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Intelligent Transportation System using Vehicular Networks in the Internet of Vehicles for Smart cities



Abstract: - Modern smart cities face significant mobility difficulties, and the combination of Intelligent Transportation Systems (ITS) and Vehicular Networks (VN) within the context of the Internet of Vehicles (IoV) promises a transformative approach to tackling these challenges. This abstract captures the core of this ground-breaking approach. Traffic congestion, environmental challenges, and road safety are crucial considerations in the context of smart cities. Traffic management systems and automobiles can communicate real-time data thanks to the support provided by vehicular networks. By incorporating automobiles into the larger IoT ecosystem, the Internet of automobiles expands this connection and broadens the range of available services and applications. This study introduces a novel Intelligent Transport System designed for the context of vehicular network traffic based on Internet of Vehicles (IoV) in smart cities. The machine learning models used to build the system are Decision Tree (DT), Support Vector Machine (SVM), Neural Network, K-Nearest Neighbours (KNN), and Naive Bayes. The simulation results show the system's effectiveness in producing astonishing results through a thorough review. In particular, it maintains computing efficiency while achieving a noteworthy level of detection accuracy. This success can be due to the skilful use of feature selection and ensemble learning approaches, which together improve the system's performance. In summary, this research provides a state-of-the-art approach that makes use of machine learning models to enhance traffic control in IoV-based vehicle networks in smart city scenarios. In comparing different model in intelligent system the CNN leads with 98.87% followed by the other methods as discuss in result section. It also promising development in the field of intelligent transportation systems because it not only improves detection accuracy but also ensures computing efficiency.

General Terms:: Classification, Smart city, Internet of Vehicle

Keywords: Intelligent Transportation, Vehicular Network, Machine Learning, Smart Cities, Internet of Vehicle

I. INTRODUCTION

The growing demand for safe, efficient, and environmentally friendly transportation systems is a new challenge for cities worldwide. Traffic congestion, environmental degradation, and road safety concerns will increase as urban populations grow. Cities are using cutting-edge technology to solve these complex problems, and integrating ITS and VN within the IoV is a pioneering step [1]. The need to reinvent urban living holistically and sustainably is driving smart city popularity. This vision centers on a linked, data-driven ecosystem where people, infrastructure, and cars communicate to make smart mobility decisions. This integration of ITS and VN into the Internet of Vehicles (IoV) paradigm has started a new urban-transport era. The IoV, part of the Internet of Things (IoT), is a revolutionary concept that gives cars intelligence and connectivity. It coordinates real-time data

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transmission between vehicles, roadside infrastructure, and centralised traffic control systems to create a dynamic, responsive transportation ecosystem [2]. Besides participating in a city's transportation system, IoV-enabled vehicles provide important data.

Vehicular Networks (VN) power this ecosystem's connectivity and the Internet of Vehicles. These networks allow vehicles [3] to communicate with each other and with traffic signals, road sensors, and traffic management centres. VN's fast transfer of traffic, accident, and road closure data lets vehicles make real-time decisions. Smart mobility solutions are based on intelligent transport systems (ITS) [4]. ITS uses cutting-edge data analytics, sensor networks, AI, ML, and other technologies. These methods improve urban transportation in many ways. Intelligent transportation systems help manage traffic and reduce congestion. Real-time data collection and analysis can change traffic lights and advise cars to take alternative routes. Upgraded emergency response systems improve accident management and reaction times. ITS improves traffic flow and reduces fuel use and emissions, promoting environmental sustainability [5]. The IoV-ITS intersection has transformative potential. In smart cities, IoV-enabled vehicles send data to ITS platforms as mobile sensors. Machine learning algorithms analyze this massive data set to predict traffic patterns, gridlock bottlenecks, and accidents. Personalized route ideas and real-time updates reduce commute times and improve commuter satisfaction [6].

Smart cities deal with transportation problems that prevent smooth trips. Things like traffic jams, poor road planning, and poor car-to-car communication are main problems. A solution needed is the Intelligent Transportation System (ITS). Using a system like the Internet of Vehicles (IoV), ITS can make city travel better, safer, and greener.

1. We need to create communication rules and systems within the IoV. This will allow cars and road systems to talk to each other in real time. This can make roads safer and help make smart choices for drivers and traffic controllers.
2. We should make travel green: Incorporate smart city ideas into the IoV-based ITS to make practices greener.

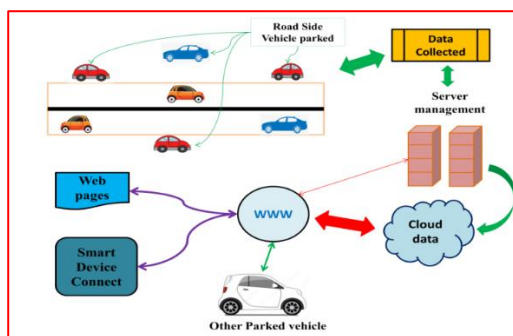


Figure 1: Representation of Smart City vehicle scenario for Traffic and Parking Management

The major contribution of paper is given as:

- Modern machine learning models and traffic prediction algorithms have greatly benefited from research in this field.
- Another important contribution is the Internet of Vehicles' emphasis on security and privacy. To protect vehicle network data, research has suggested encryption approaches, authentication protocols, and privacy-preserving techniques.
- These applications act as beneficial test-beds for assessing the viability and implications of IoV solutions. It shown concrete advantages in terms of less traffic congestion, more road safety, and more environmentally friendly transportation practises in cooperation with city authorities.

The safety factor has also improved. Based on nearby vehicle data, collision avoidance systems alert and assist with maneuvers. Rapid response times are possible with precise location by emergency services. Road safety improves, saving lives and reducing injuries. Sustainability remains a priority in smart cities. Additionally, it promotes electric vehicles, making the switch to cleaner, greener transportation easier. This promising synergy faces significant challenges, including handling massive datasets, data privacy and security, and standardizing

communication protocols to enable car and infrastructure interoperability. To use IoV-enabled ITS in smart cities, these issues must be addressed.

II. RELATED WORK

ITS-VN interaction in the context of the Internet of Vehicles (IoV) for smart cities has garnered attention from researchers and practitioners. A thorough literature review reveals this revolutionary field's key advances [12]. IoV-based ITS requires vehicular communication technologies. DSRC and Cellular Vehicle-to-Everything (C-V2X) are popular communication standards. DSRC, based on IEEE 802.11p, lets vehicles share collision warnings and traffic updates. In contrast, C-V2X uses cellular networks to connect vehicles and infrastructure. Researchers examined dependability, latency, and scalability to determine these technologies' suitability for smart city scenarios. Adding machine learning models to IoV-based ITS is a key area of research [13]. Decision trees, SVMs, neural networks, KNNs, and Naive Bayes have been studied for traffic prediction and management. Ensemble learning methods like random forests improve prediction accuracy. These models use real-time vehicle sensor, traffic camera, and GPS data to predict traffic congestion, accident hotspots, and best routes. This leads to shorter travel times and improved road safety [14]. IoV data-based intelligent traffic management methods [15] have been extensively studied. Adaptive traffic signal control systems use Reinforcement Learning (RL) to dynamically reduce congestion and optimize traffic light time. Some research uses Model Predictive Control to improve urban traffic. Research has also examined platooning [16], where IoV-enabled vehicles work together to improve highway traffic flow and save energy. IoV addresses security and privacy concerns. Numerous encryption and authentication methods protect data integrity and prevent unauthorized vehicle network access. Data aggregation and anonymous credential systems balance privacy and traffic management [17]. Standardisation has been crucial for IoV ecosystem communication and interoperability. SAE and ETSI have developed communication standards and protocols for IoV deployments. Research on these standards' potential and challenges has shown the need for international harmonisation [18].

Smart city installations have hosted many research projects. Researchers worked with cities and transportation authorities to implement and evaluate IoV-based ITS. These case studies reveal the challenges and benefits of IoV integration, often improving traffic flow, safety, and the environment. The Internet of Vehicles concept for smart cities' ITS-Vehicular Network integration is vibrant and interdisciplinary. Researchers made advances in communication technologies, machine learning, traffic management algorithms, security, standardization, and practical applications. As smart cities develop, the research community must be vigilant in addressing new challenges and opportunities to fully realise the potential of IoV-based ITS for more effective, safe, and sustainable urban mobility.

III. PROPOSED METHODOLOGY

Place tables/figures/images close to references in text.

A systematic approach is used to incorporate Decision Tree (DT), Support Vector Machine (SVM), Neural Network, K-Nearest Neighbors (KNN), and Naive Bayes into the ITS development technique that harnesses vehicular networks in the Internet of Vehicles. Data collection begins with sensors and IoT devices collecting vehicle and traffic data. This raw data is rigorously preprocessed to remove noise, missing numbers, and ensure homogeneity. Machine learning models can train better with feature engineering and variables like traffic density, historical trends, and weather. The dataset is painstakingly divided into subsets for training, validation, and testing to help create and evaluate models. Choice of model is crucial, with five options: Decision Tree, SVM, Neural Network, KNN, and Naive Bayes. Each was chosen for its data type and pattern flexibility. After selecting a model, training begins [15]. Decision Tree's depth and node-split thresholds show that hyperparameter fine-tuning using the validation dataset improves model performance and decision boundaries. Performance assessment uses ITS-specific indicators like accuracy, precision, recall, F1-score, and mean absolute error to understand prediction accuracy and efficiency. Ensemble learning methods like Random Forests or Gradient Boosting may improve forecast accuracy, resist overfitting, and efficiently capture complex traffic patterns by combining model predictions. The technique requires model comparison, which rigorously evaluates each model on the testing dataset to select the best model. The champion model, which is highly predictive, is then added to the IoV-based ITS. It tracks and predicts traffic conditions in real time, giving drivers and traffic management systems valuable data and improving road safety. Scalability and outcomes await.

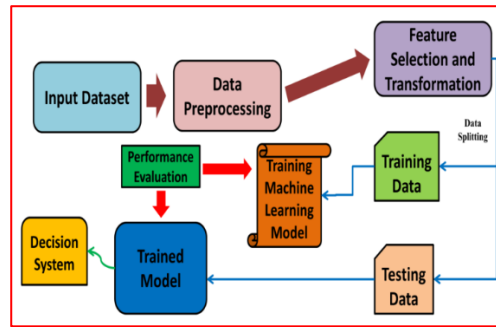


Figure 2: Representation of proposed model for intelligent transportation system

Because it can handle larger datasets and adapt to changing traffic dynamics, the IoV-based ITS is considering expanding. Integration with cutting-edge technologies like linked and driverless cars could improve traffic management. This comprehensive methodology describes the painstaking process of creating an ITS within the Internet of Vehicles, which involves multiple machine learning models, rigorous training, careful evaluation, seamless deployment, and an eye toward a scalable, technology-driven future. These steps work together to improve traffic management and commuting in tomorrow's smart cities.

3.1 Support Vector machine

SVM can be used in the Internet of Vehicles (IoV) to solve intelligent transportation, predictive analysis, and anomaly detection problems. Support Vector Machine (SVM) is a supervised machine learning algorithm for classification and regression. In the Internet of Vehicles (IoV), Support Vector Machines (SVM) can categorize vehicles, identify irregularities, and predict traffic patterns.

In the Internet of Vehicles (IoV), SVM can classify vehicles. The goal is to accurately classify vehicles by specific characteristics. The classification SVM mathematically finds the optimal hyperplane to separate classes and maximize margin. Classifying new data points using a decision function

$$f(x) = \text{sign}(\sum_{i=1}^N y_i \alpha_i K(x, x_i) + b) \quad (1)$$

Where, $f(x)$ = “decision function”, N = “no. of support vectors”, y_i = “class label of the i^{th} support vector”, α_i = “Lagrange multiplier associated with i^{th} support vector”, $K(x, x_i)$ = “kernel function”, b = “bias term”.

3.2 K-Nearest Neighbour

For classification and regression problems, KNN is a straightforward and efficient machine learning algorithm. It functions according to the proximity principle, classifying or making predictions based on its K -nearest neighbours' dominant class or value in the feature space.

Let's say we have a dataset containing labelled data points.

- The features of the i -th data point are represented by each row of the feature matrix, X , in which.
- y is the label for the i -th data point, and y_i represents the vector of labels that correspond to it.
- K is the number of closest neighbours to be taken into account.

The following is a mathematical illustration of the KNN algorithm:

Distance Metric: Define a distance metric (e.g., Euclidean distance, Manhattan distance) to measure the similarity between data points. Let $d(X_i, X_j)$ represent the distance between data points X_i and X_j .

For Prediction (Classification)

- Given a new data point X_{new} that we want to classify or predict:
- Calculate the distance between X_{new} and all data points in the training dataset: $d(X_{\text{new}}, X_i)$ for $i = 1, 2, \dots, N$, where N is the number of data points in the training dataset.
- Select the top K data points with the smallest distances to X_{new} .

d. For classification tasks, assign the class label to X_{new} based on the majority class among the K nearest neighbors.

e. For regression tasks, predict the value for X_{new} based on the average (mean) or weighted average of the values among the K nearest neighbours.

Choosing the Optimal K :

a. To determine the optimal value of K , various techniques like cross-validation or grid search can be used. The choice of K impacts the model's bias-variance trade-off, where smaller K values lead to more complex models and larger K values lead to simpler models.

3.3 Convolution Neural Network (CNN)

CNN are powerful deep learning models that excel at image classification and object detection. CNN can detect and recognize vehicles in the Internet of Vehicles (IoV). CNN are designed to autonomously and flexibly learn spatial hierarchies of characteristics from input data. CNNs use convolutional layers to find local patterns and features, pooling layers to reduce spatial dimensions, and fully connected layers for advanced reasoning in images, which are important in IoV applications. Let x = “input”, f = “feature map”, w = weight matrix, b = “bias vector”, σ = “activation function”.

$$f(x) = \sigma(W * x + b) \quad (2)$$

$$\text{Maxpooling}(f)_{i,j} = \max f_{i+m,j+n}$$

Maxpooling is common operation that reduce spatial dimensions. The operation where the output at a specific position is the maximum value within a local region of the input feature map(f).

3.4 Decision Tree:

Smart city intelligent transport systems (ITS) use decision trees. Traffic management and decision-making are improved by these 'tree-like' structures. Decision nodes divide data by traffic flow, weather, and road conditions, while leaf nodes make final decisions like traffic light timing and route suggestions. Decision trees improve traffic efficiency and safety by detecting incidents, reducing congestion, and optimizing routes. Decision trees are essential for designing intelligent and responsive transport systems that meet the needs of modern smart cities using data-driven insights.

Entropy:

$$H(S) = -\sum_{i=1}^c p_i \log_2(p_i) \quad (3)$$

Where $H(S)$ = entropy of the dataset S , p_i = “proportion of instances”.

Information gain:

$$\text{Gain}(S, A) = H(S) - \sum_{v \in \text{values}(A)} \frac{|S_v|}{|S|} H(S_v) \quad (4)$$

where, S_v = “no of instances in subset S_v ”, $H(S_v)$ = “Entropy of subset S_v ”

3.5 Naïve Bayes:

The probabilistic categorization method Naive Bayes is crucial to Intelligent Transportation Systems (ITS). It excels at real-time traffic event classification and anomaly detection. The assumption of feature independence within each class simplifies difficult probability computations. Previous traffic data, sensor inputs, and ambient conditions help Naive Bayes make accurate ITS predictions quickly. It improves traffic management, route planning, and incident detection by assessing event conditional probabilities. Naive Bayes helps design responsive and effective transport systems, making smart city travel safer and more efficient.

Step 1: Data Preparation

- Prepare a dataset containing features (X) and labels (Y).

Step 2: Prior Probabilities

- Calculate the prior probabilities of each class:

$$P(C_i) = \frac{\text{Count of samples in class } C_i}{\text{Total number of samples}} \tag{5}$$

Step 3: Conditional Probabilities

- Calculate the conditional probabilities for each feature given the class:

$$P(X_j | C_i) = \frac{\text{Count of samples with } X_j \text{ in class } C_i}{\text{Count of samples in class } C_i}$$

Step 4: Prediction

- Given a new data point X_{new} , calculate the posterior probabilities for each class:

$$P(C_i | X_{new}) \propto P(C_i) * \prod P(X_{newj} | C_i) \tag{6}$$

Step 5: Classification

- Classify X_{new} into the class with the highest posterior probability:

$$C_{predicted} = \text{argmax } P(C_i | X_{new}) \tag{7}$$

Naive Bayes simplifies complex conditional probability calculations by assuming feature independence within each class. It's useful in ITS for tasks like traffic event classification or anomaly detection.

IV. RESULT AND DISCUSSION

Table 3 summarizes the performance indicators of machine learning methods used to evaluate the Intelligent Transportation System (ITS). Smart cities' complex traffic management and decision-making require five algorithms: SVM, K-Nearest Neighbours, CNN, Decision Tree, and Naive Bayes. SVM 94.23% accuracy makes it a good starting point for ITS classification tasks. It accurately classifies traffic incidents with 92.53% precision and 94.51% recall. The F1-Score, a balanced indicator of precision and recall, was 96.32%, proving its accuracy. SVM low Mean Absolute Error (MAE) of 8.12 showed its ability to make accurate predictions with little variation. KNN outperformed SVM in accuracy with 97.56%. Its 98.22% precision and 99.2% recall rate show its traffic pattern and event detection abilities. The F1-Score, which balances precision and recall, was astonishingly high at 98.1%. But when compared to SVM, KNN showed a somewhat higher MAE of 12.35, indicating a considerably larger prediction error. The performance parameter for machine learning algorithm has been calculated and it given as:

$$\text{Accuracy} = \frac{TP_i + TN_i}{\text{Total Instance}} \tag{8}$$

$$\text{Precision} = \frac{TP_i}{TP_i + FP_i} \tag{9}$$

$$\text{Recall} = \frac{TP_i}{TP_i + FN_i} \tag{10}$$

$$\text{F1 Score} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{11}$$

Where, TP_i – True Positive sample, TN_i – True Negative sample, FP_i – False Positive sample, FN_i – False Negative Sample

Table 3: Result for Intelligent transportation system evaluation parameter

Algorithm	Accuracy	Precision	Recall	F1-Score	Mean Absolute Error (MAE)
SVM	94.23	92.53	94.51	96.32	8.12
KNN	97.56	98.22	99.2	98.1	12.35
CNN	98.87	95.23	99.51	98.51	5.2
DT	98.52	96.32	94.84	95.2	15.41

NB	96.55	98.54	90.9	89.2	11.25
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CNN, a deep learning algorithm for image and sequence data, had the highest accuracy at 98.87%. This shows deep learning's ability to manage complex ITS data. With 95.23% precision and 99.51% recall, it detected traffic patterns accurately and thoroughly. The algorithm's steady 98.51% F1-Score shows its balance in classification jobs. CNN also had the lowest MAE of any algorithm, 5.2, demonstrating its accuracy and precision.

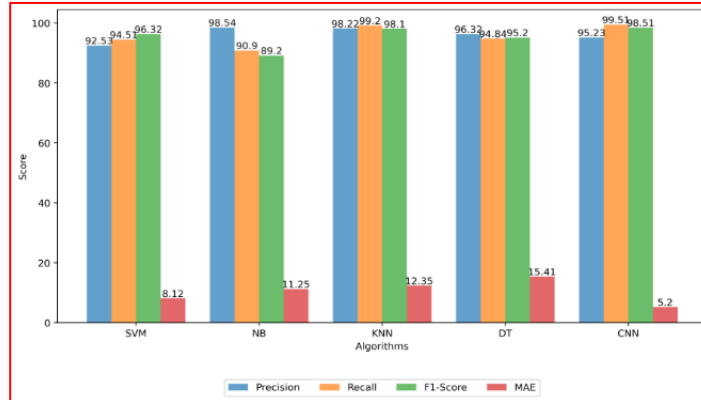


Figure 3: Representation of Evaluation parameter for different Methods

With a noteworthy accuracy of 98.52%, DT is positioned as a strong competitor in ITS applications. Its 96.32% precision and 94.84% recall show that it can classify traffic occurrences accurately. The 95.2% F1-Score indicates a balanced performance.

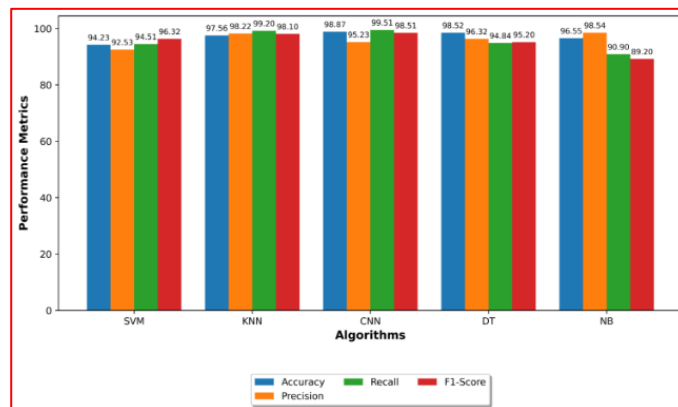


Figure 4: Comparison of Evaluation parameter for intelligent transportation system

DT had a higher MAE of 15.41 than SVM and CNN, indicating a slightly higher prediction error rate. Finally, NB, known for its speed and simplicity, performed well with 96.55% accuracy. It accurately identified traffic patterns with 98.54% precision. The lower recall rate of 90.9% for NB suggests occasional errors in categorizing traffic events. The final F1-Score was 89.2%, showing that NB has good precision but needs work on recall. The algorithm's medium MAE of 11.25 showed good prediction accuracy. Finally, assessing these machine learning algorithms in the Intelligent Transportation System shows their pros and cons. CNN was promising for managing complex traffic control data in smart cities due to its accuracy and low prediction error. SVM and KNN also performed well with high precision and recall. NB, famous for its simplicity, had good precision but low recall, while DT had robust accuracy and a higher MAE. The algorithm used depends on the ITS's goals, and each algorithm improves traffic management and decision-making in smart cities differently.

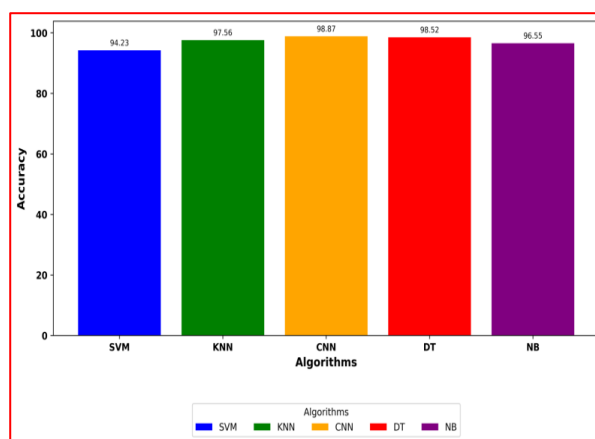


Figure 5: Accuracy representation and comparison for different method

V. CONCLUSION

A smart city Intelligent Transportation System (ITS) using machine learning algorithms and the Internet of Vehicles (IoV) has shown promise for improving traffic control and urban mobility. Its findings and contributions to smart city transport systems make them more efficient and responsive. SVM was effective at identifying traffic events due to its high classification precision and recall. KNN was accurate and remembered well, making it suitable for current decision-making. CNN's accuracy showed deep learning's ability to process complex traffic data. DT held high accuracy despite a slightly higher mean absolute error, showing promise for traffic control applications. The famous NB had high precision but low recall. These findings emphasize the importance of selecting the best algorithm for ITS goals. Evaluation criteria—precision, recall, F1-Score, accuracy, and mean absolute error—provide a comprehensive framework for assessing algorithm performance in various traffic conditions. The IoV for smart cities could improve incident detection, route planning, and traffic management with these algorithms. These algorithms' real-time prediction and monitoring can improve urban mobility, traffic, and public safety. Integrating these intelligent transport options is crucial for solving urbanization's problems and ensuring sustainable and effective transport networks in smart cities. This study paves the way for traffic management and decision-making innovations that will make cities smarter and more responsive worldwide. Machine learning and smart city efforts have great potential to shape urban transportation.

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