Multi-Factor Traffic Pattern Discovery Using Cluster Based Association Rule Mining For Smart Traffic Management

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Abstract
Efficient traffic management in smart cities requires the discovery of hidden patterns from heterogeneous traffic data generated by modern transportation systems. Traffic datasets often consist of multiple dynamic factors such as traffic volume, vehicle speed, vehicle type distribution, weather conditions, environmental parameters, accident occurrence, and signal status, making traffic pattern analysis a challenging task. To address this issue, this paper proposes a novel hybrid framework named Traffic Pattern Discovery (TPD) using Fuzzy Association Rule Mining (TPD-HFA) for intelligent traffic management. The proposed framework integrates Fuzzy C-Means (FCM) clustering and the Apriori algorithm to identify meaningful traffic behavior patterns from multi-factor traffic data. Initially, Fuzzy C-Means clustering is employed to group traffic records into similar behavioral clusters by handling uncertainty and overlapping traffic conditions more effectively than hard clustering approaches. This clustering process enhances the homogeneity of traffic data and improves the quality of pattern extraction. Subsequently, the Apriori-based Association Rule Mining technique is applied within each cluster to discover frequent traffic patterns and hidden relationships among traffic, environmental, and accident-related attributes. The extracted rules provide valuable insights into congestion formation, accident-prone situations, weather-induced traffic variations, and signal inefficiencies. Experimental analysis demonstrates that the proposed TPD-HFA framework effectively uncovers high-confidence and high-support traffic rules, enabling better decision-making for adaptive traffic signal control, congestion reduction, and road safety enhancement.

Keywords: Traffic Management, Fuzzy-C-Means, Apriori

I. Introduction

Traffic behavior is highly dynamic and depends on several interconnected parameters such as traffic volume, vehicle speed, vehicle type distribution, weather conditions, environmental factors, accident occurrences, and traffic signal status. Traditional traffic analysis methods often struggle to capture complex relationships among these diverse attributes. [1]To overcome this limitation, advanced data mining approaches can be employed to extract meaningful patterns from large-scale traffic datasets. This approach combines a hybrid method to improve traffic knowledge discovery. Clustering groups similar traffic conditions into meaningful clusters, reducing data complexity and enhancing pattern homogeneity, while association rule mining identifies frequent relationships and dependencies among traffic factors within each cluster. This hybrid framework enables the discovery of congestion patterns, accident-prone conditions, and traffic signal inefficiencies more effectively than standalone methods. By integrating these techniques, smart traffic management systems can support better decision-making for congestion control, adaptive signal management, accident prevention, and route optimization, ultimately improving urban transportation efficiency, and safety.
A road condition can simultaneously be:

- Moderate congestion
- Accident-prone
- Weather-sensitive

Traffic Management –[2] Traffic management plays a crucial role in modern urban transportation systems by ensuring smooth vehicle movement, reducing congestion, improving road safety, and minimizing travel delays. With the rapid growth of population and vehicle density, traditional traffic management approaches are often insufficient to handle dynamic traffic conditions. Smart traffic management systems utilize real-time data from sensors, cameras, and intelligent transportation infrastructure to monitor traffic flow and make adaptive decisions. Effective traffic management involves controlling signal timing, detecting congestion hotspots, analyzing accident-prone regions, and optimizing route planning. [3]By integrating data-driven techniques, traffic management systems can significantly improve transportation efficiency and enhance commuter safety.

Data Mining and Machine Learning in Traffic Management – [4]The increasing availability of traffic data has led to the adoption of data mining and machine learning techniques for extracting valuable insights and improving traffic operations. Data mining techniques help in identifying hidden patterns, correlations, and trends from large-scale traffic datasets, while machine learning enables predictive modeling for traffic forecasting, accident detection, and congestion prediction. Techniques such as classification, clustering, regression, and association rule mining are widely applied in traffic analytics. These approaches support intelligent decision-making by analyzing factors such as traffic volume, speed, weather conditions, and vehicle composition. The combination of data mining and machine learning has transformed traffic management from reactive systems into proactive and adaptive systems.

Clustering – [5] Clustering is an unsupervised learning technique used to group similar data points based on their characteristics, without prior labeling. In traffic management, clustering helps identify similar traffic conditions, congestion zones, and vehicle movement patterns by grouping records with common features such as traffic volume, average speed, weather conditions, and accident occurrences. [6]Among various clustering techniques, Fuzzy C-Means (FCM) is highly effective because it allows data points to belong to multiple clusters with varying degrees of membership, making it suitable for uncertain and overlapping traffic scenarios. This soft clustering capability improves pattern understanding and enhances the quality of subsequent analytical processes. By organizing traffic data into homogeneous groups, clustering reduces complexity and enables more meaningful knowledge extraction.

Association Rule Mining – [7] Association Rule Mining (ARM) is a data mining technique used to discover hidden relationships and frequent co-occurrence patterns among variables in a dataset. In traffic management, ARM helps uncover important traffic behavior patterns such as the relationship between high traffic volume, weather conditions, signal status, and accident occurrence. The Apriori algorithm is one of the most widely used ARM techniques, which identifies frequent itemsets based on minimum support and confidence thresholds and generates meaningful if–then rules. These rules can reveal valuable insights, such as conditions leading to congestion or accidents, enabling traffic authorities to make informed decisions. When combined with clustering, ARM becomes more effective by mining patterns within similar traffic groups, resulting in more precise and context-aware traffic knowledge discovery.

Multi Factors in Traffic Pattern Discovery

1. Accident Pattern Discovery - Find combinations that frequently lead to accidents.
Example: Traffic Volume = High + Rainy + Speed < 20 km/h→ Accident = Yes
Research use: Accident-prone situation identification, Safety alert generation

2. Congestion Pattern Analysis - Discover what conditions create heavy congestion.
Example: Peak Hour + Signal = Red + Truck Count = High→ Traffic Volume = Severe
Use: Dynamic traffic control

3. Weather Impact Analysis - Identify how environmental conditions affect traffic.
Example: Temperature > 35°C + Humidity High→ Average Speed decreases
Use: Seasonal traffic management

4. Vehicle Composition Analysis - Study the influence of vehicle types.
Example: Truck Count High + Bike Count Low→ Traffic Delay High
Use: Lane allocation optimization

5. Traffic Signal Optimization Rules - Find inefficient signal patterns.
Example: Signal Green + Traffic Volume Low→ Idle Signal Time High
Use: Adaptive signal timing

6. Peak Hour Behavior Mining - Extract patterns during rush hours.
Example: Timestamp = 8–10 AM + Cars High→ Average Speed Low
Use: Smart route planning

7. Location-wise Traffic Pattern Analysis - Compare different locations.
Example: Location ID = Industrial Zone + Trucks High→ Congestion High
Use: Area-specific traffic planning

8. Multi-factor Traffic Event Correlation - Combine weather + vehicles + signals + accidents.
Example: Rainy + Red Signal + High Bikes + Low Visibility→ Accident Probability High
Use: Intelligent traffic warning systems

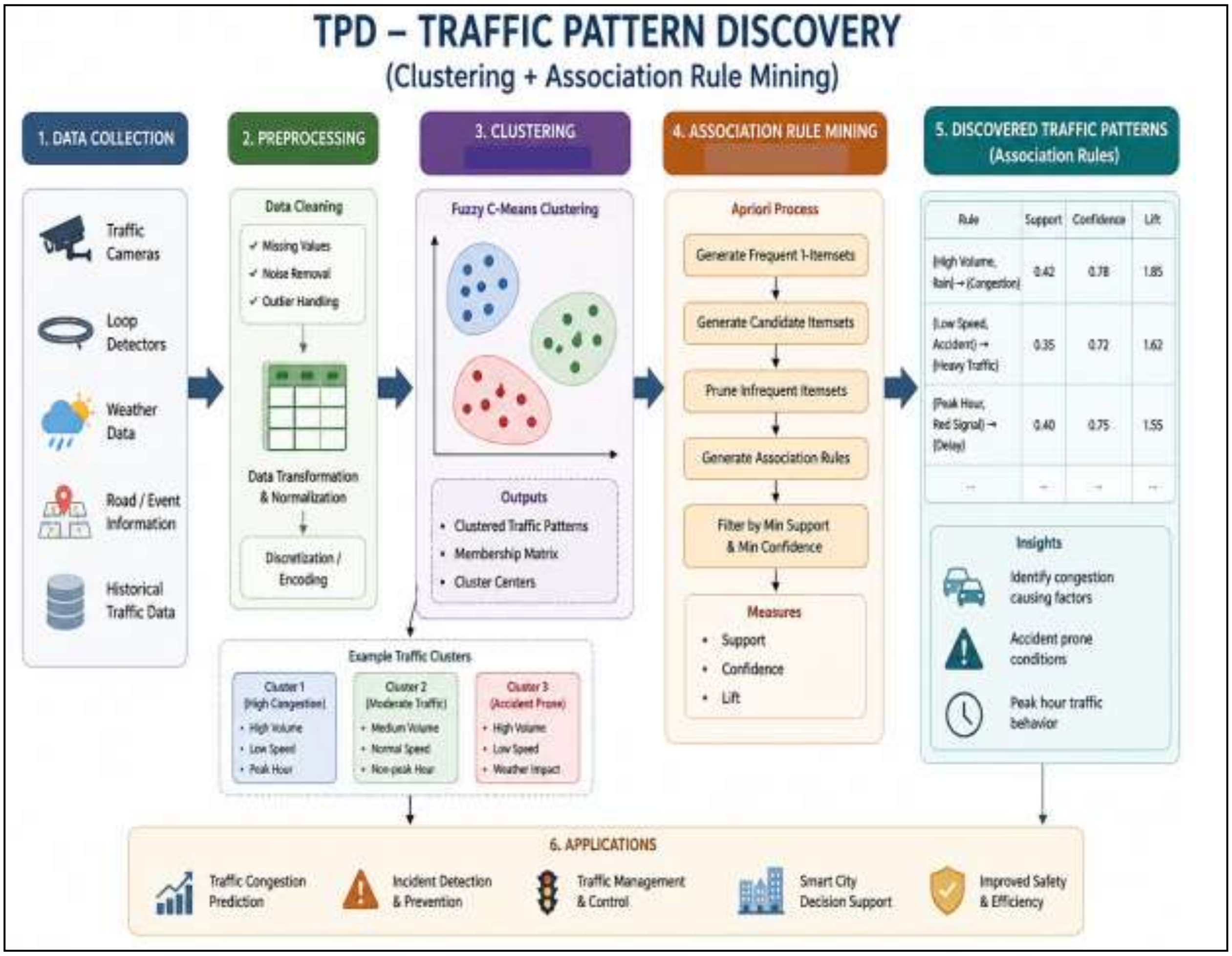

Figure 1. TPD – Hybrid Clustering with Association Rule Mining

Problem Statement: Traffic datasets often consist of multiple dynamic factors such as traffic volume, vehicle speed, vehicle type distribution, weather conditions, environmental parameters, accident occurrence, and signal status, making traffic pattern analysis a challenging task.

Objective: To integrate fuzzy clustering with association rule mining for improving the interpretability and relevance of traffic knowledge discovery thus making it a promising solution for smart traffic management systems.

II. Related Works

Christofel Rio Goenawan *et al* [8] proposed an Autonomous Smart Traffic Management framework that applies artificial intelligence techniques to optimize traffic flow and reduce congestion in urban road networks. The system utilizes the CNN for real-time vehicle detection from traffic surveillance images, enabling accurate traffic monitoring. To forecast traffic conditions, a RNN-LSTM is employed to estimate vehicle counts for the upcoming 12-hour period. The performance of the RNN-LSTM model demonstrates effective prediction capability, achieving a better MSE and a RMSE over the 12-hour forecasting horizon. The proposed ASTM system achieves a congestion flow rate of nearly **50%** compared to conventional traffic management systems.

Rahul Khokale *et al* [9] addresses global traffic congestion challenges, including road safety and environmental concerns, through a data mining-based framework. The proposed approach integrates Multiple Linear Regression, Decision Tree, Random Forest, and XGBoost models to analyze historical traffic data and identify hidden patterns influencing traffic flow. By incorporating temporal traffic behavior, the framework improves prediction accuracy and supports proactive decision-making in intelligent transportation systems. Experimental results confirm the effectiveness of the approach, with the Random Forest Regressor achieving the highest prediction accuracy among the tested models. The study contributes to congestion reduction, safer road usage, and improved traffic management strategies for sustainable transportation systems.

Nawaf O. Alsrehin *et al* [10] explains that traffic management remains a challenging domain due to the absence of a universally accepted standard framework for handling complex and dynamic traffic conditions. This creates significant challenges for researchers, software developers, and government authorities in designing effective traffic control strategies. Developing real-time applications that capture the interactions among critical traffic components, including traffic lights, road signs, and road intersections, is essential for improving traffic efficiency and safety. Recent advancements in data mining and machine learning have provided new opportunities to analyze traffic patterns and support intelligent decision-making. A systematic understanding of these technologies and their existing approaches is crucial for advancing smart traffic management systems.

Lihua Cheng *et al* [11] introduced an advanced traffic control approach using the Dynamic Zone Segmentation Algorithm (DZSA) to address urban traffic challenges more effectively. The proposed algorithm utilizes real-time traffic data and road conditions to divide city traffic into smaller manageable zones, improving adaptability and precision in traffic prediction. To enhance forecasting performance, the framework integrates Long Short-Term Memory (LSTM) with Bayesian Structural Time Series (BSTS), combining the strengths of deep learning and statistical modeling. Experimental evaluation against benchmark models demonstrates superior performance using metrics such as MAE, MASE, RMSE, accuracy, and MAPE. The proposed LSTM-BSTS model achieves a low error rate of 6.68%, highlighting its effectiveness.

Fathema Tuj Johora *et al* [12] presented a hybrid traffic congestion analysis framework that combines Association Rule Mining and Machine Learning for improved congestion prediction. Initially, traffic data is preprocessed and transformed into binary congestion indicators to represent critical traffic conditions. The Apriori algorithm is then applied to identify frequent co-occurrence congestion patterns, revealing hidden relationships among vehicle categories and traffic states. These extracted association rules are converted into binary rule-based features and integrated with conventional traffic attributes such as vehicle count and peak-hour information. A Decision Tree classifier is subsequently trained on the enriched dataset to predict road congestion. Experimental results show that the inclusion of rule-based features enhances both prediction accuracy and model interpretability. The proposed framework provides a scalable and efficient solution for proactive traffic monitoring, congestion mitigation, and intelligent decision-making in smart city transportation systems.

Mingchen Feng *et al* [13] explored the application of association rule mining techniques for analyzing Road Traffic Accidents (RTAs) using a case study based on UK traffic accident data collected between 2005 and 2017. The Apriori algorithm was applied to identify frequent accident-related patterns and uncover hidden relationships among contributing factors. The analysis revealed strong associations between accidents and factors such as environmental conditions, speed limits, and geographical locations. By setting the minimum support and confidence thresholds to 0.4 and 0.7, a total of 195 association rules were generated. Among these, 20 high-support and high-lift rules were identified, providing valuable insights for accident prevention and traffic safety planning.

Lijing Du *et al* [14] applied a classification framework integrated with association rule mining to develop a predictive model for analyzing factors contributing to road traffic casualties. The traffic accident data were grouped into clusters based on weather conditions and road characteristics, allowing separate analysis for each traffic scenario. The study identified significant interactions among variables such as day of the week, time of occurrence, and weather conditions, highlighting their influence on accident severity. The proposed predictive model achieved an average accuracy of 86.9%, demonstrating its effectiveness in casualty analysis. Additionally, the association rule analysis generated meaningful patterns, with 51 strong rules from one cluster and 56 high-lift rules from another. The interactive visualization of these rules improves interpretability and supports traffic authorities in understanding accident mechanisms and developing better traffic management strategies.

Feng Wen *et al* [15] proposed a hybrid Temporal Association Rule Mining framework for traffic congestion prediction in road networks. The approach first applies the DBSCAN clustering algorithm to identify distinct traffic environments and group similar traffic conditions. These clusters serve as the basis for generating relevant patterns for congestion analysis. A Genetic Algorithm-based Temporal Association Rule Mining technique is then employed to extract time-dependent association rules, capturing the sequential relationships among traffic events. The extracted temporal rules are further evaluated using a classification mechanism to build an effective congestion prediction model. Simulation experiments conducted on road networks of varying sizes demonstrate that the proposed hybrid framework achieves high prediction accuracy and effectively supports intelligent traffic congestion management.

III. Proposed Methodology

Traffic Pattern Discover using Hybrid Cluster based Association Rule Mining (TPD-HFA)

Traffic data is highly dynamic and uncertain because traffic conditions continuously change due to factors such as vehicle density, weather, road conditions, and accidents. Traditional data analysis methods often fail to capture these uncertain and overlapping traffic behaviors effectively. To address this challenge, a hybrid approach combining Fuzzy C-Means clustering (FCM) and Apriori algorithm shown in Figure 2 can be used for efficient traffic pattern discovery. In this framework, FCM first groups similar traffic conditions into clusters while allowing data instances to belong to multiple clusters with different membership values. This improves flexibility in handling uncertain traffic scenarios. After clustering, Apriori is applied within each cluster to identify frequent traffic patterns and hidden relationships among factors such as traffic volume, vehicle speed, weather conditions, and accidents. This hybrid methodology improves the accuracy, interpretability, and contextual relevance of traffic pattern mining.

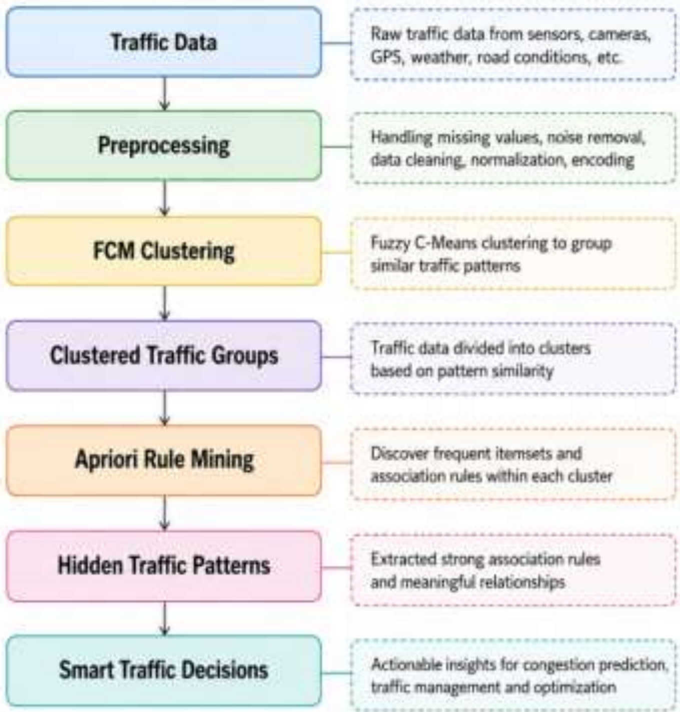

Figure 2. Flow of Work TPD-HFA

Fuzzy C-Means (FCM)
FCM is a soft clustering algorithm where each data point can belong to multiple clusters with varying membership degrees that includes, initializing - cluster centers, membership values, cluster centers, and in final repeat until convergence.
Unlike K-Means:

- K-Means → Hard assignment (one cluster only)
- FCM → Soft assignment (multiple clusters possible)

Objective Function
FCM minimizes:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \, ||x_i - c_j||^2 \qquad -(1)$$

Where : N = number of data points, C = number of clusters, u_{ij} = membership of data point x_i , m = fuzzification coefficient (m>1), c_j = center of cluster j
Membership Update Equation,

$$u_{ij} = \frac{1}{C_{k=1} \, (\frac{|| x_i - c_j||}{|| x_i - k||})^{\frac{2}{m-1}}} \qquad -(2)$$

Cluster Center Update,

$$C_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} \, x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \qquad -(3)$$

Stopping Condition,

$$|J_t - J_{t-1}| < \epsilon \qquad -(4)$$

Apriori Algorithm
Apriori is an association rule mining algorithm used to discover frequent patterns and hidden relationships. It uses three important measures namely, Support, Confidence, and Lift.
It follows: "If C occurs, D is likely to occur."
Measures
Support (X) = Count(X)/N – (5)
Frequency(X) = Count(X) - (6)
Confidence (X -> Y) = Support(X∪Y)/Support(X) – (7)
Apriori Steps

1. Generate frequent 1-itemsets.
2. Apply minimum support threshold.
3. Generate candidate itemsets.
4. Prune infrequent itemsets.
5. Generate association rules.
6. Apply confidence threshold.

Workflow:

Traffic Data → Preprocessing → FCM Clustering → Clustered Traffic Groups → Apriori Rule Mining → Hidden Traffic Patterns → Smart Traffic Decisions

Algorithm: TPD-HFA (Traffic Pattern Discovery using Fuzzy Association Rule Mining)

Input:
Traffic dataset with attributes {Timestamp, Location, Traffic Volume, Vehicle Speed, Vehicle Type Counts, Weather, Temperature, Humidity, Accident Status, Signal Status}
Output:
Clustered traffic patterns and association rules for smart traffic decision-making
FCM Clustering
Step 1: Collect traffic data from heterogeneous sources such as sensors, cameras, and environmental monitoring systems.
Step 2: Preprocess the traffic dataset.
Step 3: Initialize the number of clusters C, fuzzification coefficient m, and stopping threshold ϵ.
Step 4: Randomly initialize the fuzzy membership matrix where each traffic instance belongs to clusters with varying membership values.
Step 5: Compute cluster centers using Eq. (3).
Step 6: Update membership values for each traffic record using Eq.(2).
Step 7: Calculate the objective function using Eq.(1)
Step 8: Repeat Steps 5–7 until convergence using Eq.(4)
Step 9: Assign traffic records into clustered traffic groups based on maximum membership degree.
Apriori Extension
Step 10: Transform clustered traffic data into transactional format for association rule mining.
Step 11: Generate frequent 1-itemsets from each cluster.
Step 12: Calculate support for each itemset using Eq.(5),
Step 13: Prune itemsets whose support is less than minimum support threshold σ .
Step 14: Generate candidate k -itemsets from frequent (k−1) itemsets.
Step 15: Repeat Steps 12–14 until no new frequent itemsets are found.
Step 16: Generate association rules of the form: $X \rightarrow Y$ where $X \cap Y = \emptyset$
Step 17: Compute confidence using Eq.(6)
Step 18: Compute lift using Eq.(7)
Step 19: Select strong traffic rules satisfying minimum confidence δ and lift > 1.
Step 20: Analyze extracted rules to identify hidden traffic patterns
End

Advantages

1. Handles uncertainty in traffic data.
2. Improves rule quality by clustering similar patterns.
3. Reduces irrelevant associations.
4. Enhances interpretability.
5. Supports congestion prediction and accident prevention.
6. The Support threshold determines rule quantity and clustering improves the quality and local pattern.

TPD-HFA model:

- FCM = Pattern grouping
- Apriori = Hidden pattern extraction
- Combined = Better traffic intelligence system.

Iv. Results and discussion

4.1 Dataset Description - The Smart Traffic dataset (https://www.kaggle.com/datasets/sm/smart-traffic-management-dataset? resource =download) is taken from the repository Kaggle.

Table I. Smart Traffic Dataset

Attribute	Description	Unit / Format
Timestamp	Date and time of observation	YYYY-MM-DD HH:MM:SS

Location ID	Unique identifier for traffic junction/road segment	Integer 1-5
Traffic Volume	Total vehicles passing in a time interval	Vehicles/hour (or per sampling interval)
Average Vehicle Speed	Average of all vehicles at that location in a particular day/Time	km/h (sometimes m/s)
Counts of Cars	Number of cars detected	Count (integer)
Counts of Trucks	Number of trucks detected	Count (integer)
Counts of Bikes	Number of bikes/two-wheelers detected	Count (integer)
Weather Conditions	Road/weather status	Categorical (Sunny, Rainy, Foggy, etc.)
Temperature	Ambient temperature	°C
Humidity	Relative moisture in air	% (0–100)
Traffic Signal Status	Signal phase at the time	Categorical (Red/Yellow/Green)

4.2 Multi Factor Analysis in TPD

This research paper analyzes three factors on TPD. The Association rules that formed by the proposed method is discussed in following section. Figure 2, 3 shows the Table view and Graph view of the Association rules.

a. Accident Pattern Discovery – Accident Reported, Location_Id, Signal Status, Traffic Volume, Weather condition.

```
[0, Yellow] --> [Rainy]
[0, Green] --> [Foggy]
[0] --> [4]
[Red] --> [Sunny]
[Yellow] --> [0, Windy]
[0, Yellow] --> [3]
[0, Red] --> [Sunny]
[Windy] --> [0, 2]
[Green] --> [3]
[Red] --> [Foggy]
[0] --> [2]
[0, Yellow] --> [4]
```

b. Weather Impact Analysis – Humidity, Temperature, Average Vehicle Speed, Location _Id, Weather Condition

```
[Windy, 1] --> [15.282]
[Cloudy, 2] --> [62.597]
[5, Sunny] --> [34.231]
[Windy, 4] --> [34.313]
[Windy, 4] --> [74.678]
[Windy, 3] --> [11.826]
[1, Sunny] --> [35.980]
```

c. Location wise Analysis – Count of Trucks(T), Count of Cars(C), Count of bikes(B), Loaction Id(2,3),

```
[2] --> [T-54]
[2] --> [T-66]
[2] --> [T-59]
[3] --> [B-26]
[3] --> [T-38]
[3] --> [T-47]
[3] --> [T-74]
[3] --> [T-75]
[3] --> [T-9]
[3] --> [T-8]
```

Items	Size	Frequency
2, B-27	2	28
2, B-35	2	29
2, B-46	2	30
2, B-14	2	29
2, B-31	2	30
2, B-20	2	27
2, B-26	2	31
2, B-38	2	26
2, B-4	2	30
2, B-43	2	27

Figure 3. Table View with Itemlist, Frequency

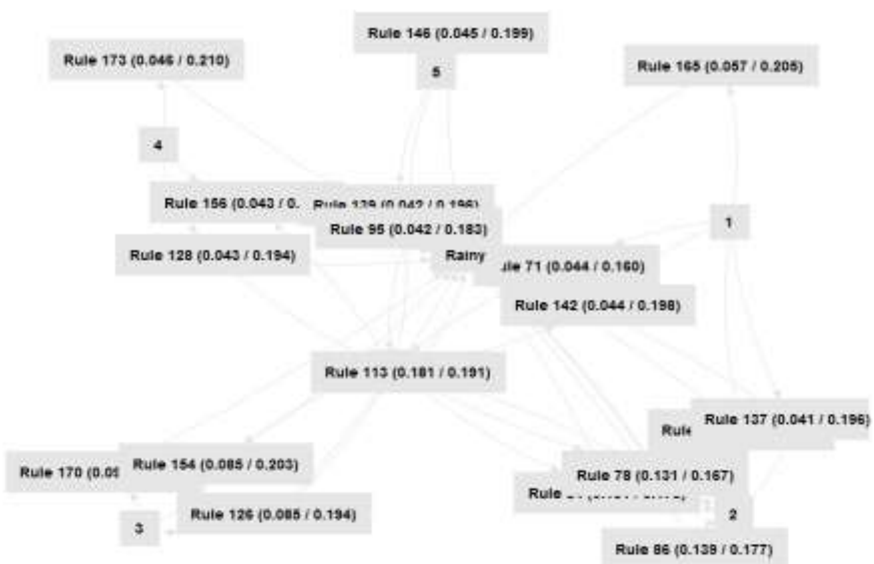

Figure 4. Association Rule in Graph view

4.3 Performance Analysis

Table 2, shows the performance analysis for the clusters formed by Fuzzy C-Means with the Support Threshold values starts from 0.01-0.1. The confidence value is fixed as 0.01 for all the support Threshold, The total number of rules generated by the proposed method is listed.

Table II. TPD-HFA Number of Association Rules for Clusters Vs. Support

No. of Clusters	Support Threshold				
	0.01	**0.03**	**0.05**	**0.07**	**0.10**
Cluster 1	328	104	79	55	31
Cluster 2	743	167	107	95	82
Cluster 3	556	129	97	71	42

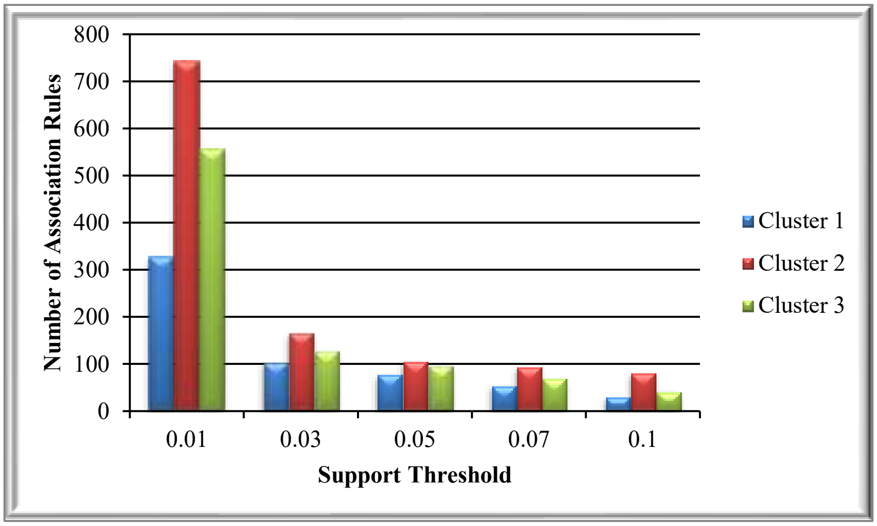

Figure 5. TPD-HFA Number of Association Rules for Clusters Vs. Support

From Figure 5, it is revealed as the number of Association rules is decreased as the number of Support Threshold value increases. While using clustering, similar traffic records are grouped together and thus the patterns inside each cluster become more homogeneous and it increase local frequency of some itemsets.

Table 3, shows the performance analysis for the clusters formed by Fuzzy C-Means with the Frequency Threshold values starts from10-50. The confidence value is fixed as 0.01 for all the Frequency Threshold, The total number of rules generated by the proposed method is listed. From Figure 6, it is revealed as the number of Association rules is decreased as the Frequency Threshold value increases.

Table III. TPD-HFA Number of Association Rules for Clusters Vs. Frequency

No. of Clusters	Frequency Threshold				
	10	**20**	**30**	**40**	**50**
Cluster 1	845	254	172	89	53
Cluster 2	1212	625	394	252	101
Cluster 3	1001	478	312	175	82

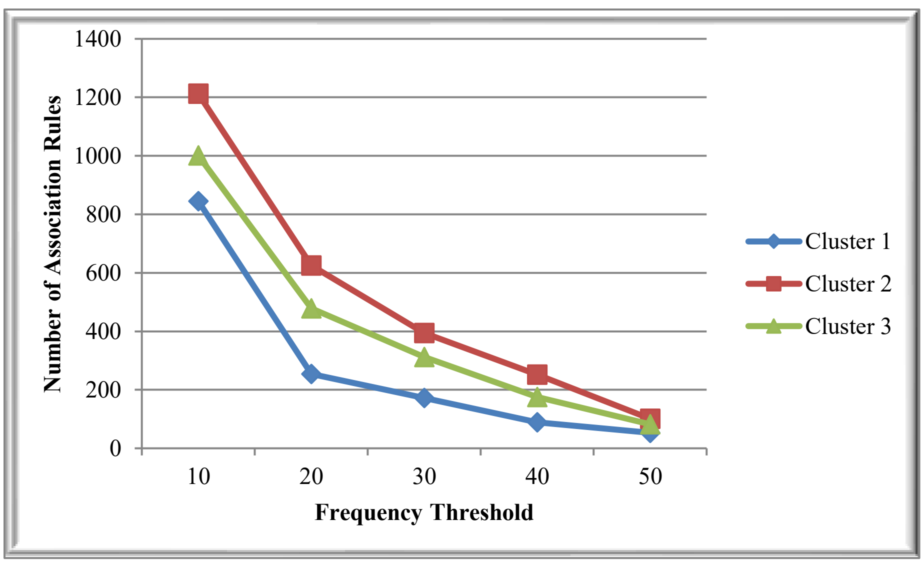

Figure 6. TPD-HFA Number of Association Rules for Clusters Vs. Frequency

Table 4, Figure 7 shows the performance of existing and proposed based on Support and Frequency threshold. Three threshold values are taken for analysis. TPD-HFA generates large number of rules than the existing ARM.

Table IV. Existing Vs. Proposed

Methods	Support Threshold			Frequency Threshold		
	0.01	**0.03**	**0.10**	**10**	**30**	**50**
ARM	521	85	63	1017	278	79

TPD-HFA	743	107	82	1212	394	101

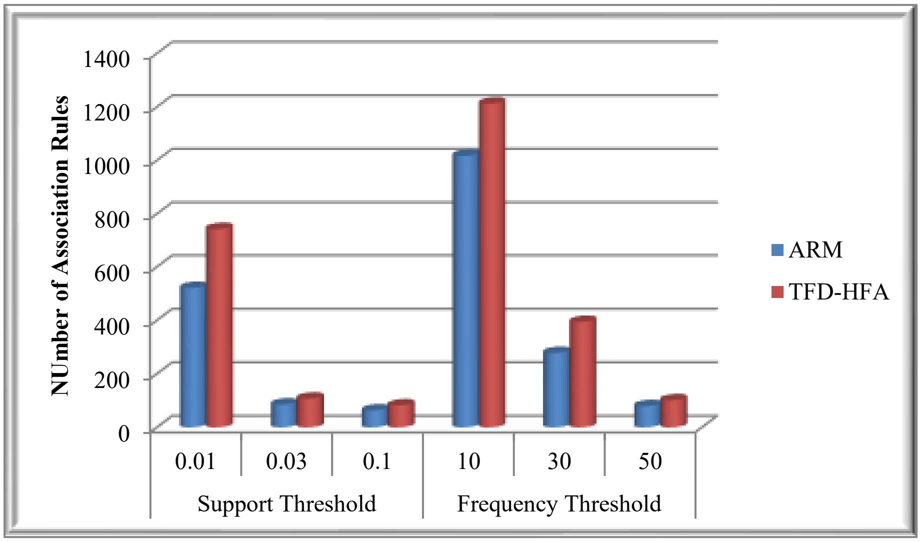

Figure 7. Existing Vs Proposed

V. CONCLUSION

The proposed framework combines Fuzzy C-Means clustering and the Apriori algorithm to uncover significant traffic behavior patterns from traffic data. In the initial phase, Fuzzy C-Means clustering is utilized to organize traffic records into similar groups, offering greater flexibility. This step improves data consistency and strengthens the effectiveness of pattern discovery. Following clustering, Apriori-based Association Rule Mining is performed within each cluster to identify frequent traffic patterns for significant factors. The rules are generated for all the attributes to get performance. Experimental results indicate that the proposed TPD-HFA model successfully extracts strong and reliable traffic rules, supporting improved decision-making for road safety.

In Future, the work can be extended for other type of applications. Measures such as Lift may be added with the performance analysis.

REFERENCES

[1] Janani, G., &Ramya Devi, N., "Road traffic accidents analysis using data mining techniques. Journal of Information Technology and Applications, 2, 2017, 84-91.

[2] Gao, Z., Pan, R., Yu, R., Wang, X., "Research on automated modeling algorithm using association rules for traffic accidents". In 2018 IEEE International Conference on Big Data and Smart Computing (BigComp), pp. 127-132. https://doi.org/10.1109/BigComp.2018.00027

[3] El Tayeb, A. A., Pareek, V., &Araar, A., "Applying association rules mining algorithms for traffic accidents in Duba", International Journal of Soft Computing and Engineering, 2015.

[4] Xiaoe Ding, "Trend analysis of traffic management based on literature data mining and graph analysis tools",IET, Volume17, Issue11, November 2023

[5] Abel Mvula, "Optimizing and Analyzing Traffic Data Using Data Mining Techniques," International Journal of Advanced Research in Science, Communication and Technology, Volume 4, Issue 3, November 2024.

[6] Soniya Mudgal, M.P., "Mining of the correlations for fatal road accident using graph-based fuzzified FPgrowth algorithm. International Journal of Engineering and Advanced Technology (IJEAT)", 9(5), 2020, 279-283.

[7] Solanki, S.K., Patel, J.T., "A survey on association rule mining. In 2015 Fifth International Conference on Advanced Computing & Communication Technologies," 2015, pp. 212-216.

[8] Christofel Rio Goenawan, "ASTM: Autonomous Smart Traffic Management System Using Artificial Intelligence CNN and LSTM", Arxiv, 2024.

[9] Rahul Khokale, Ashwini Ghate, "Data Mining for Traffic Prediction and Analysis using Big Data", IJETT, Volume 48,Number 2, Year 2017.

[10] Nawaf O. Alsrehin, "Intelligent Transportation and Control Systems Using Data Mining and Machine Learning Techniques: A Comprehensive Study", IEEE Access, 2019.

[11] Lihua Cheng, "Research on intelligent vehicle Traffic Flow control algorithm based on data mining," International Journal of Intelligent Networks, Volume 5, 2024.

[12] Fathema Tuj Johora, "Hybrid Traffic Flow Analysis: Combining Association Rule Mining and Machine Learning for Urban Traffic Optimization", IEEE, 2025.

[13] Mingchen Feng, "Association Rule Mining for Road Traffic Accident Analysis: A Case Study from UK", Springer Nature, 2020.

[14] Lijing Du, "An Association Rule Mining-Based Modeling Framework for Characterizing Urban Road Traffic Accidents," MDPI, 2024.
[15] Feng Wen, "A hybrid temporal association rules mining method for traffic congestion prediction," Computers & Industrial Engineering, Volume 130, April 2019.