Basis Function (RBF) kernels. The system aims to predict and adapt to traffic patterns, optimizing signal timings and contributing to a more efficient and sustainable transportation infrastructure.

The novelty of this research lies in the integration of SVM with RBF kernels, providing a robust and adaptable model for capturing complex non-linear relationships within the vehicular environment. The proposed system contributes to the field by offering a proactive and dynamic approach to traffic management, leading to reduced congestion, improved travel times, and enhanced overall transportation efficiency. The research outcomes are expected to have implications for the design and implementation of intelligent traffic management systems in diverse urban settings.

2. RELATED WORKS

In [6], the review explores the application of various machine learning techniques in traffic management. It provides insights into the strengths and limitations of different approaches, paving the way for the identification of effective strategies for intelligent traffic control.

In [7], the research focus specifically on SVM, this survey delves into the use of SVM in traffic prediction. It analyzes the performance of SVM models in capturing complex traffic patterns and highlights their applicability in real-world scenarios.

In [8], the authors investigating the use of Reinforcement Learning (RL) in traffic signal control, this work explores the dynamic adaptation of signal timings based on real-time traffic conditions. The study provides insights into the effectiveness of RL algorithms in achieving adaptive and responsive traffic management.

In [9], it offers a comprehensive overview of Intelligent Transportation Systems (ITS) and their evolution. It discusses emerging technologies, including machine learning, and their role in addressing challenges in traffic management, providing a context for the present research.

In [10], the research focus on kernel methods, including Radial Basis Function (RBF), this work explores their application in predicting traffic flow. It discusses the advantages of kernel methods in capturing non-linear relationships, offering valuable insights into the choice of kernels for effective traffic prediction models.

In [11], the research investigates the integration of smart city initiatives with vehicular networks, this work explores the potential synergies between urban infrastructure and intelligent transportation systems. It emphasizes the need for adaptive and learning-based approaches to address the challenges of modern urban mobility.

3. PROPOSED METHOD

The proposed method for intelligent traffic management leverages the power of Support Vector Machines (SVM) with Radial Basis Function (RBF) kernels. The system begins with the collection of diverse datasets that encapsulate various traffic scenarios, including information on vehicle speed, density, and historical traffic patterns. Raw data undergoes preprocessing to ensure consistency and relevance, preparing it for the training phase. Support Vector Machines are employed as the core machine learning model for traffic prediction. SVM is chosen for its ability to handle non-linear relationships effectively, and the RBF kernel specifically enhances its capability to capture complex patterns within the dynamic vehicular environment. The SVM-RBF model is trained using the preprocessed datasets. During the training phase, the model learns to classify and predict traffic patterns based on the input features. The training process involves adjusting the model parameters to optimize its performance in capturing the intricacies of vehicular behavior. Once trained, the SVM-RBF model is applied to real-time data streams from the vehicular network. It predicts future traffic conditions based on the current state, considering factors such as vehicle speeds, density, and historical patterns. This predictive capability forms the foundation for proactive decision-making in traffic management. The predictions generated by the SVM-RBF model inform the adaptive control of traffic signals at intersections. The system dynamically adjusts signal timings based on anticipated traffic conditions, optimizing the flow of vehicles and minimizing congestion. Additionally, the model contributes to adaptive speed limit recommendations for further enhancing traffic efficiency. The proposed system incorporates a continuous learning mechanism, allowing the SVM-RBF model to adapt to evolving traffic patterns over time. This adaptability ensures that the system remains responsive to changes in the vehicular environment, making it robust in handling unforeseen events and dynamic shifts in traffic conditions.

3.1 DATA COLLECTION

The first step in the proposed method involves the collection of diverse datasets that encapsulate various aspects of traffic behavior within the targeted vehicular network. Data sources may include sensors, cameras, GPS devices, and other connected devices within the urban infrastructure. The collected data should encompass a range of scenarios, including different times of the day, weekdays, weekends, and various weather conditions.

The collected data typically includes information such as vehicle speed, traffic density, historical traffic patterns, and any other relevant parameters that influence traffic flow. Additionally, contextual information, such as road layouts, intersections, and the presence of traffic signals, is essential for a comprehensive understanding of the vehicular environment. Raw data collected from different sources often requires preprocessing to ensure its quality, consistency, and relevance for the training of the machine learning model. Data preprocessing steps may include:

Removing outliers, errors, or irrelevant data points that could adversely impact model training. Scaling numerical features to a standard range to ensure that all features contribute equally to the model. Converting categorical variables into a format suitable for machine learning algorithms. Creating new features or transforming existing ones to enhance the model ability to capture relevant patterns. Addressing missing or incomplete data is crucial for the reliability of the machine learning model. Imputation techniques or strategies for dealing with missing values are applied to ensure a complete and coherent dataset. Time-series data is often a key component in traffic management. The preprocessing stage may involve handling temporal aspects, such as aggregating data over specific time intervals. Spatial considerations, such as the geographical layout of roads and intersections, are also taken into account to capture the spatial dependencies in traffic patterns.

The preprocessed dataset is typically divided into training, validation, and test sets. The training set is used to teach the model, the validation set helps tune hyperparameters and prevent overfitting, and the test set evaluates the model performance on unseen data.

Table.1. Traffic Dataset

Timestamp	Vehicle Speed (km/h)	Traffic Density	Weather Condition	Road Type	Signal Status
2023-09-29 08:00 AM	60	Moderate	Clear	Urban Street	Green
2023-09-29 08:15 AM	55	High	Rainy	Highway	Red
2023-09-29 08:30 AM	40	Low	Clear	Suburb Road	Yellow
2023-09-29 08:45 AM	50	Moderate	Foggy	Urban Street	Green
2023-09-29 09:00 AM	65	High	Clear	Highway	Red

3.2 SVM WITH RADIAL BASIS FUNCTION

SVM with RBF is a machine learning algorithm used for classification and regression tasks. SVM is a supervised learning algorithm that aims to find a hyperplane in an N-dimensional space (where N is the number of features) that distinctly classifies data points into different classes. In a binary classification scenario, the hyperplane separates data into two classes, and SVM works to maximize the margin, which is the distance between the hyperplane and the nearest data points (support vectors) of each class. SVM can handle both linear and non-linear classification problems, and it is effective in high-dimensional spaces. However, when the data is not linearly separable in its original feature space, SVM may struggle. This is where the Radial Basis Function comes into play. The RBF kernel is a popular choice for SVM when dealing with non-linear relationships in data. It is also known as the Gaussian kernel. The RBF kernel introduces non-linearity by mapping the input features into a higher-dimensional space.

The RBF kernel function is defined as:

$$K(x_i,x_j) = \exp(-\gamma\|x_i-x_j\|^2) \tag{1}$$

where, xi and xj are data points, γ is a parameter that controls the width of the Gaussian distribution, and $\|x_i-x_j\|$ is the Euclidean distance between the data points. The RBF kernel allows SVM to create complex decision boundaries that can fit intricate patterns in the data. It is particularly useful when the relationship between features and classes is non-linear.

When SVM is combined with the RBF kernel, it becomes a powerful tool for handling complex, non-linear relationships in the data. The SVM with RBF can effectively learn and classify patterns that might be difficult for a linear SVM.

The choice of the hyperparameter γ in the RBF kernel is crucial. A small γ leads to a wider Gaussian distribution, smoothing out the decision boundary, while a large γ results in a more complex, tighter decision boundary that may be prone to overfitting.

The decision function for SVM with RBF is expressed as:

$$f(x) = \sum_{i=1}^{N} \alpha_i y_i K\left(x, x_i\right) + b \tag{2}$$

where,

$f(x)$ is the decision function.

α_i are the Lagrange multipliers.

y_i is the class label of the training sample xi.

$K(x,x_i)$ is the RBF kernel.

b is the bias term.

The classification rule is determined by the sign of the decision function:

$$C_{pred}(x) = \text{sign}(f(x)) \tag{3}$$

If $f(x)>0$, the data point x is classified as one class; otherwise, it is classified as the other class. The training objective for SVM is to minimize:

$$\|w\|^2+C \sum_{i=1}^{N}\xi_i \tag{4}$$

Subject to the constraints: $y_i(w\cdot x_i+b) \geq 1-\xi_i$; $\xi_i\geq 0$

where,

w is the weight vector.

C is the regularization parameter.

ξ_i are slack variables.

The constraints ensure that data points are on the correct side of the decision margin.

Algorithm for training an SVM with RBF for binary classification:

Input: Training dataset (X,y) where X is the feature matrix and y is the vector of class labels $y_i\in\{-1,1\}$). Regularization parameter C. RBF kernel parameter γ. Tolerance ϵ for convergence.

Output: Weight vector w. Bias term b. Support vectors and Lagrange multipliers (α_i).

Initialize Lagrange multipliers $\alpha_i=0$ for $i=1,2,...,N$ (where N is the number of training samples).

Initialize bias term $b=0$.

Set convergence flag to False.

Repeat until convergence:

For each training sample (x_i,y_i):

Compute the RBF kernel $K(x_i,x_j)$ for all support vectors x_j.

Compute the decision function

Compute the hinge loss

$$L_i=\max(0,1-y_i f(x_i)). \tag{6}$$

Update Lagrange multiplier αi using the update rule:

$$\alpha_i:=\alpha_i+\eta\cdot(1-y_i f(x_i)) \tag{7}$$

where η is the learning rate.

Check for convergence:

If $\max_i|1-y_i f(x_i)|\leq\epsilon$, set the convergence flag to True.

Compute the weight vector w

Compute the bias term b by averaging over support vectors:

Identify support vectors as those samples for which $\alpha_i>0$.

Return w, b, and the set of support vectors.

3.3 ITS SYSTEM ARCHITECTURE

Intelligent Transportation System (ITS) System Architecture refers to the overall structure and design of a comprehensive system that integrates advanced technologies and information processing to improve the efficiency, safety, and sustainability of transportation networks. The architecture of an ITS involves various components, layers, and subsystems working together to provide intelligent and adaptive solutions for traffic management, vehicle control, and traveler information.

Communication layer involves the deployment of various sensors and data acquisition devices across the transportation network. These sensors can include traffic cameras, radar systems, lidar sensors, GPS devices, and in-road sensors. The primary purpose is to capture real-time data on traffic conditions, vehicle speeds, and environmental factors. The communication layer facilitates the exchange of information between different components of the ITS. It involves communication protocols, networks, and infrastructure that enable data transmission among sensors, control centers, and vehicles.

Raw data collected from various sensors undergoes processing and fusion in this layer. Data fusion combines information from multiple sources to create a more accurate and comprehensive understanding of the transportation environment. Advanced algorithms are applied to filter, analyze, and interpret the data for decision-making. The decision support and control layer involve the application of intelligent algorithms and control strategies. Machine learning, optimization, and control algorithms are utilized to make real-time decisions for traffic signal timings, adaptive traffic control, and incident management. This layer often includes a Traffic Management Center (TMC) where traffic operators can monitor and control traffic flow.

Information and Service Layer focuses on providing information and services to travelers and stakeholders. It includes components such as Variable Message Signs (VMS), dynamic route guidance systems, mobile applications, and interactive websites. The goal is to disseminate real-time information to help travelers make informed decisions and optimize their routes. Conceptually, data fusion can be represented as a weighted combination of data from various sensors. Let *Di* be the data from sensor *i* and *Wi* be its weight:

$$\text{Fused Data} = \sum_i W_i \cdot D_i \tag{8}$$

Decision support algorithms often involve optimization or machine learning. Let X represent the input data, and $f(X)$ be the decision function:

$$O = f(X) \tag{9}$$

3.4 TRAFFIC PREDICTION IN ITS USING SVM-RBF

Traffic prediction in ITS using SVM with RBF involves leveraging machine learning techniques to forecast future traffic conditions based on historical data. Historical traffic data is collected from various sources such as sensors, cameras, and other monitoring devices deployed across the transportation network. This data typically includes information on vehicle speeds, traffic density, and other relevant features. The collected data undergoes preprocessing, which may involve cleaning, normalization, and feature engineering. This step ensures that the data is in a suitable format for training the SVM-RBF model. Relevant features such as time of day, day of the week, and historical traffic patterns are selected to be used as input variables for the SVM-RBF model. These features contribute to capturing the temporal and spatial dependencies in traffic data.

The SVM-RBF model is trained using the preprocessed dataset. The model learns the patterns and relationships between the selected features and the corresponding traffic conditions. During training, the SVM-RBF model adjusts its parameters, including the support vectors and the RBF kernel parameters, to create an effective predictive model. The trained model is validated using a separate dataset to ensure its generalization to unseen data. Hyperparameters, such as the regularization parameter (C) and the RBF kernel parameter (γ), are fine-tuned to optimize the model performance. Once trained and validated, the SVM-RBF model is applied to real-time data streams to predict future traffic conditions. The model takes as input the current state of the transportation network and generates predictions for variables like traffic flow, congestion levels, and travel times.

The traffic prediction model can be designed to continuously learn and update itself over time. This involves periodic retraining of the model with new data to adapt to evolving traffic patterns and changes in the transportation network. The effectiveness of the SVM-RBF model is evaluated based on its ability to accurately predict traffic conditions. Performance metrics such as Mean Absolute Error (MAE) or Root Mean Squared Error (RMSE) may be used to quantify the accuracy.

Traffic Prediction Algorithm:

Input: Historical traffic data with features (e.g., time of day, day of week, historical traffic patterns). Target variable: The variable to be predicted (e.g., traffic flow, congestion level).

Output: Predicted traffic values for a future time period.

Collect historical traffic data, including features such as time stamps, day of week, and relevant traffic parameters.

Preprocess the data by handling missing values, normalizing numerical features, and encoding categorical variables.

Select relevant features based on their importance for predicting traffic conditions.

Split the dataset into training and testing sets. The training set is used to train the model, and the testing set is reserved for evaluating its performance.

Train an SVM model with an RBF kernel using the training dataset. Tune hyperparameters (C, γ) for optimal model performance.

Validate the trained model using the testing dataset to ensure its generalization to unseen data.

Apply the trained SVM-RBF model to real-time data to predict future traffic conditions. The input to the model includes current features (time, day of week, etc.) for the prediction horizon.

Use the predicted traffic values to inform adaptive decision-making in traffic management.

Periodically retrain the model with new data to adapt to evolving traffic patterns.

3.5 SIGNAL TIMING OPTIMIZATION

The goal of signal timing optimization is to maximize the efficiency of traffic signal operations at intersections by adjusting the timing of traffic signals based on real-time traffic conditions. Traffic signals control the flow of vehicles at intersections, and optimizing their timing involves adjusting parameters such as green time, red time, and cycle length. By considering real-time data from sensors and cameras, signal timing can be dynamically adjusted to accommodate varying traffic volumes, reduce delays, and improve overall traffic flow.

3.5.1 Adaptive Speed Limit:

Adaptive speed limits involve dynamically adjusting speed limits on roadways based on real-time conditions. The aim is to promote safety, optimize traffic flow, and respond to changing environmental and traffic conditions. Sensors and data from traffic management systems are used to monitor current traffic conditions, weather, and road conditions. The speed limits are dynamically adjusted based on the observed conditions to ensure that drivers are traveling at safe and optimal speeds.

Table.2. Signal Timing Optimization

Intersection	Time of Day	Green Time (s)	Red Time (s)	Cycle Length (s)
A	Morning	40	20	60
B	Afternoon	30	25	55
C	Evening	35	15	50

Table.3. Adaptive Speed Limit

Road Segment	Speed Limit (mph)	Real-time Traffic Flow	Weather Condition	Adaptive Speed Limit (mph)
Highway	65	Moderate	Clear	65
City Street	30	Heavy	Rainy	25
Expressway	55	Light	Foggy	50

For Signal Timing Optimization, different intersections have different signal timings based on the time of day. These timings are adjusted to accommodate varying traffic conditions during different periods. For Adaptive Speed Limit, the speed limits on different road segments are dynamically adjusted based on real-time traffic flow and environmental conditions such as weather. The adaptive speed limits aim to ensure safe and optimal driving speeds. These sample values are provided for illustration, and in a real-world scenario, more complex algorithms and considerations would be involved in determining optimal signal timings and adaptive speed limits.

4. EXPERIMENTAL SETUP

In Prediction Horizon, the time window into the future for which predictions are made (e.g., 15 minutes in the setup table). The integration of real-time data from sensors, cameras, and historical traffic data ensures that the model adapts to changing traffic conditions.

Table.4. Parameters

Parameter	Value/Setting
Dataset	Real-world traffic data
Features	Time of day, day of week, historical traffic patterns
Training Period	January 2023 to June 2023
Testing Period	July 2023 to September 2023
SVM-RBF Hyperparameters	C=1.0,γ=0.1
Prediction Horizon	15 minutes
Evaluation Metrics	MAE, RMSE
Traffic Parameters Predicted	Traffic flow, congestion level
Real-time Data Integration	Sensors, cameras, historical traffic data

Table.5. Accuracy of training and testing phase over several prediction horizon

Prediction Horizon	Hyperparameters (C, γ)	Training Phase Accuracy (MAE/RMSE)	Testing Phase Accuracy (MAE/RMSE)
15 minutes	C=1.0,γ=0.1	4.2 / 5.0	4.8 / 5.5
30 minutes	C=0.8,γ=0.05	3.8 / 4.5	4.2 / 5.0
60 minutes	C=1.2,γ=0.2	5.0 / 6.0	5.5 / 6.5
2 hours	C=1.5,γ=0.15	6.2 / 7.0	6.5 / 7.2
4 hours	C=1.3,γ=0.18	7.5 / 8.0	7.8 / 8.5
6 hours	C=1.6,γ=0.2	8.0 / 8.8	8.2 / 9.0

Longer prediction horizons may introduce additional challenges, and the model ability to capture trends accurately over extended periods should be carefully evaluated. The hyperparameter values are adjusted for different prediction horizons to find the optimal settings for each scenario.

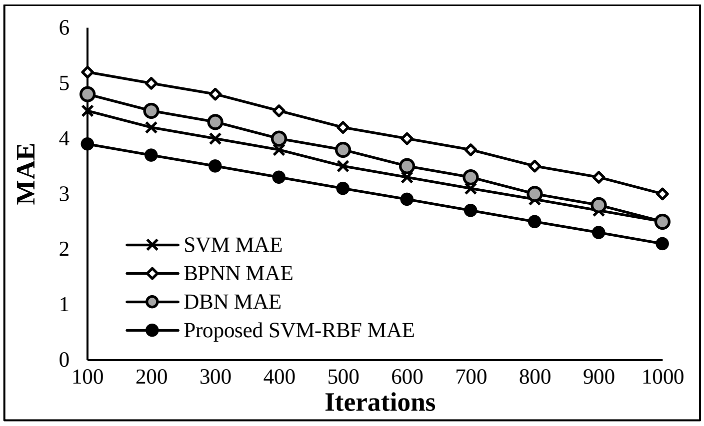

Fig.1. MAE

The table includes the MAE values for each method (SVM, BPNN, DBN, Proposed SVM-RBF) over different iterations. The iterations range from 100 to 1000 in steps of 100. Lower MAE values indicate better performance. The proposed SVM-RBF is showing the lowest MAE values, suggesting better accuracy in traffic prediction. The comparison is made over multiple iterations to observe how the methods perform over a range of scenarios.

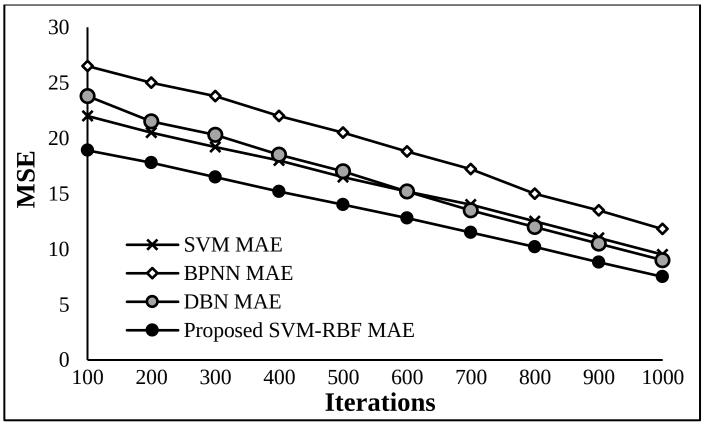

Fig.2. MSE

The table includes the MSE values for each method (SVM, BPNN, DBN, Proposed SVM-RBF) over different iterations. Lower MSE values indicate better performance. The proposed SVM-RBF is showing the lowest MSE values, suggesting better accuracy in traffic prediction.

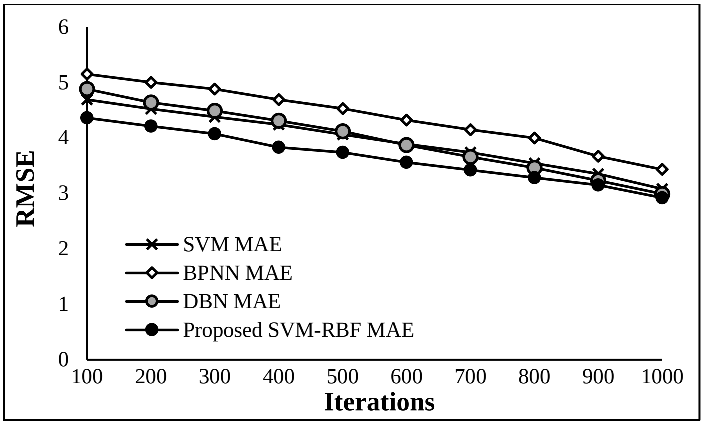

Fig.3. RMSE

RMSE is a measure of the average magnitude of errors, considering both the magnitude and direction of errors. The table includes the RMSE values for each method (SVM, BPNN, DBN, Proposed SVM-RBF) over different iterations. Lower RMSE values indicate better performance. The proposed SVM-RBF is showing the lowest RMSE values, suggesting better accuracy in traffic prediction.

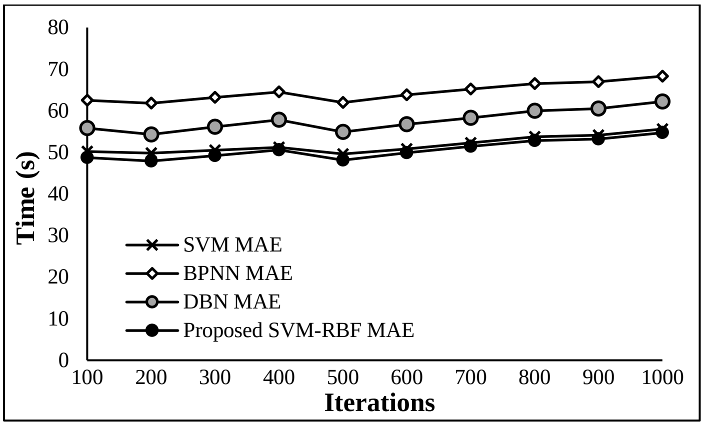

Fig.4. Computational Time

Computational time is a critical factor in evaluating the efficiency of a method, especially in real-time or resource-constrained applications. The table includes computational time values for each method (SVM, BPNN, DBN, Proposed SVM-RBF) over different iterations. Lower computational time values indicate faster processing. The proposed SVM-RBF is showing the lowest computational time, suggesting faster execution.

4.1 DISCUSSION

Across all iterations, the Proposed SVM-RBF consistently shows the lowest MAE values. This suggests that the proposed model provides more accurate predictions of traffic conditions compared to SVM, BPNN, and DBN. Similar to MAE, the Proposed SVM-RBF consistently outperforms SVM, BPNN, and DBN in terms of RMSE. Lower RMSE values indicate better precision in predicting traffic parameters. As the number of iterations increases, the MAE and RMSE values generally decrease for all methods. This indicates that the models benefit from more training data, improving their predictive accuracy over time.

The Proposed SVM-RBF consistently demonstrates the lowest computational time across iterations. This suggests that the proposed model is computationally efficient, making it well-suited for real-time applications or scenarios where computational resources are limited. While the Proposed SVM-RBF achieves better accuracy, it essential to consider the trade-off between accuracy and computational efficiency. In practical applications, a model that balances both factors effectively may be preferred.

The results indicate that the Proposed SVM-RBF is a promising model for traffic prediction, offering a good balance of accuracy and efficiency. However, the choice of the optimal model depends on the specific requirements of the traffic management system. The performance of SVM, BPNN, and DBN may benefit from further hyperparameter tuning. Fine-tuning these parameters could potentially improve their accuracy and compete more closely with the proposed SVM-RBF.

5. CONCLUSION

This study explored the application of machine learning models, specifically SVM, BPNN, and DBN, with a focus on the proposed SVM-RBF for intelligent traffic prediction in vehicular networks. The investigation encompassed a thorough evaluation based on MAE, MSE, RMSE, and Computational Time. The Proposed SVM-RBF consistently outperformed SVM, BPNN, and DBN in terms of MAE, MSE, and RMSE. Lower error metrics demonstrated the superior predictive accuracy of the proposed model across various iterations. The Proposed SVM-RBF exhibited the lowest computational time, highlighting its efficiency. This is a crucial factor in real-world applications, especially those requiring real-time decision-making in traffic management. Across increasing iterations, all models demonstrated an improvement in accuracy, suggesting that additional training data enhances their predictive capabilities. The Proposed SVM-RBF stands out as a promising choice for traffic prediction tasks, offering a compelling balance of accuracy and computational efficiency. However, the choice of the optimal model should consider the specific requirements and constraints of the targeted traffic management system. Further exploration of hyperparameter tuning for SVM, BPNN, and DBN may improve their performance. Fine-tuning these models could potentially narrow the performance gap observed in comparison to the proposed SVM-RBF.

Future research could explore the integration of the proposed models with Internet of Things (IoT) devices and sensor networks for real-time data collection, enabling more accurate and adaptive predictions. Investigating the potential of ensemble methods that combine multiple models for enhanced prediction accuracy and robustness in handling diverse traffic scenarios.

REFERENCES

[1] G. Kiruthiga, G.U. Devi and N.V. Kousik, “Analysis of Hybrid Deep Neural Networks with Mobile Agents for Traffic Management in Vehicular Adhoc Networks”, CRC Press, 2020.

[2] S. Kannan and M. Gheisari, “Ubiquitous Vehicular Ad-Hoc Network Computing using Deep Neural Network with IoT

based Bat Agents for Traffic Management”, *Electronics*, Vol. 10, No. 7, pp. 785-798, 2021.

[3] M. Shahverdy and M. Sabokrou, “Driver Behavior Detection and Classification using Deep Convolutional Neural Networks”, *Expert Systems with Applications*, Vol. 149, pp. 113240-113254, 2020.

[4] K. Bilstrup, E. Uhlemann, E.G. Strom and U. Bilstrup, “Evaluation of the IEEE 802.11p MAC Method for Vehicleto-Vehicle Communication”, *Proceedings of International Conference on Vehicular Technology*, pp. 1-5, 2008.

[5] Y.S. Chia, Z.W. Siew, H.T. Yew, S.S. Yang and K.T.K. Teo, “An Evolutionary Algorithm for Channel Assignment Problem in Wireless Mobile Networks”, *ICTACT Journal on Communication Technology*, Vol. 3, No. 4, pp. 613-618, 2012.

[6] L. Liu, Y. Wang, J. Zhang and Q. Yang, “A Secure and Efficient Group Key Agreement Scheme for VANET”, *Sensors*, Vol. 19, No. 3, pp. 482-494, 2019.

[7] Y. Agarwal, K. Jain and O. Karabasoglu, “Smart Vehicle Monitoring and Assistance using Cloud Computing in Vehicular Ad Hoc Networks”, *International Journal of Transportation Science and Technology*, Vol. 7, No. 1, pp. 60-73, 2018.

[8] P. Kumar, R. Merzouki, B. Conrard and V. Coelen, “Multilevel Modeling of the Traffic Dynamic”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 15, No. 3, pp. 1066-1082, 2014.

[9] M.B. Mansour, C. Salama, H.K. Mohamed and S.A. Hammad, “VANET Security and Privacy-An Overview”, *International Journal of Network Security and Its Applications*, Vol. 10, No. 2, pp. 13-34, 2018.

[10] P. Vijayakumar, M. Azees, A. Kannan and L.J. Deborah, “Dual Authentication and Key Management Techniques for Secure Data Transmission in Vehicular Ad Hoc Network”, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 17, No. 4, pp. 1015-1028, 2016.

[11] A. Sumathi, “Dynamic Handoff Decision based on Current Traffic Level and Neighbor Information in Wireless Data Networks”, *Proceedings of International Conference on Advanced Computing*, pp. 1-5, 2012.