International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I4P117
Volume 74 Issue 4, 225-234, April 2026

Original Article

Laplace Kernelized Adaptive Thresholding Segmentation Based Traffic Prediction in Intelligent Transport Systems

Sahira Vilakkumadathil[1], Velumani Thiyagarajan[2], M. Hemalatha[3], K. Kavitha[4]

[1,2]*Department of Computer Science, Rathinam College of Arts and Science, Coimbatore, Tamil Nadu, India.*
[3]*Department of Computer Science, Sri Ramakrishna College of Arts &Science, Coimbatore, Tamil Nadu, India.*
[4]*School of Computing, Department of AI and ML, Mohan Babu University, Tirupati, Andhra Pradesh, India.*

[2]*Corresponding Author : Velumani46@gmail.com*

Received: 04 August 2025 Revised: 09 February 2026 Accepted: 19 February 2026 Published: 29 April 2026

***Abstract** - Traffic congestion is a major challenge affecting the quality of life for millions of people worldwide. In order to improve the accuracy of the accurate traffic control prediction, A Laplace Kernel Filtering-based Hoover Index Adaptive Thresholding Segmentation (LKF-HIATS) method is introduced, used for accurate traffic control detection with minimal time complexity. The proposed method includes three different processes, namely vehicle image acquisition, image preprocessing, and segmentation. First, vehicle traffic images are collected from a dataset. After image acquisition, the Laplace kernelized Savitzky-Golay filter is applied to remove noise artifacts and enhance image contrast. The next process involves segmenting vehicle traffic images to separate the foreground and background. Followed by, the Hoover Index Adaptive Kittler-Illingworth Segmentation Algorithm is employed for threshold-based image segmentation. Experimental assessment is conducted with different evaluation metrics such as mean square error, peak signal-to-noise ratio, accuracy, and prediction time. The observed result shows the proposed LKF-HIATS method achieved better performance with higher accuracy and minimum time as well as error than the conventional segmentation methods.*

***Keywords** - Intelligent transportation system, Traffic flow prediction, Laplace Kernelized Savitzky-Golay Filtering Technique, Hoover Index Adaptive Kittler-Illingworth Segmentation Algorithm.*

1. Introduction

An Intelligent Transportation System (ITS) is a network of advanced technologies designed to enhance the safety, efficiency, and sustainability of transportation systems. In the ITS, traffic refers to the movement of vehicles on roadways, which is analyzed to determine the flow and patterns of vehicular movement. With the rapid growth of urban populations, vehicle congestion and road traffic have significantly increased, leading to challenges in maintaining smooth traffic flow. Traffic management is a vital aspect of ITS, as it helps optimize vehicle movement through various strategies such as traffic signal control, road design improvements, and the implementation of other traffic management measures. Traffic flow prediction is the process of forecasting future traffic conditions on roads based on various factors, such as current traffic data, historical trends, weather, events, and so on. The main aim is to estimate the movement of vehicles and the traffic density at specific times and locations, helping to optimize traffic management and reduce congestion. The conventional methods faced challenges in the accurate prediction of the traffic flow due to the dynamic conditions of environmental changes. Therefore, a novel control system is required in ITS to handle the complex and dynamic nature of traffic flow and to optimize traffic management. A new smart traffic control system called an Extreme Gradient Boost (XGBoost) classifier model was developed in [1] for segmenting the images and extracting foreground objects from a preprocessed image for vehicle detection and tracking. However, the design failed to achieve vehicle detection accuracy.

The semantic segmentation-based foreground extraction model was designed in [2] using Weighted Res-UNet to increase the performance accuracy of semantic segmentation for vehicle Detection. However, the designed model did not address the time complexity. A holistic deep-learning-based computer vision system was developed in [3] to detect vehicle traffic monitoring. However, segmentation-based vehicle detection remained unaddressed. A new vehicle detection and classification system was designed in [4] for smart traffic monitoring to segment aerial imagery for detecting vehicles. But it failed to improve vehicle tracking. An end-to-end deep learning network was introduced in [5] to enhance the accuracy of the vehicle detection network through the feature fusion of consecutive images. However, accurate multi-object detection and tracking were major challenging issues. Multiple object detection was performed in [6] using a random forest to categorize different objects. But it fails to segment images for detection performance.

A CNN-based Hybrid Vehicle Detection Network was developed in [7] for vehicle detection and to maximize detection accuracy by employing multi-level and multi-scale features. But the designed model failed to handle a large number of vehicles in different angles and traffic conditions. A new Optimizer with Convolutional Neural Networks (CNNs) was developed in [8] for accurate traffic flow prediction with minimal error. But the time complexity of prediction was high. A novel scene classification model was designed in [9] that integrates object detection for significantly enhancing accuracy in identifying critical traffic events. However, the accuracy in detecting traffic events such as accidents and congestion was not improved. A U-Net-based deep network was developed in [10] for segmenting the feature maps to perform vehicle detection. Time complexity was not minimized. A Faster R-CNN-based deep learning model was developed in [11] for the segmentation of vehicles to improve traffic management. However, the model failed to improve image quality.

An enhanced lightweight real-time detection approach was introduced in [12] to achieve higher accuracy for vehicle detection. However, the design failed to detect vehicles during unexpected situations. A smart traffic signal system was designed in [13] for object detection to categorize the number of vehicles on the road. However, it failed to use machine learning algorithms to predict traffic patterns. A smart city traffic monitoring framework was introduced in [14] to increase the data processing speed and accuracy. However, it failed to demonstrate adaptability and robustness across variable environmental conditions under diverse lighting and climatic scenarios. Vehicle recognition and classification methods were developed in [15] for traffic analysis, security, and urban planning based on vehicle type classification. But it failed to apply the more accurate and efficient algorithms for improving the accuracy of the model.

1.1. Research Gap

Traffic prediction is the use of historical and real-time data to predict future traffic conditions, such as volume and speed, with the goal of managing congestion, optimizing routes, and improving transportation systems. The existing method of the XGBoost classifier has failed to improve the detection accuracy. The foreground extraction model failed to focus on the time complexity. The main research gaps in traffic prediction within Intelligent Transportation Systems (ITS) are designed to enable accurate and timely traffic predictions, enabling better decision-making for route optimization, traffic signal control, and emergency response, ultimately leading to reduced congestion, improved safety, and lower environmental impact.

1.2. A Novel Contribution of the Paper

The novel contributions of the LKF-HIATS method to solving the traffic flow prediction problem are listed below,

- The LKF-HIATS method is employed to enhance the traffic flow prediction.
- A novelty of the Laplace kernelized Savitzky-Golay filtering technique is performed to improve the peak signal-to-noise ratio.
- The novelty of the Hoover Index Adaptive Kittler-Illingworth Segmentation Algorithm is designed to reduce the time consumption.
- An experimental assessment is conducted to estimate the performance of the LKF-HIATS method using various metrics and comparing it to other existing segmentation approaches.

2. Relaed Works

An intelligent vehicle flow detection approach was designed in [16] based on a single-shot multi-box detector algorithm with better accuracy and precision values. However, the algorithm lacks the ability to handle larger-scale data for testing in an intelligent transportation system. A deep learning-based vehicle detection and counting system was developed in [17] for an ITS that distinguishes vehicles and classifies them into dissimilar classes. However, vehicle detection segmentation was not performed. A Decoupled Dynamic Spatial-Temporal Graph Neural Network method was introduced in [18] for detecting traffic congestion based on traffic volume and image-based traffic tenancy. However, the complexity of time consumption was high in traffic volume prediction. A neural network and mathematical modeling approach were developed in [19] to estimate traffic density for achieving better traffic management. However, failed to estimate the traffic density accurately, even with a large volume of data.

A novel method was designed in [20] to detect, categorize, and prioritize the vehicles along with the category, size, and type of vehicle, with pedestrians on the road. But the Intelligent Traffic prediction accuracy was not improved. The Scenario Enhanced Graph Neural Network (SE-GNN) was introduced in [21] for semantic segmentation to enhance traffic prediction with better accuracy and system adaptability within complex driving scenarios. However, the error rate in segmentation remained unaddressed. A novel CNN-based semantic segmentation model was developed in [22] with higher accuracy performance. However, it failed to consider the balance between the accuracy of the model. A multi-label semantic segmentation was performed in [23] using a random forest classifier to categorize the images into different classes. However, it failed to improve the performance of the traffic monitoring system. ARIMA–LSTM time series model was developed in [24] to forecast future traffic volumes with minimal training time and high accuracy. However, it failed to perform vehicle detection. A robust deep learning model was designed in [25] for predicting traffic volume with minimal time consumption. However, it failed to integrate multiple data sources. An efficient deep learning approach was designed in [26] to effectively measure the temporal dependencies with time series traffic data for accurately forecasting traffic flow. However, the design failed to focus on traffic congestion detection.

A real-time detector network was developed in [10] for vehicle detection and trajectory prediction based on a differential segmentation-based YOLO (DS_YOLO) module to divide the input images into vehicles and backgrounds. Though the network reduces the error, the image preprocessing did not focus on enhancing the image quality.

A vision-based traffic management system was designed in [13] for object detection that distinguishes the total number of vehicles on the roads. However, it failed to use machine learning algorithms to predict traffic patterns more accurately. A conceptual intelligent transport system model was developed in [27] to predict vehicle movement by using machine learning and deep learning algorithms. However, the performance of more effective intelligent traffic systems was not achieved. A Hyper-heuristic Genetic Algorithm Diversity model was introduced in [28] to efficiently solve complex optimization and flexibility problems in image segmentation. However, it failed to congest and optimize traffic flow. In [29], Traffic modeling using a statistical filter method is designed to focus on the models' scalability, adaptability to complex traffic networks, and robustness in communication failure scenarios.

3. Methodology

An intelligent transport system plays a major role in developing traffic management and enables the user to achieve safer, more efficient transportation systems. Traffic prediction refers to the application of machine learning algorithms to analyze historical traffic data, including factors like vehicle density, to predict future traffic patterns and congestion levels on roads.

A novel intelligent traffic control system called a Laplace Kernel Filtering-based Hoover Index Adaptive Thresholding Segmentation (LKF-HIATS) is introduced for accurate traffic flow prediction through vehicle detection. Figure 1 provides a detailed representation of LKF-HIATS.

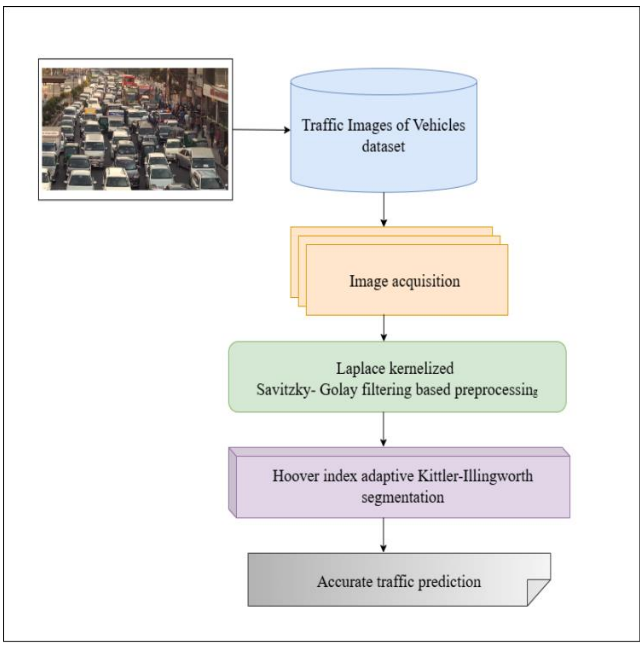

Fig. 1 Architecture of the proposed LKF-HIATS method

Figure 1 presents the architectural framework of the proposed LKF-HIATS method, designed to achieve accurate traffic prediction. The detection process is structured into three different stages, namely image acquisition, preprocessing, and segmentation. Each stage plays a vital role in ensuring the effectiveness and reliability of the LKF-HIATS method. Each of these stages contributes to the overall efficiency of the LKF-HIATS method, ensuring accurate prediction of vehicle traffic. Further details of these steps are elaborated in the following subsections.

3.1. Image Acquisition

The LKF-HIATS method is an image acquisition method for collecting a number of vehicle images taken as input. The dataset comprises 3003 images.

It contains 2703 images for training, and the remaining 300 are used for testing. The images are in JPEG format, and resolution varies across images and categories.

3.2. Laplace Kernelized Savitzky-Golay Filtering Technique-based Image Preprocessing

The proposed LKF-HIATS method undergoes preprocessing to enhance the quality of images for accurate vehicle traffic analysis. Used to extract relevant data for traffic analysis, such as vehicle counts, speed, and trajectories from video streams. Preprocessing (e.g., denoising, smoothing) is crucial for improving the accuracy of subsequent prediction models. In image preprocessing, the LKF-HIATS method uses the Laplace kernelized Savitzky-Golay filtering technique. The Savitzky–Golay filter is a digital filter used to format the input images for the purpose of smoothing without distorting the original property. The Laplace kernel is also applied to a filtering technique to further enhance the noise removal and enhance the image quality. The Laplace kernelized Savitzky-Golay filtering with adaptive segmentation advances existing methods primarily by enhancing noise suppression while preserving critical signal features in a data-driven manner, thereby addressing the traditional filter's limitations in handling signals with varying frequency components. This integrated approach avoids manual parameter tuning and improves accuracy, particularly in complex, noisy data analysis.

The number of input vehicle traffic images is denoted as $VI_1, VI_2, VI_3, \dots . VI_n$ collected from the dataset. The pixels are extracted from input images represented by $Q_1, Q_2, Q_3, \dots . Q_m$. The filtering technique selects a window of size $k * k$ for smoothing the input images.

Q_1	Q_2	Q_3
Q_4	Q_5	Q_6
Q_7	Q_8	Q_9

Fig. 2 $k * k$ Filtering window

Figure 2 illustrates the $k * k$ size of filtering windows for the pixels. $Q_1, Q_2, Q_3 \dots Q_m$ are organized in rows and columns. Once the pixels are arranged into the filtering window, the least square difference between the two pixels is estimated by using the Laplacian kernel function. The Laplace kernel-based pixel relationship is estimated as follows,

$$LK = exp\left[-\frac{|Q_j - Q_{jnn})|}{\sigma}\right] \quad (1)$$

$$Y = \begin{cases} LK > T, & Normal \\ LK < T, & Noisy \end{cases} \quad (2)$$

Where LK denotes a Laplace Kernel used to compute the difference between pixels Q_j and neighboring pixels 'Q_{jnn}', deviation (σ). The Laplace kernel function provides the output values between 0 and 1. When the value of minimal is reached, pixels are considered noisy. Otherwise, the pixels are determined as normal. The noisy pixels in the filtering window are smoothed by applying the polynomial coefficient.

$$W = \sum_{j=1}^{m} C_j Q_j \quad (3)$$

Where W indicates an image smoothing output, C_j denotes a polynomial coefficient, Q_j represents a pixel in the filtering window. Accordingly, the noisy pixels in input images are smoothed by applying a polynomial function. This filtering process considerably enhances the peak signal-to-noise ratio while reducing mean square error between the original and preprocessed images, leading to improved image quality. The algorithmic process of image quality enhancement is outlined as follows:

Algorithm 1: Laplace kernelized coefficient Savitzky-Golay filtering technique
Input: dataset, input vehicle traffic images $VI_1, VI_2, VI_3, \dots . VI_n$
Output: Quality improved traffic images
Begin Step 1: Collect a number of vehicle traffic images $VI_1, VI_2, VI_3, \dots . VI_n$ from dataset Step 2: For each input image VI_i do Step 3: Extract the number of pixels $Q_1, Q_2, Q_3, \dots . Q_m$ Step 4: Organize the pixels $Q_1, Q_2, Q_3, \dots . Q_m$ into the filtering window Step 5: Apply the Laplace kernel to the filtering window using (1) Step 6: if($LK < T$) then Step 7: Returns noisy pixels Step 8: else Step 9: Returns normal pixels Step 10: End if Step 11: Replace the noisy pixel by applying the polynomial coefficient using (3) Step 12: Return (Smoothed image) End

After preprocessing, the LKF-HIATS method performs image segmentation for accurate traffic prediction by means of the Hoover index adaptive Kittler-Illingworth algorithm. Segmentation is a process of partitioning the preprocessed images into meaningful components, i.e., distinct regions (such as vehicles, road lanes, pedestrians, and static objects).

3.3. Hoover Index Adaptive Kittler-Illingworth Segmentation

The proposed LKF-HIATS method utilizes the Hoover Index Adaptive Kittler-Illingworth Algorithm in image processing for segmenting the input traffic images with threshold-based image segmentation, particularly useful for separating foreground objects from background in grayscale images. Let us consider the number of pixel intensities of images, denoted as $Q_1, Q_2, Q_3, \dots . Q_m$. Then the likelihood between the two pixels in foreground regions is measured based on the Hoover index.

$$HI = \left[0.5 * \frac{\sum_{j=1}^{m}\sum_{k=1}^{p}|Q_j - Q_k|}{Q_j}\right] \quad (4)$$

Where, HI denotes a Hoover index, Q_j and Q_k denotes pixel intensity in foreground regions. The minimum value of HI is 0, and the maximum value is 1. After measuring the likelihood measure between the pixel intensity, an optimal threshold is identified to separate the foreground and background objects within the images to reduce segmentation error. In order to find the optimal threshold, the Bayesian Information Criterion 'BIC'is applied. The criterion function is expressed as follows,

$$BIC = R\ ln(m) - 2\,ln\ (HI) \quad (5)$$

Where R indicates a number of output regions, i.e., foreground and background, m denotes a number of pixel intensities in the image, HI denotes a Hoover Index outcome. This criterion, used for optimal threshold selection with lower BIC, is generally preferred to reduce the segmentation error between the foreground and background objects. Calculate the BIC for multiple possible thresholds and choose the one with the lowest BIC. The threshold δ_{HI} is estimated based on the minimization criterion of BIC as follows,

$$\delta_{HI} = \arg\min BIC \quad (6)$$

Where, $\arg\min BIC$ indicates an argument of minimum function. After selecting the optimal threshold, the foreground and background images are segmented as follows,

$$S = \begin{cases} HI > \delta_{HI},\ Foreground \\ HI < \delta_{HI},\ Background \end{cases} \quad (7)$$

Where S indicates a segmentation outcome, the Hoover Index 'HI' for the foreground is higher than for the background, indicating more variability in the foreground pixels. A lower Hoover Index indicates that the pixel intensities in the background region are more uniform, which helps in performing segmentation by detecting regions with less intensity variation.

The essential foreground extraction step is used to recognize objects (i.e., vehicles) within the images, resulting in enhanced accuracy for traffic prediction. The algorithm of the Hoover Index Adaptive Kittler-Illingworth segmentation-based vehicle traffic detection is given below.

Algorithm 1: Hoover index adaptive Kittler-Illingworth segmentation
Input: Number of preprocessed vehicle traffic images $VI_1, VI_2, VI_3, \dots .VI_n$ Output: Increase the traffic prediction accuracy
Begin Step 1: Number of preprocessed vehicle traffic images $VI_1, VI_2, VI_3, \dots .VI_n$ Step 2: For each vehicle image 'VI'do Step 3: Extract pixel intensity $Q_1, Q_2, Q_3, \dots .Q_m$ Step 4: Measure the Hoover similarity index using (4) Step 5: Measure Bayesian information criterion using (5) Step 6: $if\ (arg\ min\ BIC)$ then Step 7: Select optimal threshold 'δ_{HI}' Step 8: End if Step 9: $if\ (HI > \delta_{HI})$ then Step 10: Segment foreground region Step 11: else Step 12: Segment background region Step 13: End if Step 14: End for Step 15: Obtain the final segmentation results End

4. Experimental Setup

This section explains in detail each experiment conducted to validate the proposed LKF-HIATS method and the existing XGBoost [1] semantic segmentation-based foreground extraction model [2]. These three models are implemented in MATLAB simulator using the Traffic Images of Vehicles dataset taken from https://www.kaggle.com/datasets/therealshihab/traffic-detection-for-yolov5.

The Traffic Images of Vehicles dataset includes a collection of training and validation images, each labeled with traffic conditions in Dhaka city for vehicle detection. Dhaka, the capital city, has only 7% of its roads dedicated to traffic, despite a daily vehicle count of around 8 million. The traffic situation in Dhaka presents unique and significant challenges for traffic management systems, making it difficult to ensure a smooth flow of vehicles. The Traffic Images of Vehicles dataset consists of 3,003 images, with 2,703 images for training and 300 for testing. The number of training images used ranges from 250 to 2,500 to conduct the experiments for accurate traffic prediction through the segmentation process.

5. Performance Metrics and Results Analysis

The performance analysis of the proposed LKF-HIATS method and existing XGBoost [1] semantic segmentation-based foreground extraction model [2], Traffic modeling using statistical filters [29], is analyzed with different performance metrics such as Mean Squared Error, peak signal to noise ratio, accuracy, precision, and prediction time.

5.1. Performance Metrics Description

Mean Squared Error (MSE): It is a common metric used to evaluate the performance of filtering models, especially in image preprocessing. It is mathematically computed as follows,

$$MSE = \frac{1}{n}[Act_{size} - Pre_{size}]^2 \quad (8)$$

Where, PP_{size} indicates preprocessed image size, Act_{size} denotes original image size, n denotes the number of images.

Peak Signal to Noise Ratio '$PSNR$': It is a metric used to evaluate the quality of a preprocessed image by comparing it to the original image. It is expressed in decibels (dB). It is calculated based on Mean Squared Error (MSE).

$$PSNR = 10 * \log_{10}\left[\frac{255^2}{MSE}\right] \quad (9)$$

Where the maximum possible pixel value MSE indicates a mean square error. Higher values of $PSNR$' indicate better model performance.

Accuracy 'Acc ': It is defined as the ratio of the number of images in which the vehicles are correctly detected from the total number of input images.

$$Acc = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) * 100 \quad (10)$$

Where, TPdenotes the true positives, TN denotes a true negative, FP denotes a false positive, FN indicates a false negative. The accuracy is measured in percentage (%).

Prediction Time 'PT': It is referred to as the amount of time taken by the algorithm for detecting the vehicles from the given input images for accurate traffic prediction. The overall prediction time is measured as follows,

$$PT = \sum_{i=1}^{n} VI_i * TME \ \ [TP] \quad (11)$$

Where, TME indicates a time, TP indicates traffic prediction of a single image ' VI_i '. The overall time consumption is measured in terms of milliseconds (ms).

5.2. Comparison of Proposed Method Performance with Other Methods

In this section, the performance of the proposed LKF-HIATS method is compared with existing XGBoost [1] semantic segmentation-based foreground extraction model [2] and Traffic modeling using statistical filters [29].

Table 1. Comparison of Mean Squared Error

Image sizes (KB)	Mean squared error			
	LKF-HIATS	XGBoost	Semantic segmentation-based foreground extraction model	Traffic modeling using statistical filters
284	0.062	0.090	0.084	0.055
279	0.040	0.057	0.048	0.050
295	0.078	0.096	0.08	0.064
304	0.108	0.136	0.122	0.097
292	0.065	0.091	0.084	0.051
275	0.048	0.062	0.057	0.058
283	0.060	0.084	0.072	0.074
251	0.036	0.052	0.044	0.049
280	0.057	0.078	0.067	0.068
264	0.038	0.052	0.043	0.044

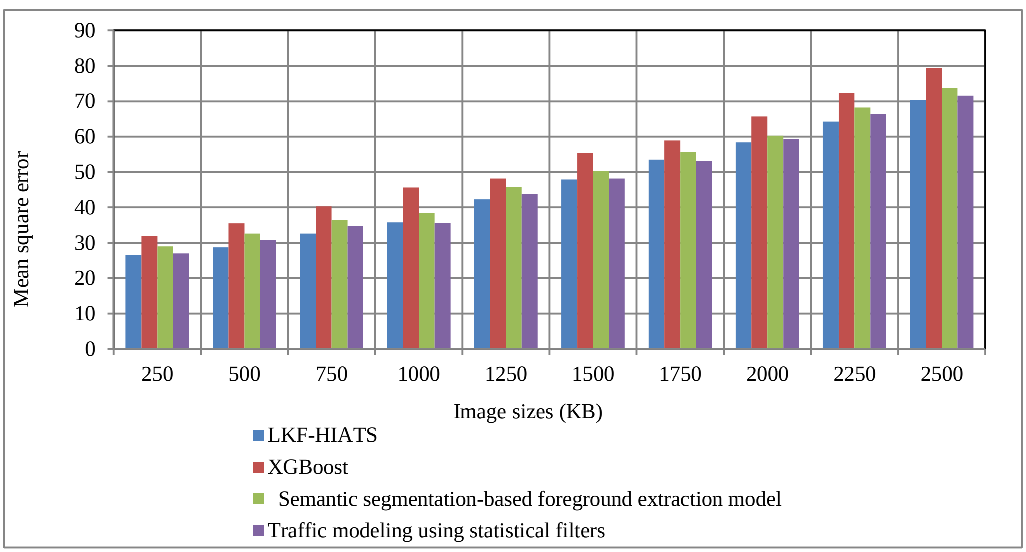

Fig. 3 Graphical representation of mean squared error

Figure 3 illustrates the Mean Squared Error (MSE) of LKF-HIATS reduced by 26%, 16%, and 4% [1, 2, 29]

Table 2. Comparison of Peak Signal to Noise Ratio

Image sizes (KB)	Peak Signal to Noise Ratio (dB)			
	LKF-HIATS	XGBoost	Semantic segmentation-based foreground extraction model	Traffic modeling using statistical filters
284	60.17	58.58	58.88	59.73
279	62.11	60.52	61.28	61.47
295	59.18	58.30	58.58	59
304	57.76	56.76	57.24	57.20
292	60	58.53	58.88	59.57
275	61.28	60.17	60.52	61.07
283	60.34	58.88	59.50	59.55
251	62.55	60.89	61.68	61.38
280	60.52	59.18	59.83	59.82
264	62.28	60.89	61.76	61.72

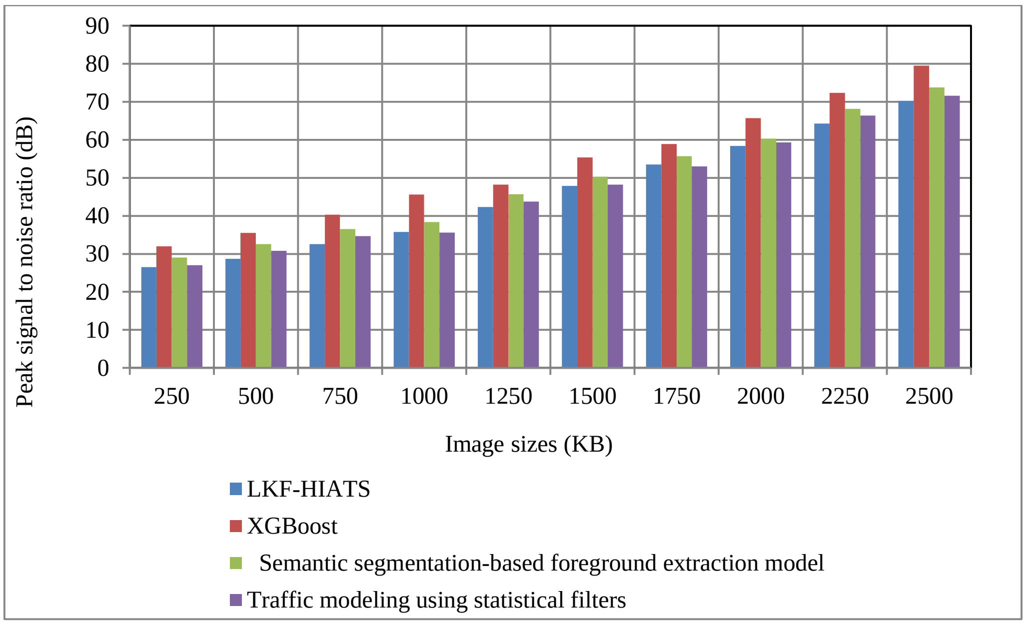

Fig. 4 Graphical representation of Peak Signal to Noise Ratio

In Figure 4, the PSNR of LKF-HIATS increases by 2% and 1% over [1, 2, 29].

Table 3. Comparison of accuracy

Image sizes (KB)	Accuracy (%)			
	LKF-HIATS	XGBoost	Semantic segmentation-based foreground extraction model	Traffic modeling using statistical filters
250	92.8	86	88	90.5
500	92.36	85.25	87.56	89.42
750	91.78	85.74	87.05	90.38
1000	92.45	86.05	88.12	91.76
1250	92.69	86.45	88.95	91.95
1500	92.74	87.01	89.45	90.47
1750	91.89	86.06	88.74	90.20
2000	92.78	87.47	89.05	91.65
2250	92.37	86.33	88.74	90.53
2500	92.77	87.46	89.45	91.86

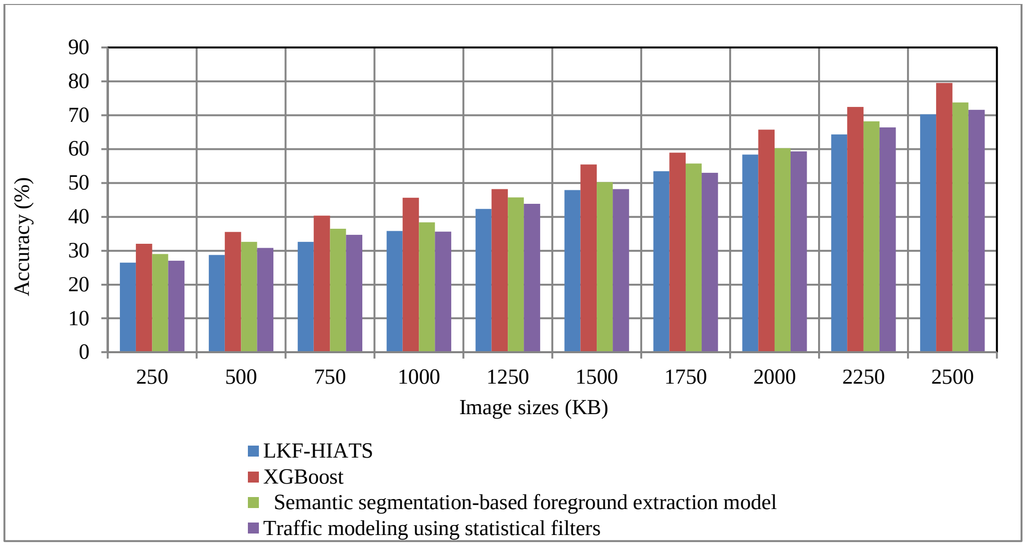

Fig. 5 Graphical representation of accuracy

Figure 5 illustrates the accuracy of LKF-HIATS enhanced by 7% and 4% and 2% compared to [1, 2, 29].

Table 4. Comparison of Prediction Time

Image sizes (KB)	Prediction Time (ms)			
	LKF-HIATS	XGBoost	Semantic segmentation-based foreground extraction model	Traffic modeling using statistical filters
250	26.5	32	29	27
500	28.7	35.5	32.6	30.8
750	32.6	40.3	36.5	34.7
1000	35.8	45.6	38.4	35.6
1250	42.3	48.2	45.7	43.8
1500	47.9	55.4	50.3	48.2
1750	53.5	58.9	55.7	53
2000	58.4	65.7	60.3	59.3
2250	64.3	72.4	68.2	66.4
2500	70.3	79.5	73.8	71.6

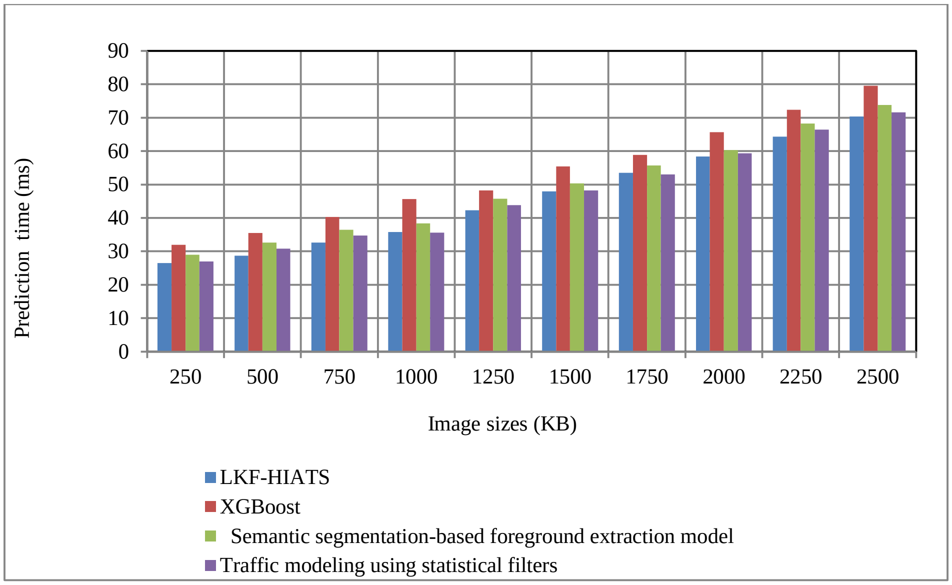

Fig. 6 Graphical representation of prediction time

Figure 6 shows that the prediction time of LKF-HIATS is reduced by 15% and 7% and 2% compared to [1, 2, 29].

6. Discussion

This study compares the proposed LKF-HIATS method with the existing XGBoost [1] and semantic segmentation-based foreground extraction model [2] using the Traffic Images of Vehicles dataset based on different performance metrics such as Mean Squared Error, peak signal to noise ratio, accuracy, precision, and prediction time. In this approach, image preprocessing using Laplace kernelized Savitzky-Golay filtering technique to enhance image quality, contributing to an improved peak signal-to-noise ratio while minimizing the mean squared error. The Hoover index adaptive Kittler-Illingworth segmentation algorithm has been developed in image processing to accurately detect vehicles, thereby enhancing the accuracy of vehicle traffic flow prediction while minimizing time consumption. The results confirm that the proposed LKF-HIATS method improves 1% and 4% of PSNR and accuracy, with 15% and 8% of minimum MSE and prediction time, compared to existing methods [1, 2, 29] using the Traffic Images of Vehicles dataset.

7. Conclusion

The proposed LKF-HIATS method is developed for accurate traffic flow prediction. Preprocessing using Laplace kernelized Savitzky-Golay filtering technique to enhance image quality, contributing to an improved peak signal-to-noise ratio while minimizing the mean squared error. The Hoover Index Adaptive Kittler-Illingworth Segmentation Algorithm has been developed in image processing to accurately detect vehicles, thereby enhancing the accuracy of vehicle traffic flow prediction while minimizing time consumption. A comprehensive experimental assessment is carried out by applying various metrics such as mean squared error, peak signal-to-noise ratio, accuracy, and prediction time. The quantitatively analyzed results exhibit that the LKF-HIATS method outperforms existing approaches by achieving higher accuracy and reducing time consumption than the existing methods.

The major limitations of traffic prediction in intelligent transport systems comprise the data quality and accessibility issues, the high complexity and non-linearity of traffic flow, the inability to generalize models across different urban environments, and challenges in long-term prediction. These limitations stem from factors like inconsistent or sparse data, the influence of external variables such as weather and events, and the difficulty of creating models that are both accurate and scalable. In the future, the proposed model involves the deeper integration with smart city infrastructure, the use of advanced AI and machine learning techniques, and seamless support for autonomous and connected vehicles. Key areas of development include more accurate, real-time predictions through complex models, decentralized and privacy-preserving data sharing via technologies like federated learning and blockchain, and a greater focus on sustainability by reducing emissions and improving safety through better congestion management.

References

[1] Mohammed Alonazi et al., “A Smart Traffic Control System based on Pixel-Labeling and SORT Tracker,” *IEEE Access*, vol. 11, pp. 80973-80985, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Asifa Mehmood Qureshi et al., “Semantic Segmentation based Real-Time Trafc Monitoring via Res-UNet Classifer and Kalman Filter,” *SN Computer Science*, vol. 6, no. 1, pp. 1-17, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[3] Dang Minh Tan, and Le-Minh Kieu, “TRAMON: An Automated Traffic Monitoring System for High Density, Mixed and Lane-Free Traffic,” *IATSS Research*, vol. 47, no. 4, pp. 468-481, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Adnan Ahmed Rafique et al., “Smart Traffic Monitoring through Pyramid Pooling Vehicle Detection and Filter-based Tracking on Aerial Images,” *IEEE Access*, vol. 11, pp. 2993- 3007, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Guan-Wen Chen, Min-Te Sun, and Tsì-Uí İk, “PairingNet: A Multi-Frame based Vehicle Trajectory Prediction Deep Learning Network,” *IEEE Access*, vol. 11, pp. 29566-29575, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[6] Muhammad Ovais Yusuf et al., “Enhancing Vehicle Detection and Tracking in UAV Imagery: A Pixel Labeling and Particle Filter Approach,” *IEEE Access*, vol. 12, pp. 72896-72911, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[7] Muhammad Hassaan Ashraf et al., “HVD-Net: A Hybrid Vehicle Detection Network for Vision-based Vehicle Tracking and Speed Estimation,” *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 8, pp. 1-19, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[8] Zhizhong Wu, “Deep Learning with Improved Metaheuristic Optimization for Traffic Flow Prediction,” *Journal of Computer Science and Technology Studies*, vol. 6, no. 4, pp. 47-53, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Sang-Hyun Lee, Soomok Lee, and Ilsoo Yun, “Mosaic-Mixed Attention-based Unexpected Traffic Scene Classification,” *IEEE Access*, vol. 13, pp. 15712-15722, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] Nafiseh Zarei, Payman Moallem, and Mohammadreza Shams, “Real-Time Vehicle Detection using Segmentation-based Detection Network and Trajectory Prediction,” *IET Computer Vision*, vol. 18, no. 2, pp. 191-209, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Arindam Chaudhuri, "Smart Traffic Management of Vehicles using Faster R-CNN based Deep Learning Method," *Scientific Reports*, vol. 14, no. 1, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Deqi Huang et al., "A Lightweight Vehicle Detection Method Fusing GSConv and Coordinate Attention Mechanism," *Sensors*, vol. 24, no. 8, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Anakhi Hazarika et al., "Edge ML Technique for Smart Traffic Management in Intelligent Transportation Systems," *IEEE Access*, vol. 12, pp. 25443-25458, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Ru An et al., "GC-YOLOv9: Innovative Smart City Traffic Monitoring Solution," *Alexandria Engineering Journal*, vol. 106, pp. 277-287, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[15] S. Kanagamalliga et al., "Traffic Management through Cutting-Edge Vehicle Detection, Recognition, and Tracking Innovations," *Procedia Computer Science*, vol. 233, pp. 793-800, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Guodong Su, and Hao Shu, "Traffic Flow Detection Method based on Improved SSD Algorithm for Intelligent Transportation System," *PLoS ONE*, vol. 19, no. 3, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] A. Vikram et al., "Deep Learning based Vehicle Detection and Counting System for Intelligent Transportation," *Computer Systems Science and Engineering*, vol. 48, no. 1, pp. 115-130, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Bowie Liu et al., "A Graph-based Framework for Traffic Forecasting and Congestion Detection using Online Images from Multiple Cameras," *IEEE Access*, vol. 12, pp. 3756-3767, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] C. Mala, Manipriya Sankaranarayanan, and Snigdha Jain, "Traffic Density Estimation for Traffic Management Applications using Neural Networks," *International Journal of Intelligent Information Technologies*, vol. 20, no. 1, pp. 1-19, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Wania Tahir et al., "Enhanced Vehicle Detection Mechanism for Traffic Management in Smart Cities," *Wireless Personal Communications*, vol. 135, no. 4, pp. 1925-1945, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[21] Seungwoo Nham et al., "Scenario-based Segmentation: Traffic Image Segmentation by GNN based Driver's Scenario," *IEEE Access*, vol. 12, pp. 13088-13099, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[22] Gürkan Doğan, and Burhan Ergen, "A New CNN-based Semantic Object Segmentation for Autonomous Vehicles in Urban Traffic Scenes," *International Journal of Multimedia Information Retrieval*, vol. 13, no. 1, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Asifa Mehmood Qureshi et al., "Intelligent Traffic Surveillance through Multi-Label Semantic Segmentation and Filter-based Tracking," *Computers, Materials and Continua*, vol. 76, no. 3, pp. 3707-3725, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[24] Junwoo Lim et al., "Enhancing Real-Time Traffic Volume Prediction: A Two-Step Approach of Object Detection and Time Series Modeling," *IET Intelligent Transport System*, vol. 18, no. 12, pp. 2744-2758, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Xiexin Zou et al., "Deep Learning for Traffic Prediction and Trend Deviation Identification: A Case Study in Hong Kong," *Data Science for Transportation*, vol. 6, no. 3, pp. 1-18, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[26] Fouzi Harrou et al., "Enhancing Road Traffic Flow Prediction with Improved Deep Learning using Wavelet Transforms," *Results in Engineering*, vol. 23, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[27] Anas Saleh Alkarim, Abdullah S. Al-Malaise Al-Ghamdi, and Mahmoud Ragab, "Ensemble Learning-based Algorithms for Traffic Flow Prediction in Smart Traffic Systems," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13090-13094, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[28] Erick Rodríguez-Esparza et al., "Optimizing Road Traffic Surveillance: A Robust Hyper-Heuristic Approach for Vehicle Segmentation," *IEEE Access*, vol. 12, pp. 29503-29524, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[29] Younus Hasan Taher et al., "Filter for Traffic Congestion Prediction: Leveraging Traffic Control Signal Actions for Dynamic State Estimation," *IEEE Access*, vol. 13, pp. 8140-8157, 2025. [CrossRef] [Google Scholar] [Publisher Link]