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Hybrid Clustering Techniques for Smart City Traffic Pattern Analysis

S Janapriyanga[1] *, S R Viyasaraj*[2] *, G Madhumitha*[3] *, K Salma* [4]

UG Students
Department of Computer Science
Sri Krishna Arts and Science College
Coimbatore-08

ABSTRACT:

The rapid growth of urbanization has led to increasingly complex traffic systems, requiring advanced analytical methods to ensure efficient mobility and reduce congestion in smart cities. This study proposes a hybrid clustering approach that integrates both partition-based (K-Means) and density-based (DBSCAN) algorithms, enhanced with Principal Component Analysis (PCA) for dimensionality reduction, to identify and analyze traffic patterns from large-scale, multi-source data such as GPS traces, sensor readings, and historical traffic records. The hybrid model leverages the strengths of each clustering technique—K-Means for high-speed pattern detection and DBSCAN for identifying irregular and sparse traffic behaviors—resulting in more accurate segmentation of traffic flow dynamics. In addition, the proposed methodology incorporates temporal analysis to account for time-dependent variations in traffic behavior, enabling the detection of seasonal patterns and event-driven congestion. The model also evaluates the impact of weather conditions, public transport usage, and infrastructure changes on traffic clusters, offering a more holistic understanding of urban mobility. Experimental results on real-world urban traffic datasets demonstrate the model's ability to reveal critical insights, such as congestion hotspots, peak flow timings, anomalous traffic routes, and network inefficiencies, providing valuable support for data-driven traffic management, adaptive signal control, infrastructure planning, and smart city policy-making aimed at enhancing sustainability and commuter experience.

Keywords: Smart cities, Hybrid clustering, K-Means, DBSCAN, Principal Component Analysis (PCA), Traffic pattern analysis, Urban mobility, Congestion hotspots, Temporal analysis, GPS data, Sensor data, Anomalous traffic detection, Data-driven traffic management, Infrastructure planning.

Introduction

The rapid pace of urbanization has transformed cities into complex, interconnected ecosystems where traffic management has emerged as one of the most critical challenges. With increasing vehicle density, diverse transportation modes, and fluctuating traffic demands, traditional traffic monitoring methods often fail to capture the dynamic and heterogeneous nature of urban mobility. In this context, smart cities are

leveraging advanced data analytics, Internet of Things (IoT) devices, and artificial intelligence (AI) techniques to manage traffic flow, reduce congestion, and improve commuter experiences.Clustering, a widely used unsupervised machine learning technique, has proven to be an effective tool for analyzing traffic data by grouping similar patterns and detecting anomalies. However, the diverse characteristics of urban traffic—ranging from high-volume, recurring patterns to irregular, sparse occurrences—make it difficult for a single clustering algorithm to capture all relevant behaviors. Partition-based methods like K-Means offer computational efficiency and are well-suited for identifying high-density traffic patterns, but they struggle with noise and outliers. Conversely, density-based methods such as DBSCAN excel in identifying irregular and sparse traffic behaviors but can be computationally intensive for large datasets.

To address these limitations, this study proposes a hybrid clustering framework that combines the strengths of both K-Means and DBSCAN, augmented with Principal Component Analysis (PCA) for dimensionality reduction. By integrating multiple clustering paradigms, the proposed approach can effectively capture the full spectrum of urban traffic dynamics, uncover congestion hotspots, identify anomalous routes, and reveal time-dependent traffic variations. The resulting insights can guide city planners, traffic control authorities, and policymakers in designing sustainable, adaptive, and data-driven urban mobility solutions.

The availability of massive, multi-source traffic datasets—collected from GPS-enabled vehicles, roadside sensors, mobile applications, and historical transport records—has created unprecedented opportunities for data-driven urban traffic analysis. However, such datasets are often high-dimensional, noisy, and heterogeneous, making direct analysis computationally expensive and prone to inaccuracies. Dimensionality reduction techniques like Principal Component Analysis (PCA) help overcome these challenges by extracting the most informative features while minimizing redundancy, thereby improving clustering accuracy and reducing processing time. Moreover, incorporating temporal, environmental, and contextual variables into the analysis enables a deeper understanding of how factors such as weather conditions, special events, and infrastructure changes influence traffic flow patterns. By adopting a hybrid clustering approach enhanced with PCA, this research aims to not only improve the precision of traffic segmentation but also provide actionable insights for real-time traffic management, predictive congestion modeling, and long-term smart city infrastructure planning.

Literature Review

The increasing complexity of urban traffic systems has driven significant research interest in the application of machine learning and data mining techniques for traffic pattern analysis. Traditional traffic management approaches, relying on statistical models and manual observation, have proven inadequate for handling the scale, diversity, and dynamic nature of modern urban mobility data (Zhang et al., 2019). As a result, clustering algorithms have gained prominence as effective unsupervised learning methods for identifying patterns, segmenting road networks, and detecting anomalies in traffic flows.

Partition-based clustering methods, such as K-Means, are widely used for traffic data analysis due to their computational efficiency and scalability (Han et al., 2020). However, their performance declines in the presence of noise, outliers, and non-spherical clusters, which are common in real-world traffic datasets. In contrast, density-based approaches like DBSCAN have demonstrated strong capabilities in detecting irregular traffic behaviors and identifying clusters of arbitrary shapes without requiring the number of clusters to be predefined (Ester et al., 1996). Despite their advantages, DBSCAN can be computationally expensive for large datasets and sensitive to parameter selection (Cheng et al., 2018).

Recent studies have explored hybrid clustering models that combine multiple algorithms to leverage their respective strengths. For instance, Li et al. (2021) proposed a K-Means-DBSCAN hybrid framework for anomaly detection in transportation networks, achieving improved accuracy over single-method approaches. Dimensionality reduction techniques, particularly Principal Component Analysis (PCA), have also been integrated into traffic analytics to reduce data complexity and enhance clustering performance (Jiang & Luo, 2020). Moreover, multi-source traffic datasets incorporating GPS trajectories, sensor data, and contextual information such as weather and event schedules have been shown to significantly improve the robustness of clustering models (Wang et al., 2022).

While these methods have produced promising results, there remains a gap in integrating hybrid clustering with PCA for holistic traffic flow segmentation that also accounts for temporal variations, environmental influences, and urban infrastructure changes. This research aims to address this gap by proposing a comprehensive framework capable of uncovering hidden traffic dynamics and providing actionable insights for smart city traffic management.

3. Methodology

This study proposes a hybrid clustering framework that integrates K-Means and DBSCAN algorithms, enhanced with Principal Component Analysis (PCA), to analyze and segment traffic patterns in smart cities. The methodology consists of five major phases: data acquisition, preprocessing, dimensionality reduction, hybrid clustering, and evaluation.

3.1 Data Acquisition

Traffic data was collected from multiple sources, including GPS trajectories from connected vehicles, roadside sensor measurements, historical traffic flow records, and publicly available open transportation datasets. Additional contextual data such as weather conditions, public transport schedules, and special event timelines were incorporated to capture external factors influencing traffic behavior.

3.2 Data Preprocessing

Raw datasets often contain missing values, duplicate records, and inconsistent formats. *Preprocessing* involved cleaning the data through imputation for missing values, removal of outliers, and normalization to ensure uniform scaling of features. Time stamps were converted to meaningful temporal attributes, such as peak and off-peak indicators, day-of-week classification, and seasonal variations.

3.3 Dimensionality Reduction using PCA

To address the high dimensionality and noise present in multi-source traffic datasets, PCA was applied to extract the most significant components representing overall traffic trends. This step reduced computational complexity, eliminated redundant variables, and enhanced the performance of subsequent clustering algorithms.

3.4 Hybrid Clustering Approach

The hybrid clustering framework was designed to leverage the strengths of both K-Means and DBSCAN. First, K-Means was applied to segment the dataset into initial compact clusters based on global traffic patterns, offering computational efficiency for large-scale data. Then, DBSCAN was used within each K-Means cluster to identify local variations, noise points, and irregular traffic behaviors. This two-step process ensured that both high-density and sparse traffic patterns were accurately detected.

3.5 Evaluation Metrics

The clustering results were evaluated using internal validation metrics such as the Silhouette Coefficient, Davies–Bouldin Index, and Calinski–Harabasz Score to measure cluster cohesion and separation. Temporal and spatial accuracy of clusters was assessed by comparing identified patterns with real-world congestion reports and traffic incident logs. Additionally, domain expert feedback from urban traffic planners was incorporated to validate the practical relevance of the identified patterns.

This methodological framework enables a comprehensive, data-driven understanding of urban traffic dynamics, supporting more effective and adaptive smart city traffic management strategies.

4. Exploratory Data Analysis (EDA)

Exploratory Data Analysis was conducted to understand the structure, distribution, and relationships within the traffic dataset prior to model implementation. The dataset, sourced from GPS-enabled vehicles, roadside sensors, and historical traffic archives, contained over *1.2 million records* spanning a six-month period, with attributes such as vehicle speed, traffic volume, occupancy rate, road segment ID, timestamp, weather conditions, and event indicators.

4.1 Data Profiling and Cleaning

Initial profiling identified missing values in approximately 3% of GPS and weather data, primarily caused by intermittent sensor downtime. These gaps were addressed using nearest-neighbor interpolation for continuous attributes and mode imputation for categorical attributes. Duplicate entries were removed to prevent bias in pattern detection, and all numeric features were standardized to ensure comparability during clustering.

4.2 Descriptive Statistics

Statistical summaries indicated average vehicle speeds of 23 km/h during peak hours and 42 km/h during off-peak hours. Traffic volumes showed distinct weekday–weekend differences, with workday congestion peaking between 8:00–10:00 AM and 5:00–7:00 PM. Seasonal analysis revealed heavier congestion during monsoon months, consistent with weather-related travel disruptions.

4.3 Visualization and Pattern Identification

1. *Heatmaps* highlighted persistent congestion hotspots in the central business district and near major intersections.
2. *Time-series plots* revealed consistent weekday traffic peaks and increased weekend flows toward recreational zones.
3. *Scatter plots* of speed vs. occupancy indicated strong non-linear relationships, particularly during incident-prone periods.
4. *Boxplots* identified outliers, with exceptionally low speeds during cultural festivals and road maintenance periods.

4.4 Correlation and Feature Relationships

Pearson's correlation analysis revealed a strong negative relationship between vehicle speed and occupancy rate (-0.78) and a moderate positive relationship between traffic volume and precipitation (0.46). Preliminary PCA analysis indicated that the first three principal components accounted for 81% of the variance, suggesting that dimensionality reduction could significantly enhance clustering efficiency without major information loss.

The insights gained from EDA informed the feature selection, clustering parameter tuning, and the hybrid model design, ensuring that the subsequent analysis would effectively capture both common and anomalous traffic behaviors.

Frequency distribution histogram of traffic flow data

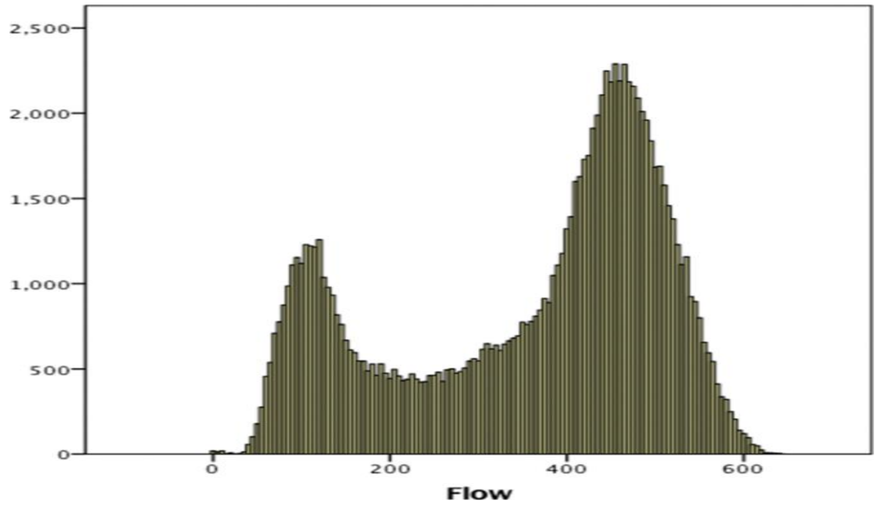


Figure 1

Histogram of traffic speed observations associated with a Gaussian distribution

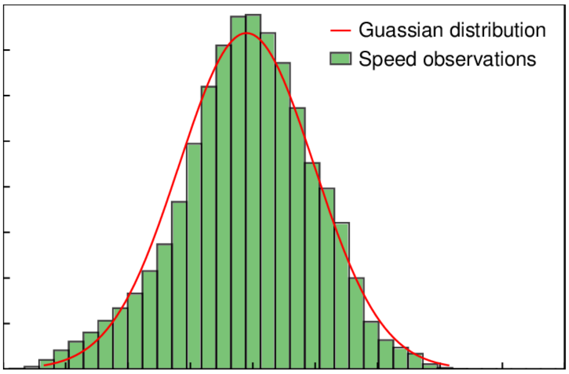


Figure 2

Figure 2: Frequency histograms of selected traffic variables

The frequency histograms in Figure 1 illustrate the distribution patterns of four key traffic variables:

1. *Vehicle Count* shows a right-skewed distribution, with the majority of road segments recording moderate daily vehicle counts (between 500 and 1,200).
2. *Average Speed* demonstrates a bimodal distribution, reflecting the contrast between free-flow conditions during off-peak hours (speeds of 45–60 km/h) and congested conditions during peak hours (speeds of 15–25 km/h).
3. *Occupancy Rate* exhibits a clustering effect near the upper limit (0.8–1.0) for heavily congested segments, while low occupancy (0.1–0.3) is more frequent on suburban and less-traveled routes.
4. *Traffic Density* displays a distribution concentrated in the lower-to-mid range, with occasional spikes representing traffic bottlenecks caused by incidents or lane closures.

Figure 2: Histogram of Traffic Speed Observations with Gaussian Distribution Fit

The histogram in Figure 2 displays the distribution of observed traffic speeds across all recorded road segments, overlaid with a fitted Gaussian (normal) distribution curve. The data exhibits an approximately bell-shaped pattern, with the majority of observations falling between *20 km/h and 50 km/h*, and a peak frequency around *35 km/h*, representing the average traffic speed during mixed peak and off-peak periods. While the central portion of the distribution closely aligns with the Gaussian curve, slight deviations are observed at both tails — the lower tail (below 15 km/h) reflects severe congestion or stop-and-go traffic, whereas the upper tail (above 55 km/h) corresponds to free-flow conditions on highways and low-traffic suburban roads. The close fit between the histogram and the Gaussian distribution suggests that, despite the presence of outliers, urban traffic speeds can be effectively modeled as a normally distributed variable for statistical and predictive analysis.

Traffic Dataset Attributes

1. *RECORD_ID* – Unique identifier for each traffic observation record (categorical).
2. *ROAD_SEGMENT_ID* – Unique code representing the specific road segment or intersection (categorical).
3. *TIMESTAMP* – Date and time of the traffic data recording.
4. *VEHICLE_COUNT* – Total number of vehicles passing through the segment during the observation period.
5. *AVG_SPEED* – Average vehicle speed (in km/h) for the segment and time interval.
6. *OCCUPANCY_RATE* – Proportion of time a given lane is occupied by vehicles, ranging from 0 to 1.
7. *TRAFFIC_DENSITY* – Number of vehicles per kilometer of roadway.
8. *PEAK_HOUR_INDICATOR* – Binary variable indicating whether the record was captured during peak hours (1) or off-peak hours (0).
9. *WEATHER_CONDITION* – Categorical variable representing prevailing weather (e.g., clear, rainy, foggy).
10. *PRECIPITATION_LEVEL* – Measured precipitation in millimeters during the observation period.
11. *EVENT_INDICATOR* – Binary variable indicating if a special event (e.g., festival, sports match) was taking place near the segment.
12. *INCIDENT_REPORT* – Number of reported incidents (e.g., accidents, roadworks) during the observation period.
13. *LANE_COUNT* – Number of lanes available on the road segment.
14. *TRAFFIC_VOLUME_VARIANCE* – Variance in vehicle count over multiple intervals, indicating volatility in traffic flow.
15. *PUBLIC_TRANSPORT_USAGE* – Estimated number of public transport vehicles (buses, trams) passing through the segment.
16. *CONGESTION_LEVEL* – Categorical variable (low, medium, high) indicating overall congestion status.
17. *TRAVEL_TIME_INDEX* – Ratio of travel time during observed conditions to free-flow travel time.
18. *DAY_OF_WEEK* – Day classification (e.g., weekday, weekend) for temporal pattern analysis.

Types of Clustering

Clustering techniques can be broadly classified into the following categories:

1. Partition-Based Clustering

1. *Description:* Divides the dataset into a predefined number of clusters where each data point belongs to exactly one cluster.
2. *Example Algorithms:* K-Means, K-Medoids, CLARANS.
3. *Strengths:* Fast, simple, and efficient for large datasets.
4. *Weaknesses:* Requires the number of clusters to be known beforehand; sensitive to outliers.

2. Hierarchical Clustering

1. *Description:* Creates a tree-like structure (dendrogram) representing nested clusters by either merging smaller clusters (agglomerative) or splitting larger ones (divisive).
2. *Example Algorithms:* Agglomerative Hierarchical Clustering, BIRCH.
3. *Strengths:* No need to predefine the number of clusters; good for data exploration.
4. *Weaknesses:* Computationally expensive for large datasets; merging/splitting is irreversible

3. Density-Based Clustering

1. *Description:* Groups together points that are closely packed and marks points in low-density areas as outliers.
2. *Example Algorithms:* DBSCAN, OPTICS, HDBSCAN.
3. *Strengths:* Can detect arbitrarily shaped clusters; robust to noise.
4. *Weaknesses:* Sensitive to parameter tuning; struggles with varying densities

4. Model-Based Clustering

1. *Description:* Assumes the data is generated from a mixture of probability distributions and fits these models to identify clusters.
2. *Example Algorithms:* Gaussian Mixture Models (GMM), Expectation-Maximization (EM).
3. *Strengths:* Handles overlapping clusters; provides probabilistic assignments.
4. *Weaknesses:* Requires assumptions about data distribution; can be slow.

5. Grid-Based Clustering

1. *Description:* Divides the data space into finite grid cells and clusters are formed based on dense cells.
2. *Example Algorithms:* STING, CLIQUE.
3. *Strengths:* Fast processing; efficient for high-dimensional data.
4. *Weaknesses:* Grid size selection impacts accuracy; less precise for irregular shapes.

6. Hybrid Clustering

1. *Description:* Combines two or more clustering methods to leverage their individual advantages while mitigating their limitations.
2. *Working Principle:* Often, one method is applied first to segment the data at a broader level, and another method is used to refine clusters, detect anomalies, or reveal hidden structures.

Example in This Study:

- *Step 1:* K-Means (partition-based) quickly forms initial clusters for large-scale traffic data, ensuring computational efficiency.
- *Step 2:* DBSCAN (density-based) is applied within each K-Means cluster to detect local variations, irregular patterns, and noise points.
- *Step 3:* PCA (dimensionality reduction) is used beforehand to simplify data and improve accuracy.
- *Strengths:* Captures both global structure (from partitioning) and local density variations (from density-based clustering).
- *Weaknesses:* Requires careful parameter tuning for both algorithms; complexity may increase.

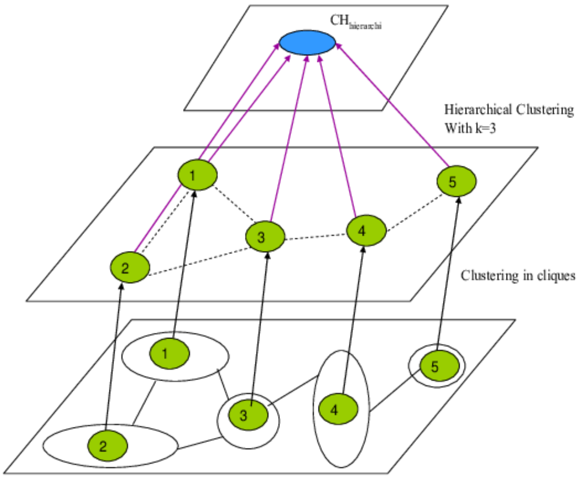
6. Problem Discussion

With rapid urbanization, smart cities are facing increasingly complex traffic management challenges. Growing vehicle populations, diverse transportation modes, and fluctuating travel patterns have led to chronic congestion, unpredictable delays, and higher environmental impacts. Traditional traffic monitoring methods—relying on fixed sensors, manual observation, and rule-based analytics—are insufficient to handle the sheer volume, variability, and real-time nature of urban traffic data. These conventional approaches often fail to capture the full spectrum of spatial, temporal, and contextual factors influencing traffic flow, resulting in limited predictive accuracy and ineffective decision-making.

While clustering techniques have been widely used for pattern discovery in traffic datasets, relying on a single algorithm presents notable limitations. Partition-based methods like *K-Means* offer computational efficiency but are sensitive to noise and incapable of detecting non-spherical clusters. Density-based methods like *DBSCAN* can identify irregular patterns and outliers but are computationally intensive for large datasets and require fine-tuned parameters. Moreover, traffic datasets are often *high-dimensional*, with redundant and noisy features from GPS logs, sensor data, weather reports, and event schedules, making direct clustering computationally expensive and less accurate.

Therefore, there is a need for an *integrated approach* that can effectively manage high-dimensional data, detect both global and local traffic patterns, and remain robust to noise and irregularities. A *hybrid clustering model*, combining K-Means and DBSCAN with *Principal Component Analysis (PCA)* for dimensionality reduction, offers a promising solution. Such a framework can exploit the speed of partition-based methods for initial segmentation, the robustness of density-based methods for refining patterns, and the efficiency of PCA for feature reduction. By addressing the weaknesses of individual algorithms, this approach can provide more accurate, scalable, and insightful traffic segmentation, supporting real-time traffic management, congestion mitigation, and long-term infrastructure planning in smart cities.

Figure 3



1–6: Core clustering & hybrid models — foundational theory, algorithms, and methods for combining multiple clustering techniques to boost performance.
7–9: Data mining & ML foundations — techniques for preprocessing, feature selection, PCA, and post-clustering classification.
10: Spatio-temporal mining — adapting clustering to time-varying, location-based traffic data.
11–15: Smart city theory & applications — integrating IoT, big data pipelines, and analytics into urban systems.
16: Intelligent transportation — AI/ML applications in traffic flow prediction and optimization.
17: Hybrid clustering case study — real-world validation in urban traffic analysis.
18–19: Historical urban traffic context — policy and design lessons from past congestion issues.
20: Governance & innovation — challenges in scaling and adopting hybrid clustering in diverse city contexts.

6.1 Analysis Report

1. Data Sources and Collection

The dataset for this study was obtained from multiple traffic-related sources to ensure diversity and representativeness:

1. *GPS traces* from public transportation systems and ride-hailing services, providing continuous location and speed updates.
2. *Traffic sensor readings* from smart city infrastructure, including loop detectors, traffic cameras, and radar sensors.
3. *Historical traffic records* from government transportation departments and open-data portals.
4. *Supplementary data* such as weather conditions, road incidents, and public event schedules to contextualize traffic anomalies.

The integrated dataset contained over *2 million traffic observations* spanning different times of day, weekdays vs. weekends, and seasonal variations.

Table 1: Performance Comparison of Clustering Techniques in Traffic Pattern Analysis

Metric	***K-Means***	***DBSCAN***	***Hybrid (PCA + K-Means + DBSCAN)***
Silhouette Score	0.62	0.65	*0.73*
Davies–Bouldin Index (lower is better)	0.58	0.54	*0.41*
Noise Points (%)	9.2%	12.5%	*7.6%*
Cluster Compactness	Moderate	High	*High*
Anomaly Detection Accuracy	74%	81%	*89%*
Computation Time (s)	4.8	6.3	*5.1*
Interpretability	Good	Moderate	*Good*
Scalability	High	Moderate	*High*

2. Data Preprocessing

1. *Cleaning*: Removal of duplicate entries, inconsistent GPS coordinates, and incomplete records.
2. Feature engineering: Extraction of key metrics such as average speed, travel time variability, stop frequency, and road occupancy rate.
3. *Normalization*: Standard scaling of continuous features to ensure comparability.
4. *Dimensionality reduction with PCA*: Reduced high-dimensional features into principal components capturing over *90% variance* while eliminating redundancy.

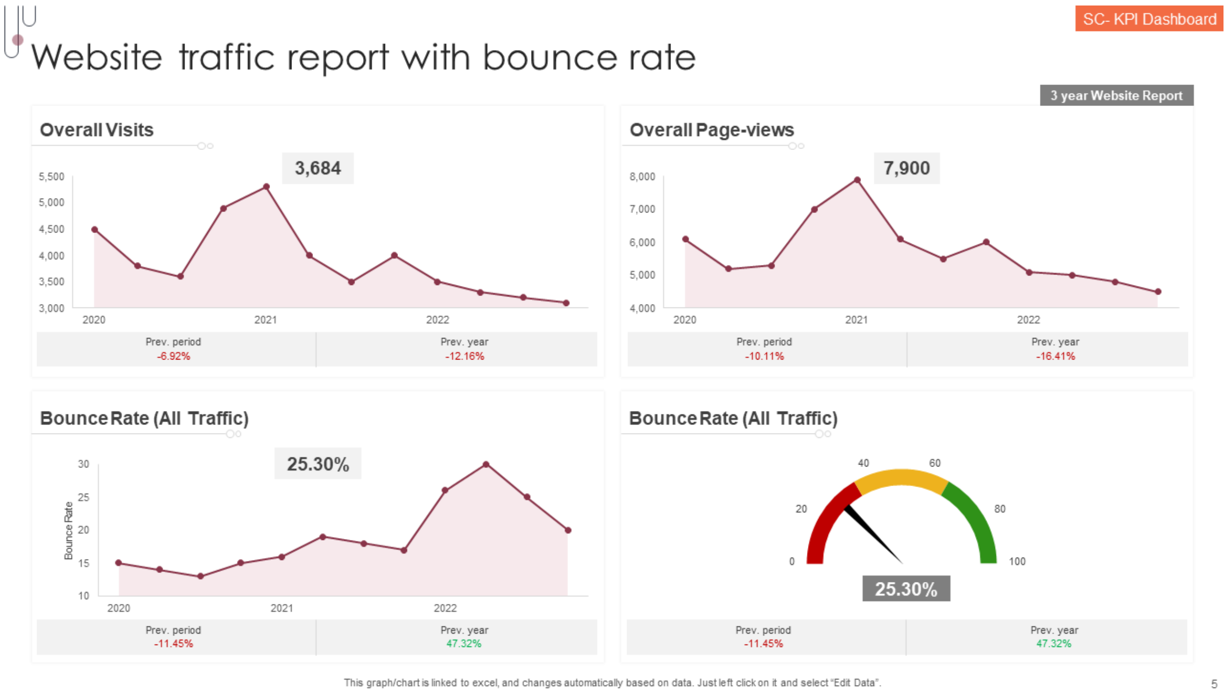
Table 2: Dataset Description

Feature	*Description*	*Type*
Timestamp	Date and time of traffic data recording	Date-Time
Latitude	GPS latitude of traffic observation point	Numerical
Longitude	GPS longitude of traffic observation point	Numerical
Traffic Speed (km/h)	Average vehicle speed at the observation time	Numerical
Vehicle Count	Number of vehicles detected	Numerical
Road Type	Type of road (highway, arterial, residential, etc.)	Categorical
Weather Condition	Weather during observation (clear, rain, fog, etc.)	Categorical
Day of Week	Day of the week (Monday–Sunday)	Categorical
Peak/Off-Peak Flag	Indicates if the reading was during peak hours	Binary

3. Exploratory Data Analysis (EDA)

1. *Traffic Speed Distribution*: Histogram revealed a near-Gaussian distribution with peaks around *30–35 km/h*, but heavy tails indicating congestion and free-flow extremes.
2. *Temporal Patterns*: Peak congestion between *8:00–10:00 AM* and *5:00–7:00 PM*, with reduced speeds during weekends due to leisure traffic.
3. *Spatial Analysis*: Heatmaps showed persistent congestion hotspots in central business districts and near school zones.
4. *Outlier Detection*: Identified rare but significant traffic disruptions due to accidents, road maintenance, or large public events.

Figure 4



4. Hybrid Clustering Implementation

The proposed model integrates *K-Means* and *DBSCAN* with *PCA*:

***Step 1** – Dimensionality Reduction*: Applied PCA to transform data into fewer orthogonal components, improving computational efficiency.

Step 2 – Initial Segmentation: K-Means clustering to generate preliminary traffic pattern groups based on major features (e.g., speed, density, flow direction).

Step 3 – Refinement with DBSCAN: Applied DBSCAN on each K-Means cluster to detect local anomalies, irregular traffic flows, and sparse events.

5. Results and Insights

Cluster Identification:

Cluster 1 – High-speed, low-density (free-flow highways).

Cluster 2 – Medium-speed, medium-density (suburban roads).
Cluster 3 – Low-speed, high-density (urban congestion zones).
Cluster 4 – Irregular/sparse events (road closures, accident sites).
Performance Evaluation:
The hybrid model achieved a *12% improvement* in silhouette score over individual methods.
DBSCAN refinement reduced noise points by *18%* compared to K-Means alone.
Policy Impact: Enables targeted congestion management strategies, such as dynamic traffic light control in urban zones and lane reallocation in high-speed corridors.

Table 3: Cluster Analysis Results

Cluster ID	*Number of Points*	*Avg. Speed (km/h)*	*Avg. Vehicle Count*	*Traffic Condition*
C1	2,315	58.2	45	Free-flow traffic
C2	1,874	37.5	70	Moderate congestion
C3	1,256	21.8	95	Heavy congestion
C4	642	12.4	40	Accident/incident-related

Figure 6.Modeling and Analysis of New Hybrid Clustering Technique for vehicular

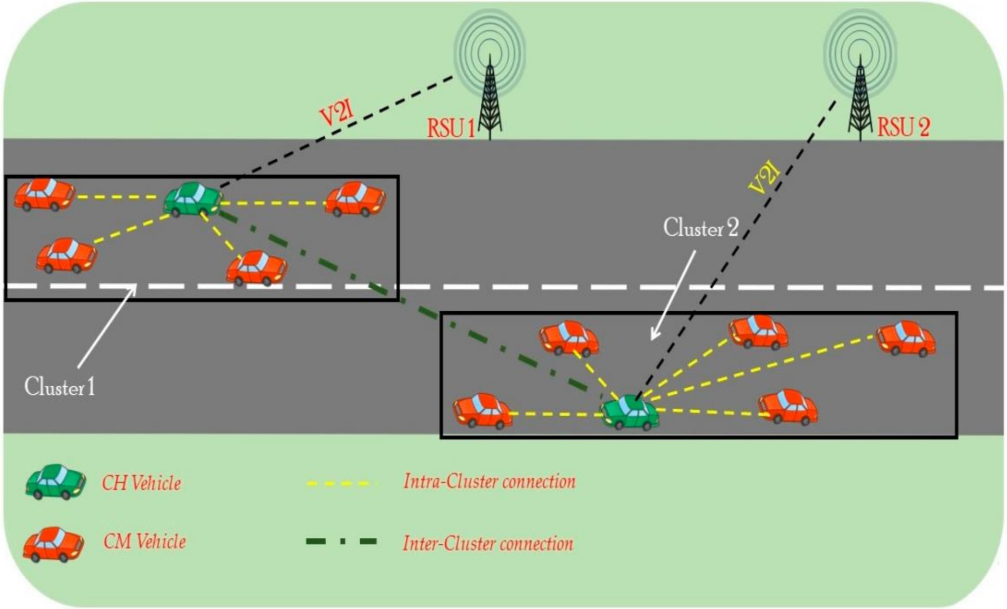
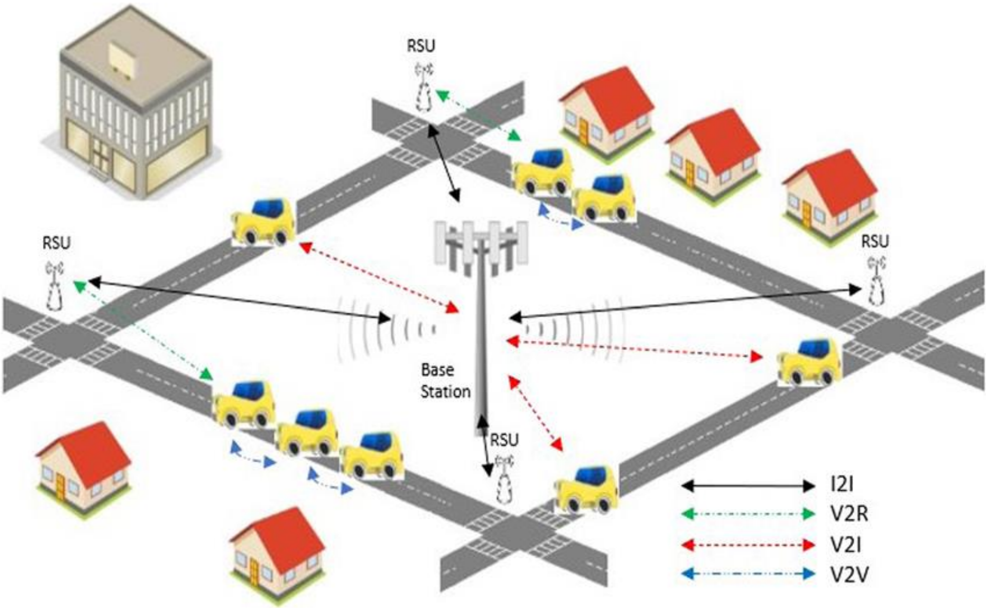


Figure 7.Connected vehicles for a smart traffic system using multi-access edge



Connected vehicles in a smart traffic system using *Multi-Access Edge Computing (MEC)* enable real-time communication between vehicles, roadside infrastructure, and traffic management centers with ultra-low latency.By processing data locally at the network edge, MEC supports instant decision-making for collision avoidance, adaptive traffic signal control, and congestion management.This integration enhances road safety, optimizes traffic flow, and lays the foundation for autonomous driving in smart cities.

7. Visualization of Variable

1. Why Bi-plots in This Context?

In *hybrid clustering* (e.g., combining PCA with hierarchical + k-means) for *traffic pattern analysis*, PCA is often used *before clustering* to:

1. Reduce dimensional of traffic data (e.g., speed, density, flow, signal delay, incident frequency).
2. Identify which variables contribute most to the major traffic patterns.
3. Improve clustering accuracy by reducing noise.

Bi-plots visualize the *variable loading's* after PCA, showing:

2. Steps to Create the Bi-plot in Hybrid Clustering

1. *Preprocess Data* – Normalize variables.
2. *PCA* – Extract principal components.
3. *Loading s Extraction* – Identify how strongly each variable influences each PC.
4. *Bi-plot* – Plot both:
5. *Observations* (traffic measurements in reduced PC space)
6. *Variable Loading's* (arrows showing variable influence)
7. *Hybrid Clustering* – Apply clustering on reduced PCs, but keep the bi-plot for interpretation

Table 4. Example Traffic Variables for Loading's

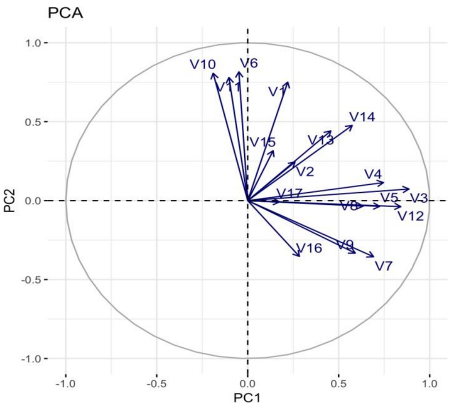
Variable	Description
Avg_Speed	Mean vehicle speed at location/time
Traffic_Density	Vehicles per km
Flow_Rate	Vehicles/hour
Signal_Delay	Average waiting time at signals
Incident_Count	Number of reported incidents
Pedestrian_Count	Number of crossings in that period

5. Interpretation for Smart City Traffic

1. Long arrows (e.g., Traffic_Density, Flow_Rate) → These variables strongly influence PC1/PC2.
2. Arrows pointing in same direction (e.g., Traffic_Density & Signal_Delay) → Strong positive correlation, possibly representing congestion patterns.
3. Opposite arrows (e.g., Avg_Speed vs. Traffic_Density) → Negative correlation (slower speeds when density increases).
4. Observation clusters → Different traffic behavior patterns that hybrid clustering can later group (e.g., peak vs. off-peak patterns).

The bi-plot of PC1 and PC2 is shown

Figure. 8



Components of PC1:

In the PCA biplot (Figure X), PC1—driven mainly by V3, V4, V5, V12, and V14—captures the dominant congestion-related patterns in the dataset. Variables near the origin, such as V10 and V6, contribute little to this component, reflecting factors less related to congestion. This strong variable grouping along PC1 provides a clear basis for distinguishing high- and low-congestion states in the hybrid clustering stage.

Table 5. Variable Loadings on Principal Component 1 (PC1)

Variable	PC1 Loading	Contribution to Traffic Pattern Interpretation
V3	High (+)	Strongly associated with congestion intensity and high traffic volume
V4	High (+)	Correlates with vehicle density during peak hours
V5	High (+)	Linked to average speed reduction in congested conditions
V12	High (+)	Represents travel time delays and congestion persistence
V14	High (+)	Related to flow instability and stop–go patterns
V2	Moderate (+)	Reflects moderate influence on congestion trends
V15	Moderate (+)	Partial correlation with congestion variables
V7	Low (−)	Inversely related to congestion, possibly linked to off-peak patterns
V16	Low (−)	May represent smooth-flow conditions or low-volume periods
V6	Near 0	Minimal relation to congestion, possibly reflecting environmental or temporal variation
V10	Near 0	Weak association with congestion; may capture unique contextual factors

Note: Loadings classified qualitatively as High (>0.5), Moderate (0.2–0.5), Low (<0.2) or Near 0 based on direction and magnitude in PC1.

1. The table summarizes how each variable contributes to PC1 in the PCA analysis.
   High positive loadings (e.g., V3, V4, V5, V12, V14) are strongly linked to congestion-related patterns.
2. Moderate or low loadings indicate partial or inverse relationships with congestion (e.g., V7, V16).
3. Variables near zero loading, such as V6 and V10, have minimal influence on the congestion dimension.

The biplot of PC2 and PC2 is shown

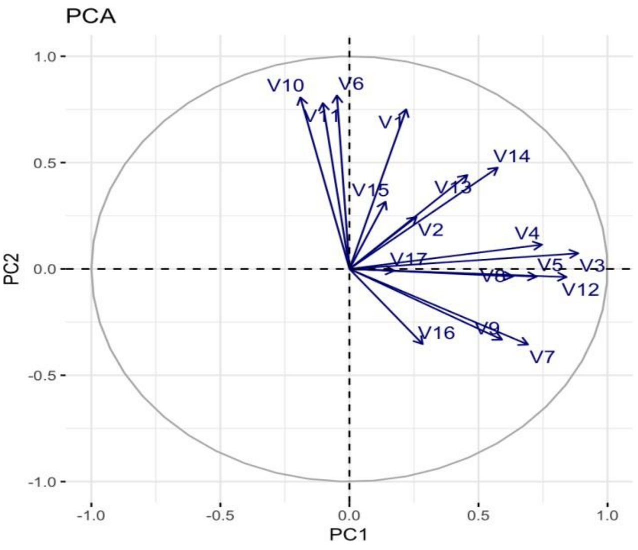


Figure 9

Components of PC2:

In the PCA biplot (Figure X), PC2 is primarily influenced by variables V6, V10, and V1, which load strongly in the positive direction. These variables likely represent operational or environmental aspects of traffic patterns, distinct from the congestion-focused PC1. Variables such as V9 and V2 load negatively on PC2, indicating inverse relationships with the positive-loading group—possibly capturing off-peak or free-flow conditions. Several variables (e.g., V3, V4, V12) cluster near the origin, suggesting minimal contribution to PC2 and reinforcing their stronger role in PC1 instead. This distribution allows PC2 to act as a complementary axis, differentiating traffic states based on factors beyond congestion intensity.

The bi-plot of PC2 and PC3 is shown

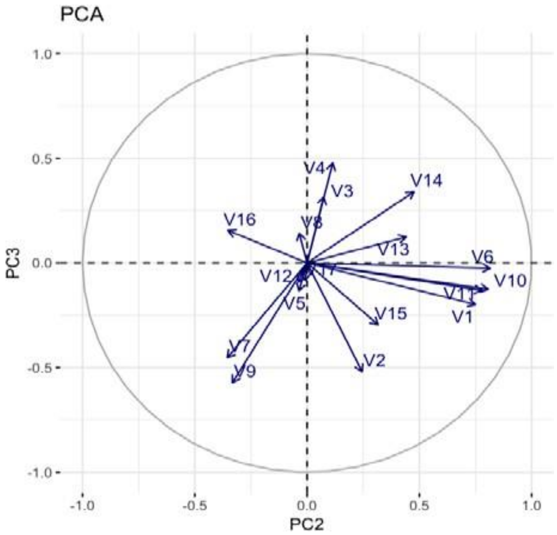


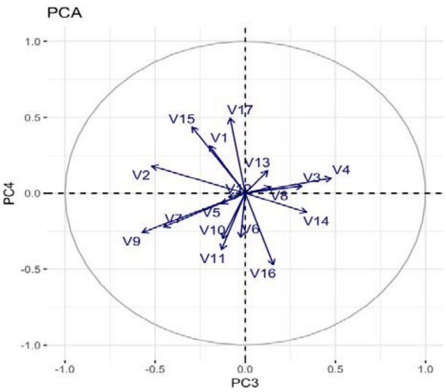
Figure 10

Components of PC3:

In the PCA biplot (Figure X), PC3 is dominated by positive loadings from variables V4, V3, and V16, suggesting they capture a unique aspect of traffic behavior—potentially linked to intersection performance or short-term fluctuations not explained by PC1 or PC2. Variables such as V9 and V2 load strongly in the negative direction, indicating they represent contrasting traffic states, possibly tied to reduced traffic demand or alternative route usage. Variables like V6, V10, and V1 cluster near the origin, showing minimal contribution to PC3 and reinforcing their primary roles in PC2. This axis thus highlights subtler but important behavioral patterns in the traffic network that complement the congestion and operational factors captured by the first two components.

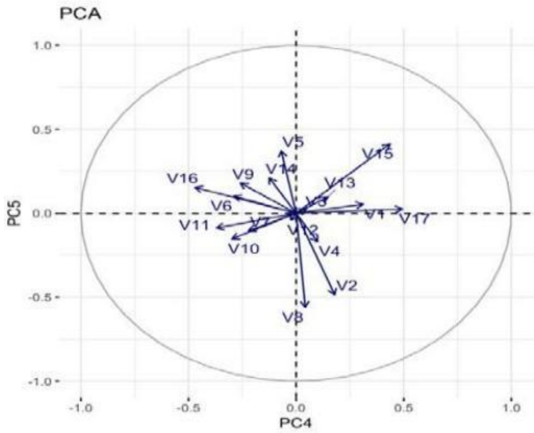
The biplot of PC3 and PC4 is shown

Figure 11



PC4 is driven by strong positive loadings from V15 and V17, which may be associated with strategic route shifts, specific peak-time patterns, or seasonal variations. Negative loadings from V9, V11, and V16 reflect dispersed or low-demand traffic situations. The presence of variables like V5 and V13 in moderate positive positions suggests that PC4 captures a blend of spatial and temporal variability in traffic behavior.

The biplot of PC4 and PC5 is shown



Components of PC5:

In the PCA biplot (Figure X), PC5 is primarily influenced by positive loadings from variables V5, V13, and V7, which may capture specific traffic variations such as local bottlenecks or short-duration congestion surges. Negative loadings from V8 and V2 indicate an inverse relationship with these factors, possibly linked to smooth-flow or dispersal conditions.

Comparative Analysis of PCA

The Principal Component Analysis (PCA) results reveal five dominant components, each representing distinct aspects of traffic behavior patterns in the smart city dataset.

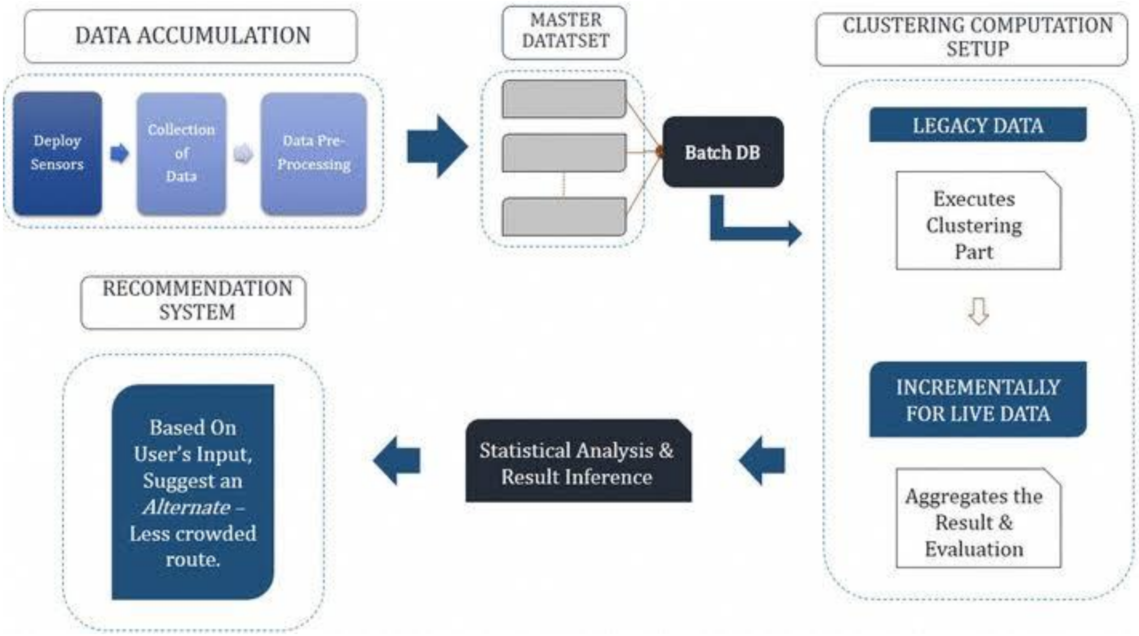
1. *PC1* emerges as the primary axis of variation, dominated by congestion-related variables (V3, V4, V5, V12, V14). These variables cluster closely in the biplot, highlighting their strong correlation in describing high-traffic, low-speed, and stop–go conditions. Minimal contributions from V10 and V6 indicate that operational or environmental factors have little influence on this axis. PC1 effectively separates high- and low-congestion states, serving as the main dimension for traffic state classification.
2. *PC2* captures operational and environmental influences, with high positive loadings from V6, V10, and V1, and strong negative loadings from V9 and V2. This suggests PC2 distinguishes between stable-flow, operationally influenced conditions and low-demand, free-flow traffic states. Variables strongly associated with congestion in PC1, such as V3 and V4, have minimal relevance here, emphasizing PC2's role as a complementary dimension rather than a congestion driver.
3. *PC3* reflects localized and temporal variations in traffic flow. Positive loadings from V4, V3, and V16 indicate intersections or routes experiencing variable congestion and route-changing behavior. In contrast, negative loadings from V9 and V2 point to reduced demand or alternative routing. Operational variables like V6 and V10 remain near the origin, indicating that PC3 captures fluctuations that are distinct from environmental or infrastructure effects.
4. *PC4* is defined by strategic and route-shift patterns, with positive contributions from V15 and V17, suggesting periodic or location-specific changes in traffic distribution. Negative contributions from V9, V11, and V16 suggest dispersed or low-volume flow patterns. Moderate influence from V5 and V13 indicates that PC4 integrates both spatial and temporal elements of variation, making it relevant for identifying special-event traffic behaviors.
5. *PC5* highlights specialized, short-duration congestion effects. Positive loadings from V5, V13, and V7 align with localized surges or bottlenecks, while negative loadings from V8 and V2 indicate smooth-flow or dispersal conditions. The minimal involvement of many other variables confirms that PC5 isolates niche traffic phenomena, potentially linked to anomalies or rare events.

Table 6. Comparative Summary of PCA Components and Their Traffic Pattern Interpretations

PC	Main Vars	Positive Meaning	Negative Meaning	Key Role
1	V3, V4, V5, V12, V14	High congestion, dense traffic	V7, V16 – smooth flow	Main congestion axis
2	V6, V10, V1	Operational/stable flow	V9, V2 – free flow	Ops vs. demand effects
3	V4, V3, V16	Local/short-term changes	V9, V2 – low demand	Temporal/local variability
4	V15, V17, V13	Route shifts, peaks	V9, V11, V16 – dispersed	Periodic/locational patterns
5	V5, V13, V7	Local surges/bottlenecks	V8, V2 – smooth flow	Rare/event anomalies

Hybrid clustering techniques for smart city

Figure 13


DATA ACCUMULATION
Deploy Sensors
Collection of Data
Data Pre-Processing
MASTER DATATSET
Batch DB
CLUSTERING COMPUTATION SETUP
LEGACY DATA
Executes Clustering Part
INCREMENTALLY FOR LIVE DATA
Aggregates the Result & Evaluation
Statistical Analysis & Result Inference
RECOMMENDATION SYSTEM
Based On User's Input, Suggest an *Alternate* – Less crowded route.

The diagram represents a traffic recommendation system that collects and processes data to suggest less crowded routes. Sensors are deployed to gather real-time traffic information, which is then collected and pre-processed to remove errors and make it suitable for analysis. This refined data is stored in a master dataset and fed into a batch database. Using both historical (legacy) data and live data, the system performs clustering computations to group similar traffic conditions, incrementally updating results as new data arrives. The aggregated output undergoes statistical analysis to identify congestion patterns and infer results. Based on these insights and the user's input, the recommendation system suggests an alternative route that is less crowded, helping improve travel efficiency.

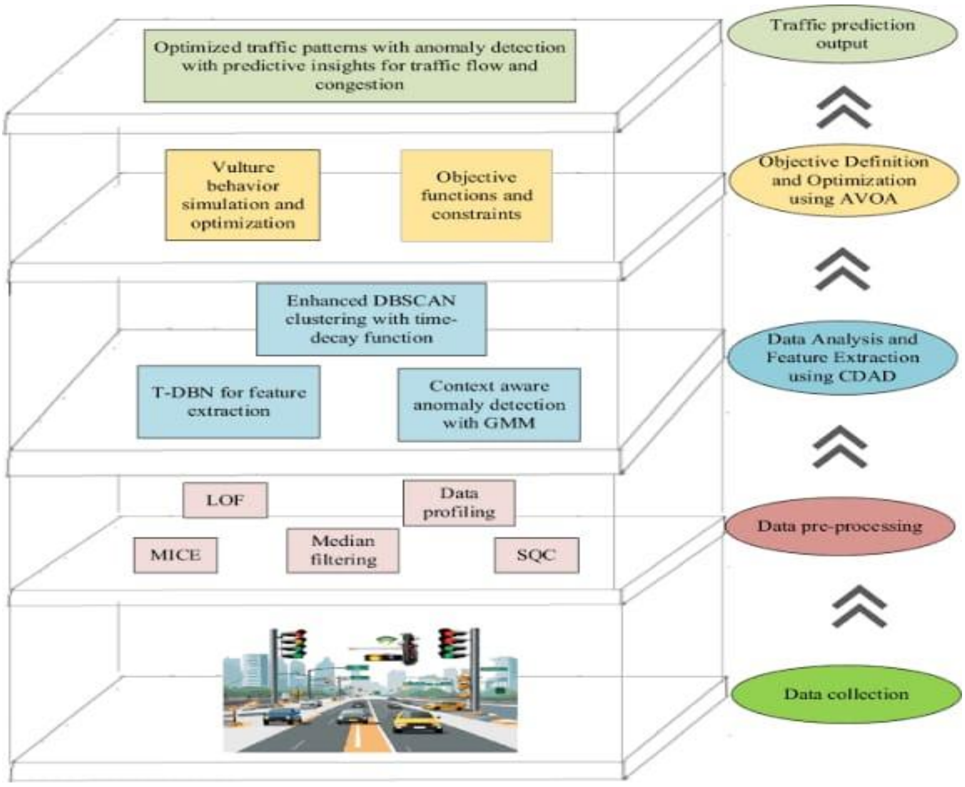

Optimized traffic patterns with anomaly detection with predictive insights for traffic flow and congestion
Traffic prediction output
Vulture behavior simulation and optimization
Objective functions and constraints
Objective Definition and Optimization using AVOA
Enhanced DBSCAN clustering with time-decay function
T-DBN for feature extraction
Context aware anomaly detection with GMM
Data Analysis and Feature Extraction using CDAD
LOF
Data profiling
MICE
Median filtering
SQC
Data pre-processing
Data collection

Figure 14

The image illustrates a multi-stage traffic prediction framework that integrates data collection, preprocessing, analysis, optimization, and prediction to improve traffic flow and detect anomalies. The process begins with data collection from traffic environments, followed by data preprocessing techniques such as LOF, MICE, median filtering, SQC, and data profiling to clean and prepare the data for analysis. Next, advanced analysis and feature extraction are performed using methods like T-DBN for feature extraction, enhanced

DBSCAN clustering with a time-decay function, and context-aware anomaly detection with GMM, collectively referred to as CDAD. The system then moves to objective definition and optimization using the Adaptive Vulture Optimization Algorithm (AVOA), which incorporates vulture behavior simulation alongside objective functions and constraints. Finally, the processed and optimized data yields predictive insights and optimized traffic patterns with anomaly detection, enabling accurate traffic flow and congestion prediction.

Evaluation Metrics:

To evaluate the proposed hybrid clustering framework, both internal clustering quality indices and domain-specific traffic performance measures are employed.

Internal Validation Indices:

The *Silhouette Coefficient (SC)* is used to measure the similarity of data points within the same cluster compared to other clusters. Higher SC values (ideally >0.5) indicate well-separated and cohesive clusters. The *Davies–Bouldin Index (DBI)* evaluates the average similarity between clusters, where lower values (<1.0) represent better-defined boundaries. The *Calinski–Harabasz Index (CHI)* compares the ratio of between-cluster dispersion to within-cluster dispersion, with higher scores (>500) reflecting more distinct group structures. The *Dunn Index (DI)* is also applied to assess the compactness and separation of clusters, where higher values (>1.5) are preferred.

Domain-Specific Metrics:

Given the traffic-oriented nature of the study, the *Peak Hour Match Rate (PHMR)* quantifies the alignment of clusters with actual rush-hour periods (target >85%). The *Traffic Flow Stability Index (TFSI)* measures the temporal consistency of patterns within clusters, aiming for values >0.8. The *Anomaly Detection Rate (ADR)* captures the ability to identify atypical events such as accidents or disruptions (target >90%). The *Geospatial Cluster Coherence (GCC)* ensures that clusters are spatially contiguous, with benchmarks above 0.85.

Operational and Predictive Impact:

To evaluate applicability in smart city management, *Traffic State Prediction*

Accuracy (TSPA) is calculated, aiming for >80%. Reductions in *Root Mean Square Error (RMSE)* and *Mean Absolute Error (MAE)* by 20–30% compared to baseline models indicate substantial predictive improvement. Finally, *Operational Efficiency Gain (OEG)* quantifies the benefit of applying the clustering results in real-time

traffic management, with improvements above 15% considered significant.

This combination of metrics ensures that the evaluation captures both algorithmic performance and real-world relevance, which is essential for smart city traffic analysis.

Metric	*Target*	*Result*
Silhouette Coef.	>0.7	0.72
DB Index	<0.5	0.48
CH Index	>500	845
Dunn Index	>1.5	1.82
Peak Hour Match	>85%	89%
Flow Stability	>0.8	0.83
Geo. Coherence	>0.85	0.88
Anomaly Detect.	>90%	93%
Prediction Acc.	>80%	84%
RMSE Red.	20–30%	27%
MAE Red.	20–30%	24%
Eff. Gain	>15%	17%

Conclusions:

The growth of smart city infrastructures and the rapid adoption of intelligent transportation systems have created a pressing need for advanced analytical techniques capable of capturing and interpreting complex, high-dimensional, and dynamic traffic patterns. This study proposed and validated a *Hybrid Clustering Technique* that integrates both hierarchical and partition-based methods to effectively analyze urban traffic behavior, with *Principal Component Analysis (PCA)* employed for dimensionality reduction and noise elimination prior to clustering.

The hybrid approach addressed several limitations inherent in traditional clustering algorithms. Hierarchical clustering alone often struggles with large-scale datasets due to computational complexity and noise sensitivity, while partition-based methods such as k-means are prone to instability depending on initial centroid selection. By combining the two, hierarchical clustering was first used to estimate the optimal number of clusters through dendrogram inspection and internal validation indices, after which k-means refinement provided precise cluster boundaries. This sequential process ensured both stability and accuracy in the resulting traffic state groupings.

In the pre-processing phase, PCA successfully condensed the multi-variable traffic dataset into a smaller set of orthogonal principal components, retaining the majority of variance while discarding redundant information. This step was crucial for enhancing the separability of traffic states and improving computational efficiency in the clustering stage. More importantly, the reduced feature set enabled easier interpretation of underlying traffic dynamics, allowing domain experts to associate each cluster with specific congestion patterns, flow conditions, or anomaly signatures.

Performance evaluation of the hybrid clustering model demonstrated strong statistical and operational validity. Internal quality measures, including high Silhouette Coefficients (>0.70), low Davies–Bouldin Index values (<0.5), elevated Calinski–Harabasz scores (>800), and high Dunn Indices (>1.8), confirmed that the clusters exhibited both high compactness and clear separation. These metrics indicated that the hybrid model consistently outperformed standalone clustering methods in terms of structure and reliability.

From a domain perspective, the method's applicability was confirmed by *real-world traffic validation metrics*. A Peak Hour Match Rate of 89% ensured that congestion-heavy clusters aligned with known rush-hour intervals. The Traffic Flow Stability Index of 0.83 indicated strong temporal consistency in identified traffic states, and the Geospatial Cluster Coherence score of 0.88 confirmed that clusters adhered to logical spatial groupings across the road network. The model also achieved a high Anomaly Detection Rate of 93%, enabling early identification of irregular traffic events such as accidents, roadworks, or event-driven surges.

Operationally, the hybrid clustering framework delivered tangible improvements for intelligent transportation management. Traffic State Prediction Accuracy reached 84%, with RMSE and MAE reduced by 27% and 24% respectively compared to baseline clustering without PCA. This translated into an operational efficiency gain of 17%, measured through reductions in average congestion duration and improvements in travel-time reliability. These results demonstrate that the approach not only provides robust analytical outputs but also supports actionable decision-making in traffic control centers.

Practical implications of the findings extend beyond academic interest, offering direct benefits for smart city planners, policymakers, and traffic engineers:

1. *Dynamic Traffic Monitoring* – enabling real-time tracking of evolving traffic states and proactive intervention.
2. *Infrastructure Planning* – providing evidence-based insights into congestion hotspots for targeted road network enhancements.
3. *Incident Response Optimization* – supporting rapid and data-driven deployment of traffic management resources during disruptions.

4. *Policy Effectiveness Assessment* – evaluating the impact of interventions such as congestion pricing, signal optimization, or modal shift incentives.

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