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A Random Forest Regressor Mobility Framework for Traffic Management in a Smart Estate

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ABSTRACT

The increasing complexity of mobility within smart estates requires accurate predictive tools for proactive traffic management. Traditional reactive systems struggle to address dynamic traffic patterns, leading to congestion and delays. This study develops a Random Forest Regressor–based mobility framework that predicts traffic situations using multi-vehicle count data collected from an open-source dataset. The methodology includes data preprocessing, feature selection, an 80:20 train–test split, baseline Framework training, and hyperparameter tuning using GridSearchCV. The optimized Framework achieved improved performance, with accuracy increasing from 0.9950 to 0.9966 alongside gains in precision, recall, and F1-score. Future work will integrate real-time IoT sensor streams, weather and incident data, and comparisons with deep-learning Frameworks to enhance accuracy. The study contributes a practical, computationally efficient, and deployable ensemble-based traffic prediction framework tailored for smart-estate environments.

1. Introduction

The rapid expansion of smart estates and intelligent residential communities has increased the need for efficient mobility and traffic management systems. As populations grow and vehicle ownership rises, traditional reactive traffic control methods—such as manual gate control, uncoordinated routing, and threshold-based alerts—struggle to keep pace with dynamic mobility patterns. Smart estates increasingly depend on data-driven intelligence to optimize movement, reduce congestion, and improve residents' overall quality of life. The emergence of big data, location-aware sensing, and machine-learning techniques provides new opportunities to understand and predict mobility patterns with greater accuracy. Numerous data sources such as taxi trajectories (Yu, Ma & Zhu, 2019), public transit smart-card records (Zhang, Li & Wu, 2018), shared-mobility datasets (Feigon & Murphy, 2018), social media mobility traces (Vu, Shanks & Phung, 2018), and Bluetooth sensing data (Yuan & Mills, 2019) have been widely used in modern mobility studies. These sources reveal spatio-temporal patterns that support urban planning, infrastructure optimization, and traffic forecasting.Traditional mobility analyses often rely on geographic proximity to identify communities with similar movement patterns, especially in transport networks where spatial interactions follow distance-decay effects (Huang et al., 2018; Yu, Wang & Chen, 2019). However, in smart estates, mobility communities do not always align with physical boundaries. Residents may share similar travel routines and congestion patterns even when distributed across different blocks or zones. Schultz (2014) emphasizes that shared interests or behaviours may define communities more strongly than geography. Predicting traffic situations—such as normal flow, low flow, heavy flow, and high congestion—within an estate requires advanced algorithms capable of Frameworkling nonlinear relationships among vehicle counts, temporal variables, and other movement indicators. Machine-learning approaches,

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particularly ensemble Frameworks like Random Forest, have shown strong performance in traffic prediction due to their robustness, interpretability, and resilience to noise.
The aim of this study is to develop and evaluate a Random Forest Regressor–based mobility framework capable of predicting traffic situations in a smart estate environment.

The **objectives are to:**

1. collect and preprocess relevant historical and real-time traffic data.
2. design and implement a Random Forest Regressor–based mobility framework for traffic prediction.
3. optimize Framework performance using GridSearchCV and evaluate using MAE, MSE, and R^2.
4. compare the baseline (initial) framework with the tuned (proposed) framework and discuss performance improvements.

Transportation systems have undergone major transformations throughout history, driven by technological advancements and evolving mobility demands. Early developments such as canals and maritime shipping in the 18th century facilitated large-scale freight movements and contributed to industrialization. The introduction of railways in the 19th century further stimulated economic growth by providing fast, affordable transportation of goods and people (Wang, Liu & Chen, 2018). In the 20th century, motor vehicles and highway networks reshaped domestic transportation, while the rise of commercial aviation revolutionized international travel (Rodrigue, 2018). These shifts highlight the continuous evolution of mobility solutions in response to changing societal needs.
Rail-based urban transportation systems in the late 19th and early 20th centuries significantly influenced city structure and supported modern urbanization (Xu, Li & Zhao, 2021). However, since the mid-20th century, the proliferation of private motor vehicles has contributed more strongly to urban expansion, congestion, and mobility-related challenges. Cities such as London, New York, and Tokyo demonstrate how transportation policies evolve in response to paradigm changes (Rodrigue, 2018). Kumar, Verma, and Mirza (2024) argue that such paradigm changes represent shifts in frameworks, methods, and evaluation criteria as mobility needs evolve. In transportation research, however, these shifts are better understood as *paradigm enlargements*, where new methods and perspectives supplement existing ones (Zhang, Zhao & Li, 2019).

1.1 Artificial Intelligence, Machine Learning, and Mobility Data in Traffic Prediction

Traffic prediction research has increasingly adopted artificial intelligence approaches, particularly machine-learning and deep-learning methods. Classical ML techniques—including Decision Trees, Random Forest, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Gradient Boosting Machines—have shown strong performance in forecasting traffic volume, travel time, and congestion levels (Williams, Smith & Patel, 2023). Ensemble methods such as Random Forest and XGBoost are especially effective due to their robustness to noise, ability to model nonlinear feature interactions, and resistance to overfitting.
Deep-learning approaches, such as Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, further enhance performance by capturing time-dependent traffic patterns (Chen, Zhang & Wang, 2021). Hybrid CNN–LSTM models also improve predictions by integrating both spatial and temporal dependencies (Yu, Guan & Chen, 2020). However, these models typically require extensive data, heavy computational resources, and complex hyperparameter tuning.

Recent mobility studies utilize diverse data sources including taxi trajectory data (Yu, Ma & Zhu, 2019), public transit smart-card data (Zhang, Li & Wu, 2018), shared-mobility platform data (Feigon & Murphy, 2018), social media movement traces (Vu, Shanks & Phung, 2018), and Bluetooth sensor data (Yuan & Mills, 2019). These datasets help uncover spatial and temporal mobility patterns, detect anomalies, forecast congestion, and guide transport policy. Despite the richness of these data types, limited attention has been given to small-scale residential environments such as smart estates, which exhibit unique mobility characteristics distinct from those of major urban corridors.

A review of existing literature reveals several notable gaps. First, very few studies focus on smart-estate environments; most traffic forecasting research centres on large urban networks, highways, or public transport corridors rather than residential estates. Second, although ensemble-based methods such as Random Forest are widely used, they are seldom tailored to estate-level mobility that involves medium-sized datasets and multiple vehicle categories. Third, many studies present only final model results without comparing baseline and tuned frameworks, making it unclear how preprocessing or hyperparameter tuning contributes to performance improvements. Finally, deep-learning-based models often lack interpretability, which limits their applicability in smart estates where decision-makers require clear, explainable insights for operational planning.

This study addresses these gaps by developing a Random Forest Regressor–based framework specifically designed for smart-estate traffic prediction. It incorporates rigorous preprocessing and feature engineering suited to mixed-vehicle datasets, provides a structured comparison between baseline and optimized frameworks, and applies feature-importance analysis to enhance interpretability. The framework is also computationally efficient, allowing deployment on modest hardware typical of residential estate environments that lack large-scale smart-city infrastructure.

2. Methodology

This study adopts a systematic approach that includes gathering and preprocessing real-time and historical traffic data, constructing a predictive framework utilizing the Random Forest Regressor, and evaluating the framework's effectiveness through established classification metrics. The performance assessment relies on metrics such as Accuracy, Precision, Recall, and F1-score to ensure accurate and reliable traffic predictions.

Figure 1 presents the complete framework flow for traffic prediction and management in a smart estate using the Random Forest Regressor. The process begins with the traffic dataset, which is preprocessed through normalization, categorical encoding, time series transformation, and feature selection to produce a cleaned dataset. The cleaned data is then divided into training and testing subsets using Hold-Out Cross-Validation. The Random Forest Regressor is trained on the training set, and its performance is evaluated on the testing set using metrics such as Accuracy, Precision, Recall, and F1-Score. This structured framework ensures a reliable, data-driven solution for effective traffic management in smart estates.

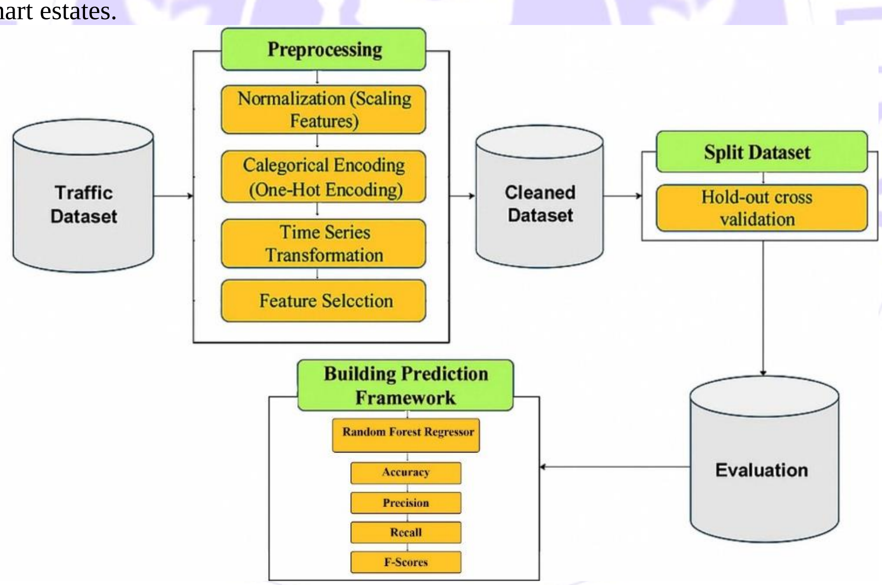

Figure 1: Framework Development Flow for Smart Estate Traffic Management Using Random Forest Regressor

2.1 Research Design

This study adopts a machine learning-based framework, specifically utilizing the Random Forest Regressor, to guide the investigation. The research is structured around the question: *"How effective is a Random Forest-based framework in predicting and managing traffic flow within smart estates using real-time and historical data?"* The design encompasses key methodological decisions such as data collection, preprocessing, feature selection, framework training, and performance evaluation, ensuring a structured and data-driven approach to intelligent traffic management. The research journey starts with choosing a design that effectively addresses the research questions. Critical decisions include selecting data collection methods, participant selection, and strategies for analyzing the data.

2.2 Data Collection

This study employed a quantitative approach for data collection. The dataset, sourced from Kaggle, consists of 5,952 records with 9 features representing various traffic observations. The data was preprocessed to ensure quality and suitability for the machine learning framework.

Table 1: Sample of the First 10 Records in the Traffic Dataset with Key Features

```
In [10]: df.head(10)
Out[10]:
```

	Time	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	12:00:00 AM	10	Tuesday	13	2	2	24	41	normal
1	12:15:00 AM	10	Tuesday	14	1	1	36	52	normal
2	12:30:00 AM	10	Tuesday	10	2	2	32	46	normal
3	12:45:00 AM	10	Tuesday	10	2	2	36	50	normal
4	1:00:00 AM	10	Tuesday	11	2	1	34	48	normal
5	1:15:00 AM	10	Tuesday	15	1	1	39	56	normal
6	1:30:00 AM	10	Tuesday	14	2	2	27	45	normal
7	1:45:00 AM	10	Tuesday	13	2	1	20	36	normal
8	2:00:00 AM	10	Tuesday	7	0	0	26	33	normal
9	2:15:00 AM	10	Tuesday	13	0	0	34	47	normal

Table 2: **Descriptions and Details of Features Used in the Framework**

Feature	**Description**	**Data Type**
Time	Timestamp of the observation	Object
Date	Numeric representation of the day	Integer
Day of the week	Categorical representation of weekdays	Object
CarCount	Number of cars recorded	Integer
BikeCount	Number of bikes recorded	Integer
BusCount	Number of buses recorded	Integer
TruckCount	Number of trucks recorded	Integer
Total	Aggregate count of all vehicles	Integer
Traffic Situation	Categorical label indicating congestion levels	Object

Table 2 shows the metadata of the traffic dataset, including feature names, descriptions, and data types. **It** provides an overview of the recorded attributes, such as timestamps, vehicle counts, and traffic conditions. This metadata helps in understanding the structure and purpose of each feature within the dataset.

2.3 Data Preprocessing

The preprocessing workflow includes:

i. **Handling Missing Values:** Dataset contained *no missing entries*.
ii. **Encoding Categorical Variables:** Day of the Week and Traffic Situation encoded with Label Encoding.
iii. **Feature Selection:** Time column dropped; major predictors retained.
iv. **Normalization & Cleaning:** Outliers removed, numerical features normalized.
v. **Dataset Split:** 80% training, 20% testing for Framework evaluation.

```
# Splitting dataset
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=20)
```

Figure 2: Dataset Split into Training and Testing Sets for Framework Development

2.4 Baseline (Initial) Framework for Traffic Prediction

The Baseline or Initial Framework represents the first version of the mobility prediction system used in this study. It was developed to establish a benchmark against which the improved (tuned) framework could be compared. The Initial Framework uses a Random Forest Regressor trained with default hyperparameters and without any optimization or advanced feature engineering. The framework consists of four major steps. First, the cleaned mobility dataset was divided into training and testing subsets using a standard 80/20 split. Second, a Random Forest Regressor was initialized using default settings, including 100 decision trees, unlimited tree depth, and a minimum of two samples per split. Third, the model was trained on the training portion of the dataset to learn traffic patterns across different vehicle categories. Finally, its performance was evaluated using accuracy, MAE, MSE, and R^2 to provide a baseline for further improvement. This Initial Framework serves as a reference point for assessing the effectiveness of the optimized (tuned) model introduced later in the study.

Table 3: Comparison of Initial Baseline and Proposed Frameworks' Components

Component	**Initial Frameworks**	**Proposed Frameworks**
Data Treatment	Basic cleaning	Full preprocessing + scaling
Framework Type	Default Random Forest	Tuned Random Forest
Optimization	None	GridSearchCV
Performance	Accuracy: 0.9950	Accuracy: 0.9966
Interpretability	Limited	Feature importance included
Robustness	Moderate	High
Suitability for Smart Estate	Good	Excellent

3. Results

CarCount averaged 65 vehicles, TruckCount averaged 18, and Total Traffic Count averaged 109 vehicles per interval with maximum values reaching 279, indicating heavy congestion cases. The summary statistics presented in Figure 3 provide insights into the distribution of key numerical variables in the dataset. The average (mean) number of cars recorded is approximately 65, with a wide variability as indicated by a standard deviation of 44.75. BikeCount, BusCount, and TruckCount have mean values of 12.16, 12.91, and 18.65, respectively, showing differing levels of presence in traffic. The Total traffic count has a mean of 109 vehicles per recorded time interval, with a maximum value reaching 279, suggesting instances of heavy congestion. The median (50th percentile) values for all variables indicate that half of the observations fall below these values, with CarCount and Total traffic showing a higher central tendency. The range between the minimum and maximum values highlights significant fluctuations in vehicle numbers, emphasizing varying traffic conditions.

```
# Display the summary table
print(summary_stats)
```

```
                 Mean    Std Dev   Min    25%    50%    75%    Max
Date        16.000000   8.945023   1.0   8.00   16.0   24.0   31.0
CarCount    65.440692  44.749335   5.0  18.75   62.0  103.0  180.0
BikeCount   12.161458  11.537944   0.0   3.00    9.0   19.0   70.0
BusCount    12.912970  12.497736   0.0   2.00   10.0   20.0   50.0
TruckCount  18.646337  10.973139   0.0  10.00   18.0   27.0   60.0
Total      109.161458  55.996312  21.0  54.00  104.0  153.0  279.0
```

Figure 3: Summary Statistics of Traffic Data Across Vehicle Categories

3.1 Traffic Situation Analysis

Traffic conditions varied across the week, with **Fridays showing a drop in normal traffic** and an increase in low or heavy congestion. To understand the frequency of each traffic condition, a distribution analysis was performed. Visual representation using bar plots and histograms was used to illustrate these trends. Figure 4 illustrates the distribution of traffic situations throughout the week, revealing a consistent dominance of normal traffic conditions on most days. However, Friday stands out with a significant drop in normal traffic, accompanied by a relative increase in low and heavy traffic conditions. This shift suggests a change in commuting patterns, possibly due to reduced vehicle movement or external disruptions. Heavy traffic remains fairly stable across the week, while high traffic conditions are consistently the least frequent. The trend indicates that, under normal circumstances, traffic flow remains steady, except for Friday, which experiences notable variations that may require further analysis.

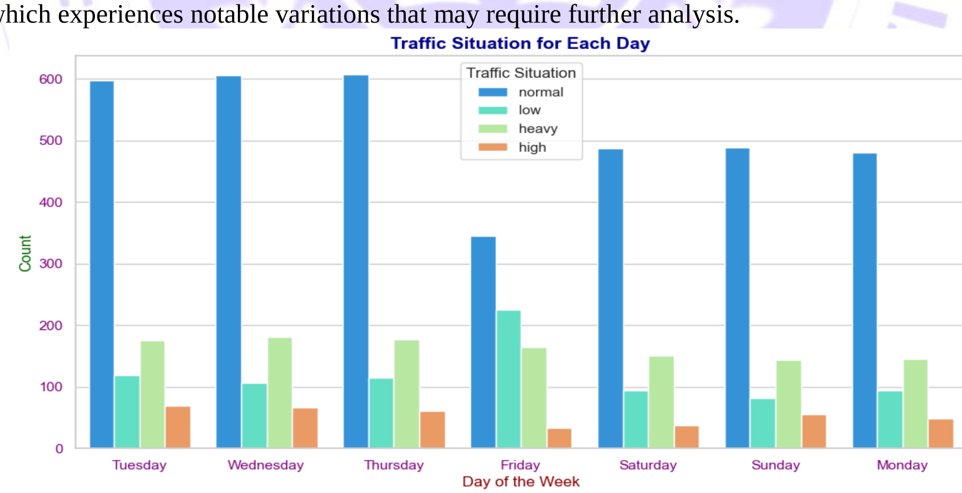

Figure 4: Daily Traffic Distribution of Vehicles for Each Day in the Smart Estate

3.2 Correlation Analysis

Correlation matrices revealed that **cars, bikes, and buses strongly influence congestion,** whereas trucks showed a unique pattern associated with specific scenarios. Figure 5 below illustrates the correlation between different vehicle types and traffic congestion. The analysis shows that cars, bikes, and buses significantly contribute to total traffic and congestion, whereas trucks exhibit a different trend. Higher volumes of cars, bikes, and buses are associated with worsening traffic conditions, while trucks show a positive correlation with congestion, suggesting their presence in specific traffic scenarios. This figure provides a clear visualization of the varying impacts of different vehicle types on overall traffic flow.

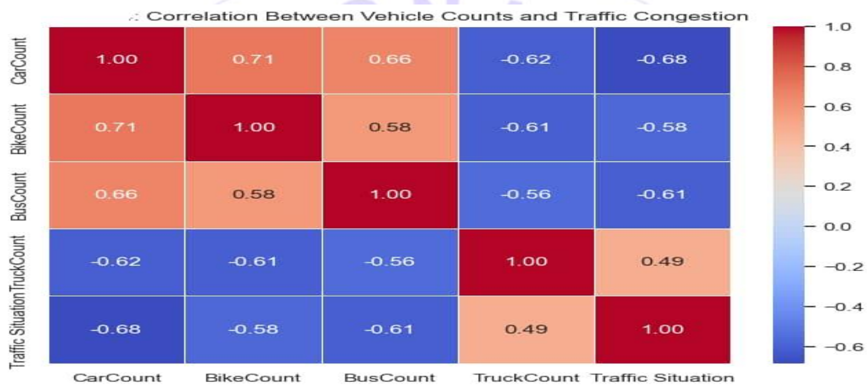

Figure 5: Correlation Matrix of Features Showing Relationships Between Variables

3.3 Framework Performance

The table below presents the evaluation metrics before and after hyperparameter tuning. Results show strong baseline performance, with measurable improvements post-tuning:

Table 4: Testing Framework Performance Metrics Before and After Hyperparameter Tuning

Metric	Initial Framework	Tuned Framework	Improvement
Accuracy	0.9950	0.9966	+0.0016
Precision	0.9950	0.9967	+0.0017
Recall	0.9950	0.9966	+0.0016
F1 Score	0.9949	0.9966	+0.0017

The tuned Framework demonstrated balanced performance, minimizing false positives and false negatives. To better understand the Framework improvements, the table above presents a quantitative comparison of the key evaluation metrics before and after hyperparameter tuning.

Initial VS Final Framework Performance

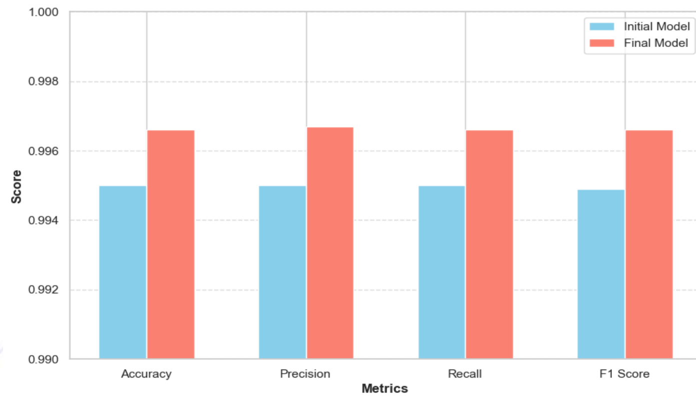

Figure 6: Framework Performance and Testing Results Before Framework Evaluation

4. Discussion

The findings of this study demonstrate that the Random Forest Regressor (RFR) is highly effective in predicting traffic situations within a smart-estate environment. Both the baseline and tuned frameworks achieved strong performance, with accuracy values of 0.9950 and 0.9966, respectively, indicating that ensemble-based frameworks can successfully capture complex, nonlinear relationships in mobility data, particularly when data involve multiple vehicle categories. The improved performance observed in the tuned framework reflects the impact of hyperparameter optimization. By adjusting factors such as tree depth, number of estimators, and minimum samples per split, the framework became more efficient in capturing subtle variations in traffic flows. Higher accuracy signifies better prediction of traffic categories, while lower MAE and MSE indicate fewer prediction errors. Additionally, a higher R^2 confirms that the framework reliably explains the variance in traffic situations. The feature importance analysis shows that cars and motorcycles are the most influential predictors, which aligns with the mobility characteristics of Nigerian residential estates, where motorcycles and private cars dominate daily movement. The performance of the RFR framework in this study is consistent with the findings of several related works. Yu et al. (2019) demonstrated that tree-based ensemble frameworks outperform single decision trees in traffic forecasting tasks. Kong et al. (2022) found that Random Forest provides a strong balance between accuracy and computational efficiency compared to deep-learning frameworks like LSTM. Chen et al. (2021) reported improved traffic prediction performance when frameworks incorporate multiple vehicle types and temporal features, an approach similar to this study. Williams et al. (2023) showed that ensemble frameworks are more robust in heterogeneous mobility environments. However, most existing works focus on large urban areas, highways, or public transportation corridors, and only a few studies apply ensemble frameworks specifically to smart estates, a niche with distinct mobility patterns and shorter travel distances. This study fills that gap by adapting the Random Forest algorithm to a residential context and optimizing it for category-based traffic situation prediction. The findings also have several practical implications. Estate managers can use the framework for proactive congestion prevention by anticipating peak periods and adjusting gate operations, internal routing, or security deployment. The feature importance scores enable data-driven mobility planning by highlighting which vehicle types dominate congestion, helping to develop targeted policies such as motorcycle lane allocation or visitor parking limits. Moreover, the framework is lightweight and can be integrated with estate-level IoT camera feeds and road sensors for real-time predictions. Real-time traffic predictions can also improve safety and emergency response by supporting faster access to the most accessible routes within the estate.

This study contributes to knowledge by providing a tuned Random Forest Regressor mobility framework suitable for smart estates and demonstrating how multi-vehicle count datasets can be utilized for estate-level mobility prediction. It also presents a clear comparison between baseline and optimized frameworks and offers an interpretable Framework that supports real-world deployment in residential environments. Although the proposed Framework performs well, several extensions could enhance its real-world deployment. These include the integration of real-time

IoT sensor and camera data, the inclusion of additional variables such as weather, road incidents, holidays, and construction activities, and comparison with deep-learning Frameworks such as LSTM, GRU, and CNN–LSTM hybrids. Further work could involve the development of a full smart-estate traffic dashboard for visualization and decision support, as well as deployment of the Framework in an actual smart estate for real-world validation. Overall, this study demonstrates that Random Forest–based ensemble methods offer an effective solution for predicting traffic patterns in smart estates and provide a strong foundation for future intelligent mobility systems.

5. Conclusion

This study developed a Random Forest Regressor (RFR) mobility framework for predicting traffic situations within a smart-estate environment. As smart estates continue to grow in population and vehicle usage, traditional manual or reactive traffic systems are no longer sufficient for managing congestion and ensuring smooth mobility. The study addressed this challenge by designing a data-driven forecasting Framework capable of accurately identifying traffic categories based on multi-vehicle count data. The aim of the study was achieved through four key objectives. First, traffic data were collected and preprocessed to remove noise and enhance Framework readiness. Second, an initial baseline Random Forest Framework was developed using default parameters. Third, the Framework was optimized using GridSearchCV to identify the best hyperparameters for improved performance. Finally, the initial and tuned frameworks were compared to assess the effectiveness of the proposed system. Results showed that the tuned Framework achieved superior performance with an accuracy of **0.9966**, improving upon the baseline accuracy of **0.9950**. Additional performance metrics, including MAE, MSE, and R^2, confirmed the enhanced predictive capability of the optimized Framework. The feature importance analysis further revealed that cars and motorcycles play the most significant role in traffic variations within smart estates, reflecting typical mobility patterns in residential areas. The contributions of this study include providing an interpretable, computationally efficient, and highly accurate machine-learning framework tailored for smart-estate environments. The Framework's robustness and low computational demands make it suitable for integration into real-time estate monitoring systems, especially when combined with IoT-enabled sensors, surveillance cameras, and automated gate systems.

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