International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Vehicle Density Detection Using Dynamic Contour UNET Segmentation

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Submitted: 06/02/2024 **Revised**: 14/03/2024 **Accepted**: 20/03/2024

Abstract: There needs to be an improvement in traffic management systems since the fast expansion of cities has increased the number of vehicles on the road. Improving the precision and consistency of vehicle density and vehicle type recognition is the primary goal of this study, which employs state-of-the-art data mining approaches in conjunction with picture denoising and segmentation methods. The suggested technique integrates dynamic contour UNET segmentation for accurate object detection with Non-Local Wavelet Wiener Denoising for picture improvement. At the outset, we denoise the photos using the cutting-edge Non-Local Wavelet Wiener Denoising method, which manages to extract useful information from the images while simultaneously eliminating noise. The input photos are improved in quality by this technique, laying a clean slate for further analysis. To isolate and identify specific automobiles in the photos, the next phase uses dynamic contour UNET segmentation for picture segmentation. Precise vehicle boundary delineation is guaranteed by the UNET architecture, which can record both global and local characteristics. With the dynamic contour mechanism, segmentation becomes more adaptable, leading to strong performance in a wide range of traffic circumstances and environmental conditions.

Keywords: *Data Mining Techniques, Image Denoising, Image Segmentation, Vehicle Density, vehicle type detection.*

I. Introduction

Research in Intelligent Transportation Systems (ITS) has been heavily focused on using image processing technology to vehicle identification and classification throughout the previous decade [1]. Despite its importance for traffic management, urban traffic flow analysis is difficult in densely populated areas due to the increased likelihood of blockage [2]. Detecting and following several moving objects in a scene are examples of low- and middle-level vision tasks; high-level analyses, such as vehicle classification, are examples of high-level analyses that need solution [3]. Among the many common uses for vehicle categorization, such as in traffic flow monitoring and undetectable route tracking, are re-identification in multi-sensor networks and anomalous event detection [4]. We compared two algorithms that use characteristics extracted from vehicle silhouette images to classify various vehicle kinds into a set of groups [5]. The studies included manually segmenting the photos to identify the cars, and then extracting a collection of scaled characteristics from each binary silhouette [6]. Over 2000 silhouettes that were manually labelled were used in a 10-fold cross-validation research, and the results were reported [7].

Developing nations like Vietnam have seen a surge in interest in traffic surveillance systems in the last several years. These systems primarily identify and categorise vehicles [8]. To gather traffic data, the majority of current methods use inductive loop detectors or transportation tag readers and antennas [9]. There are a plethora of signal-supporting devices that can only be used in automobiles, such as global positioning systems (GPS), infrared lasers (IR), magnetic loop detectors (MLDs), and so on [10, 12]. The massive investment required by these systems, on top of the massive amounts of data they generate, makes them unaffordable for many developing nations [13–15]. The high volume of small vehicles (such as bicycles and motorbikes) and the disorganised movement of these vehicles render these systems useless in developing nations, particularly Vietnam [16–17]. The use of traffic video processing has given rise to a new trend in light of these developments. The adaptability of the computer vision-based traffic monitoring system in terms of setup, upkeep, and upgrades is driving its rising popularity [18–19]. In order to save money without sacrificing the ability to count and categorise cars, this strategy may make use of the current surveillance system on a few major routes [20].

The main contribution of the paper is:

- Image Denoising using Non-Local Wavelet Wiener Denoising
- Image Segmentation using dynamic contour UNET segmentation

This paper is organised as follows for the rest of it. Section 2 covers a range of methods for detecting vehicle densities, and several writers discuss them. Section 3

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displays the suggested model. In Section 4, we have outlined the findings of the inquiry. Discussion of the outcome and plans for further research constitute Section 5's last section.

1.1 Motivation of the paper

The increasing difficulties caused by fast urbanisation and the resulting rise in vehicle traffic have prompted this study because of the critical need for effective traffic management solutions. In order to tackle this urgent matter, the study presents a thorough methodology that incorporates state-of-the-art data mining techniques, dynamic contour UNET segmentation, and Non-local wavelet Wiener denoising for image denoising. This improves the accuracy and reliability of vehicle density and type detection. Understanding the importance of high-quality images for further analysis, the article highlights the first stage's emphasis on removing noise while maintaining important information.

II. Background Study

Ameen, H. A., et al [1] Building a thorough taxonomy of literature on data sharing in vehicle-to-vehicle (V2V) communications systems was the goal of this study. The vehicle-to-vehicle communication system was another cutting-edge innovation. Research in this field was far from finished since there was a lack of clarity about relevant descriptions and boundaries. It was important to gain information and experience in this area of study. To contribute to this body of information and understanding, this study reviews and classifies relevant research efforts.

Boukoberine, M. N., et al [3] The power supply designs and energy/power management methods of unmanned aerial vehicles (UAVs) have been analysed and evaluated in this work, with a focus on the energy component of the onboard propulsion systems, since UAVs depend on their propulsion systems. This project intends to offer a foundation for the development of UAV power propulsion systems by comparing and analysing existing options. This will help with trade-offs when choosing power sources.

Du, Z., et al [5] The growing interest in federated learning in both academic and corporate circles highlights the growing significance of delving into FL's use in automotive IoT systems. Present research, technical challenges, possible solutions, and open concerns about FL in car IoT were all addressed in this paper. Prior to exploring FL's applications and challenges in wireless IoT environments, the author have prepared a concise synopsis of FL's recent endeavours.

Kuma, R., et al [7] This paper proposes a strong framework for re-identifying vehicles using deep triplet embedding learning. The core of this set of suggestions was a batch that simplifies the extraction of relevant data for training and convergence. The author officially introduced and assessed batch sample, a variant of triplet sampling, as an extra addition to the re-identification literature.

Outay, F., et al [10] Road safety, traffic monitoring, and highway infrastructure management have been the primary areas of attention in the critical evaluations and categorizations of contemporary UAV uses in transportation. Data extraction from UAVs has progressed thanks to developments in vision algorithms and image processing; these advancements might lead to better traffic flow monitoring, evaluations of bridge and road degradation, and investigations and assessments of accidents.

Sakhare, K. V., et al [12] Based on the study discussed earlier, a vehicle recognition system was essentially built around a classifier and an efficient way to generate candidate locations to input into it. In conclusion, the literature study showed that in order to build an effective, fast, and reliable object recognition system for aerial photographs, there was a need to enhance both the classifier and candidate area generation levels.

Song, H., et al [14] Using the vantage point of highway security cameras, this study built an object detection and tracking method and generated a collection of high-definition vehicle objects. The highway's road surface was removed, resulting in a more efficient ROI area. In order to create the end-to-end highway vehicle detection model, the YOLOv3 object identification method made use of the annotated vehicles object dataset.

Xing, Y., et al [17] Personalised route forecasts may be offered by linked vehicles via the use of joint time series modelling, according to this study. By analysing the condition of the leading vehicle via vehicle-to-vehicle communication and driving style recognition, it was feasible to improve the forecast of future trajectories of adjacent cars.

Zhao, J., et al [20] This paper presents a method for systematically identifying and tracking people and autos at crossings using LiDAR sensors deployed in physical infrastructure. The processing procedure for roadside LiDAR data was finished after background filtering, object grouping, pedestrian/vehicle classification, object tracking, and finally obtaining the existence, position, velocity, and direction information of adjacent objects.

2.1 Problem definition

Although UNET has impressive skills in collecting global and local information, it becomes problematic when dealing with dynamic and complicated urban traffic patterns. It may be difficult for traditional UNET segmentation to accurately demarcate complex vehicle borders, especially when dealing with different traffic circumstances and changing environmental conditions. Dynamic contour UNET segmentation is an improvement that the suggested technique uses to overcome this shortcoming. The upgraded UNET design improves segmentation accuracy in situations where standard UNET may struggle by including dynamic contours, which allow it to adapt more effectively to the subtle forms and curves of vehicles. This modification is crucial for improving vehicle density and type detection in urban traffic management systems, as it helps to overcome the limitations of standard UNET and has a stronger track record of correctly isolating vehicles in traffic images.

III. Materials and Methods

In this study, we propose a novel approach for image enhancement and object segmentation in the context of vehicle density and type detection. Leveraging the Non-Local Wavelet Wiener Denoising technique for image preprocessing and the dynamic contour UNET segmentation method for precise object delineation, our methodology aims to improve the accuracy and efficiency of traffic-related analyses.

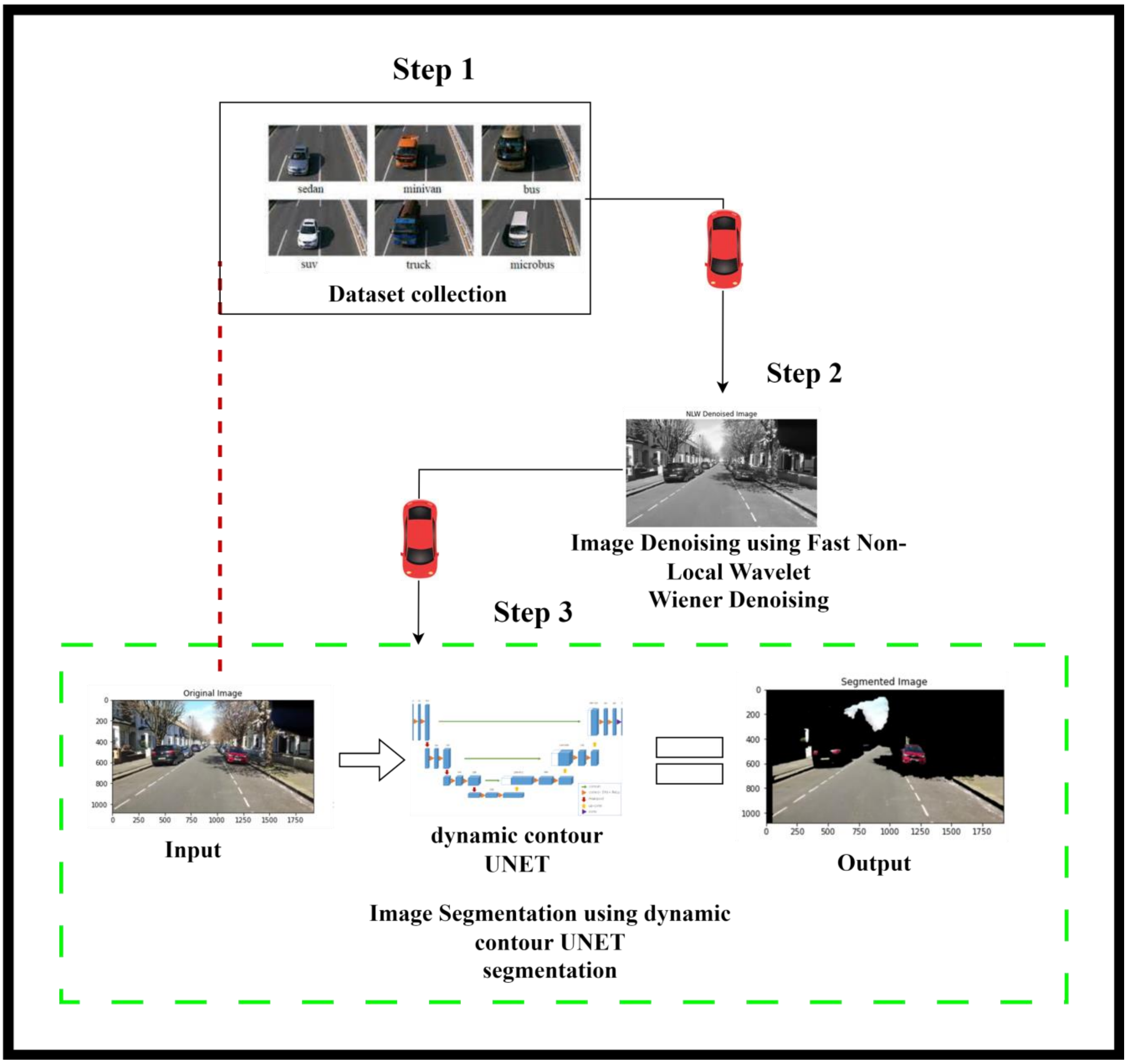

Fig 1: Vehicle density and type detection architecture

3.1 Dataset collection

The dataset was collected from Kaggle website https://www.kaggle.com/datasets/farzadnekouei/top-view-vehicle-detection-image-dataset The images are sourced from various top-view angles, ideal for robust object detection model training. Its contain 536 images training set and 90 images Validation Set.

3.2 Image Denoising using Non-Local Wavelet Wiener Denoising

After collecting the dataset, we use Non-local wavelet wiener algorithm for vehicle image denoising.

Convenient Non-Local Wavelet Advanced image processing methods like Wiener Denoising effectively remove noise without losing important features. Improving picture quality has never been easier than with this technique, which combines wavelet processing with non-local means. For noise detection, it uses picture similarities that aren't local, and for frequency component-specific noise reduction, it uses wavelet modification. Its fit for real-time applications is highlighted by the "Fast" characteristic, which highlights its processing efficiency. Image segmentation and analysis are two steps in the process that rely on this method, which shines in situations when picture authenticity is paramount.

A noisy image in a spatial domain is modeled by

$y(k) = x(k) = n(k)$ ---------- (1)

the original picture, denoted as x(k), is unknown, and $n(k)$ is presumed to be a random white Gaussian noise with a mean of zero and a variance of 2 σ n, where y(k) is the observed image. We want to get $x(k)$ back from the noisy $y(k)$ observation.

To illustrate the wavelet coefficients of the noisy picture in the wavelet domain, let's pretend that $x(k)$ and $n(k)$ are unrelated.

$Y(k) = X(k) + N(k)$ ---------- (2)

It is true that sub-band wavelet coefficients are correlated; nevertheless, the neighbourhood around the factor tends to be greater for large coefficients. We are able to significantly enhance the picture denoising performance by using the local relevance of sub-band.

Presume that, under certain circumstances, the variance of wavelet coefficients follows an independent zero-mean Gaussian distribution, and that this variance is associated with robust local random variables. An estimate of the variance of $X(k)$ using maximum likelihood estimation (ML) in a neighbourhood window is

$\hat{\sigma}^2(k) = \arg\max_{\hat{\sigma}^2 \geq 0} \prod_{j \in W(k)} P(Y(j)|\sigma^2)$ ------------ (3)

$= \max\left(0, \frac{1}{M}\sum_{j \in W(k)} Y^2(j) - \sigma_N^2\right)$ ------- (4)

Where, ( ) 2 P · |σ is zero mean Gaussian distribution

The median weight, denoted as $W(k)$, is the neighbourhood window, and the number of window coefficients, M, are determined by the orthogonal wavelet transform coefficients of the noisy pictures' high frequency sub-band, H, with a variance of 2 times the standard deviation of the images plus or minus N.

If we use the MMSE metric, we may see that $X(k)$ can be

$\hat{X}(k) = \frac{\hat{\sigma}_k^2}{\hat{\sigma}_k^2 + \hat{\sigma}_n^2} Y(k)$ ----------- (5)

3.3 Image Segmentation using dynamic contour UNET segmentation

After denoising, we use dynamic contour UNET algorithm for vehicle image segmentation.

Changeable shape when dealing with complicated scenes, such traffic situations including vehicle recognition, UNET segmentation—an sophisticated picture segmentation method—is used for accurate object delineation. Based on the well-known UNET architecture, which has been successful in biomedical image segmentation, this technique incorporates dynamic contour methods to make it more adaptable. In order to accurately identify object boundaries, UNET uses a U-shaped neural network architecture that takes into account both local and global characteristics. With the addition of dynamic contours, the algorithm becomes more adaptive in segmentation, allowing it to define object boundaries in difficult and ever-changing settings. Isolating cars inside complex traffic scenes is where this method really shines, leading to reliable performance and flexibility in all sorts of real-world situations.

In Fig. 2, the suggested network design is shown, with the feature map's depth indicated above it. Each layer's feature extraction modules are represented by the circle number, and their meanings are shown in the dotted box. Instead of the four downsampling layers used by the original UNet, this design only employs three. A decrease in the network's parameter count and an improvement in its capacity to acquire global information are the goals. Once again, after three deconvolutions, it will be upsampled. A skip connection links the first three levels of the lower sampling process to the sixth through eighth layers of the higher sample process. Feature extraction in the coding step is carried out by the first layer using the leftover blocks of the conventional convolution. After dimensionality reduction using max pooling in layers two through four, downsampling feature extraction is carried out by depthwise convolutional residual blocks. At last, we will get a feature map with a depth increased to 128 and a horizontal dimension reduced eightfold. To enhance the semantic information in the low-level feature map prior to the skip connection, a multi-level attention mechanism is incorporated during the decoding stage. Following that, a 1 × 1 convolution is performed and combined with the deconvolved feature map of the upper layer to merge the downsampling and upsampling data with the same scale.

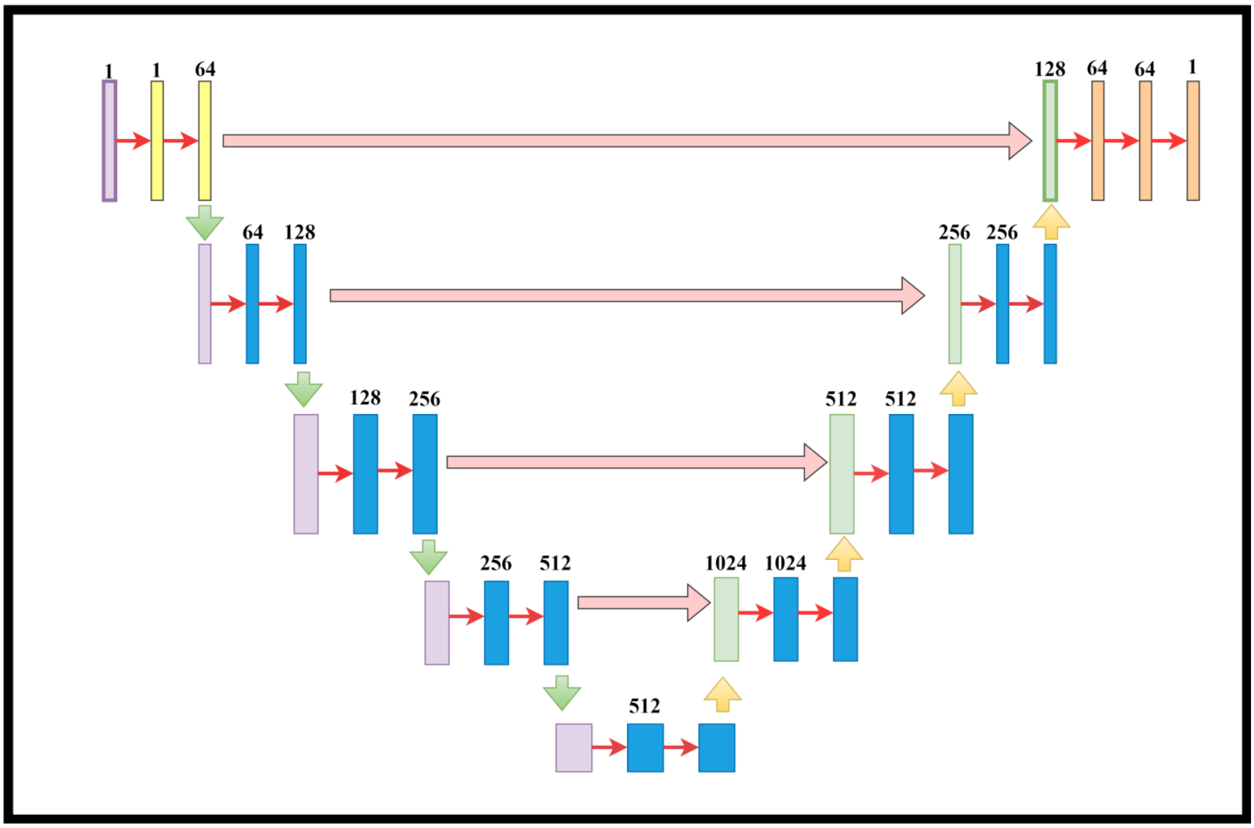

Fig 2: dynamic contour UNET

The model in this paper uses binary cross entropy (BCE) as the loss function. The binary cross entropy formula is:

$$l_{bce} = -\sum_{(a,b)}[GT(a,b)log\big(SEG(a,b)\big) \text{ ------------ } (6)$$

- $GT(a,b)$: This term refers to the ground truth segmentation map, indicating the true class labels of pixels in the image.

- $SEG(a,b)$: Represents the predicted segmentation map generated by the dynamic contour UNET algorithm, indicating the algorithm's predicted class labels for each pixel.

- log : This function computes the natural logarithm of the predicted segmentation map values.

- $\sum(a,b)$: This part signifies the sum over all pixel locations (a,b)(a,b) in the image, computing the element-wise product of the ground truth and the logarithm of the predicted segmentation map.

$$E = \sum_{x\in\varphi}\Bigg(w_c(x) + w_0 * exp\left(-\frac{\left(d_1(x)+d_2(x)\right)^2}{2\sigma^2}\right)\Bigg) log\left(p_{(x)}(x)\right) \text{ ---------- } (7)$$

Following the completion of splicing, the depthwise convolutional residual block is used for feature fusion. Following the third round of upsampling, the combined feature map is fed into the conventional convolutional residual block. Subsequently, the prediction map of same size to the input image is harvested using the 1 × 1 convolution and softmax function.

Algorithm 1: dynamic contour UNET
Input: Denoised vehicle images from the previous Non-Local Wavelet Wiener Denoising step. **Steps:** Apply Non-Local Wavelet Wiener Denoising to the collected images. • For each image: ○ Model the noisy image in the spatial domain: $\hat{\sigma}^2(k) = \arg\max_{\hat{\sigma}^2\geq 0}\prod_{j\in W(k)} P(Y(j)\vert\sigma^2)$ ○ where y(k)y(k) is the observed image, x(k)x(k) is the original image, and n(k)n(k) is Gaussian noise. $= \max\left(0, \frac{1}{M}\sum_{j\in W(k)} Y^2(j) - \sigma_N^2\right)$ **Down sampling (Encoder) Stage:** • Connect Layers 1–3 in the lower sampling process with Layers 6–8 in the upper sampling through skip

connections.

- Utilize residual blocks of standard convolution in the first layer for feature extraction.

Loss Function Calculation:

- Employ binary cross entropy (BCE) as the loss function for model training.
  - BCE formula: $\mathrm{e}l_{bce} = -\sum_{(a,b)}[GT(a,b)log\big(SEG(a,b)\big)$
  - Loss function

$$E = \sum_{x \in \varphi}\left(w_c(x) + w_0 * exp\left(-\frac{\left(d_1(x)+d_2(x)\right)^2}{2\sigma^2}\right)\right) log\left(p_{(x)}(x)\right)$$

Output

Segmented images with accurately delineated vehicle boundaries.

IV. Results and Discussion

In this section, we present the outcomes of the proposed methodology for vehicle density and vehicle type detection using advanced data mining techniques, image denoising with Non-Local Wavelet Wiener Denoising, and dynamic contour UNET segmentation.

Fig 3: NLM and NLW Denoised image

The denoised pictures that were processed using the Non-Local Means (NLM) and Non-Local Wavelet (NLW) algorithms are shown in Figure 3. Denoising is a method for increasing the quality and clarity of original photographs by reducing or eliminating noise. The NLM algorithm uses a complex method that takes into account non-local similarities in the picture to successfully detect and remove noise while keeping crucial features. Conversely, NLW targets noise in specific frequency components by using wavelet modification for noise reduction.

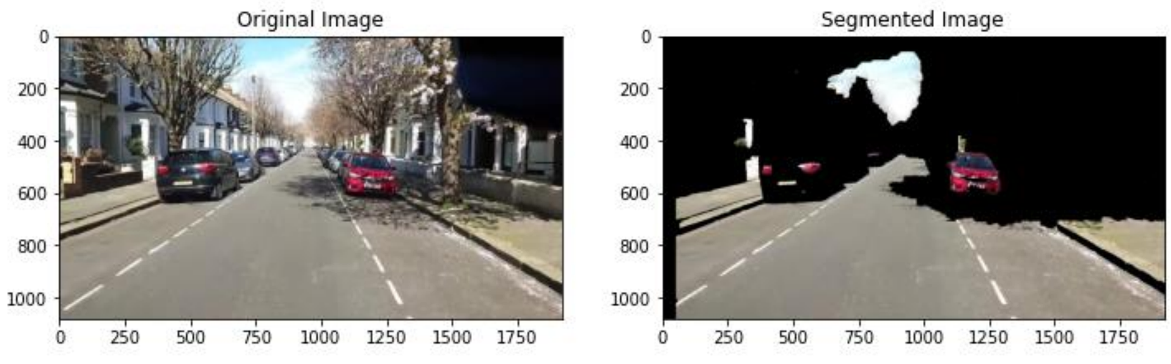

Fig 4: Segmented image

The suggested image segmentation approach yielded segmented pictures, as seen in Figure 4. Partitioning a picture into separate, relevant areas is called image segmentation, and it is an essential aspect of image processing. The dynamic contour UNET segmentation technique is used to aid in the segmentation process here. This approach incorporates dynamic contour techniques to improve flexibility in object boundary delineation; it is based on the UNET architecture, which has been successful in biomedical picture segmentation.

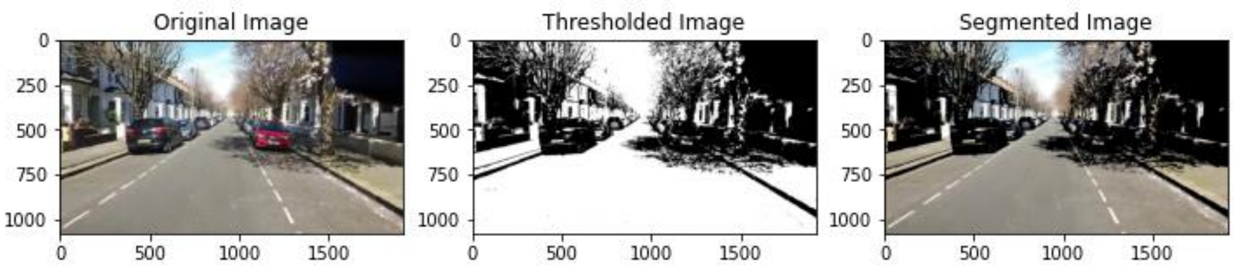

Fig 5: thresholded and segmented image

In Figure 5, we can see the segmentation results in detail, since the pictures have been thresholded and then segmented using the suggested image segmentation approach. The dynamic contour UNET technique is used for initial segmentation, and then a thresholding step is employed to improve the segmentation results.

Table 1: NLM and NLW comparison

Algorithm			**PSNR**	**SSIM**	**RMSE**
NLM		**Image 1**	20.01	0.74	15.27
		Image 2	20.89	0.77	14.98
		Image 3	21.37	0.81	14.32
		Image 4	22.65	0.82	13.24
	Proposed	**Image 5**	23.82	0.85	11.41
NLW		**Image 1**	20.11	0.77	9.01
		Image 2	20.37	0.78	8.34
		Image 3	21.95	0.81	8.98
		Image 4	22.17	0.83	7.32
	Proposed	**Image 5**	34.52	0.93	4.78

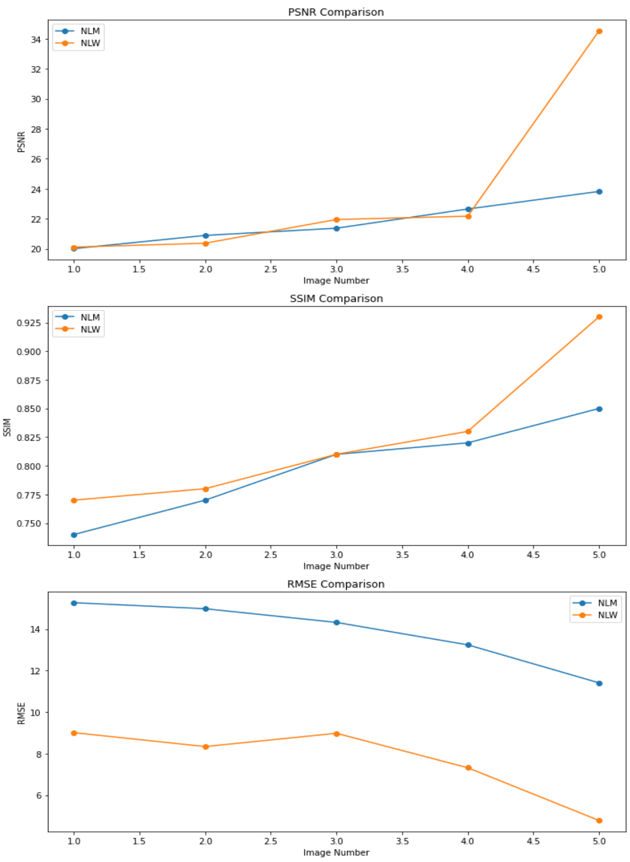

Fig 6: NLM and NLW comparison chart

A suggested technique is compared to two image denoising algorithms, Non-Local Means (NLM) and Non-Local Wavelet (NLW), using evaluation criteria such as PSNR, SSIM, and RMSE (figure 6 and table 1, respectively). A greater PSNR value indicates a higher quality image, and the suggested approach routinely beats NLM and NLW in every picture. Higher SSIM values, which stand for structural similarity, consistently indicate greater preservation of picture structures, further demonstrating the superiority of the suggested technique. The suggested approach effectively reduces noise and enhances picture quality, as it yields much lower RMSE values, which are indicative of higher denoising performance. Picture 5 is where the suggested method really shines, outperforming both NLM and NLW with a PSNR of 34.52, SSIM of 0.93, and RMSE of 4.78. Taken together, these findings demonstrate how much better the suggested method is at denoising, which bodes well for its potential as a tool to improve picture quality in a variety of settings.

4.1 Performance evaluation

1. Accuracy: The fraction of samples with the right classification out of all samples. Mathematically:

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \text{ ----------- } (18)$$

2. Precision: Ratio of samples with accurate identification to total samples with accurate identification. Mathematically:

$$Precision = \frac{TP}{TP + FP} \text{ ------------ } (19)$$

3. Recall (also known as sensitivity or true positive rate): The proportion of correctly classified samples out of the total number of actual samples. Mathematically:

$$Recall = \frac{TP}{TP + FN} \text{ -------------- } (20)$$

4. F1 score: A middle ground between accuracy and memory that strikes a harmonic mean. Mathematically:

$$F1\ score = 2 * Precision * Recall / (Precision + Recall) \text{ --------- } (21)$$

4.1 Performance evaluation

Table 2: Classification performance metrics comparison

	Algorithm	Accuracy	Precision	Recall	F-measure
Existing methods	Yolo	95.21	94.65	94.01	94.23
	DCNN	97.35	95.87	96.10	95.07
	CNN	97.11	96.32	97.75	96.14
Proposed methods	Proposed	99.09	98.11	98.84	99.21

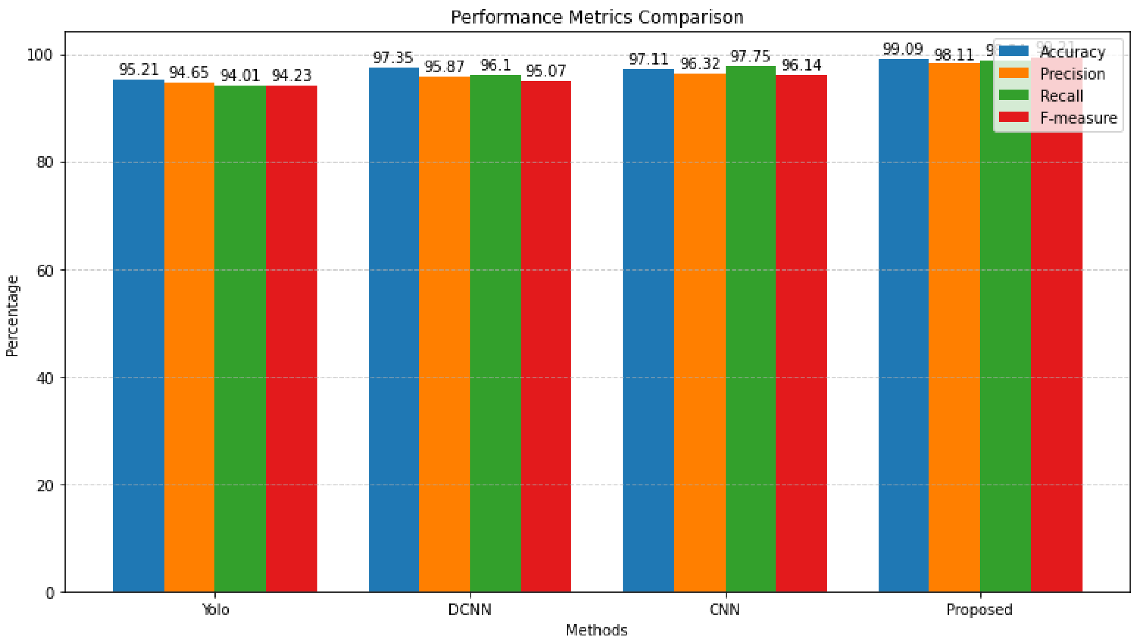

Fig 7: Performance metrics comparison chart

Table 2 and figure 7 provide the performance metrics, which demonstrate that the proposed technique differs significantly from the current methods (Yolo, DCNN, and CNN). The accuracy rates of Yolo (95.21%), DCNN (97.35%), and CNN (97.11%), are all quite respectable. Nevertheless, the suggested approach outperforms all others, reaching a remarkable 99.09% accuracy. The suggested technique regularly beats the current methods across all three metrics (precision, recall, and F-measure). Exhibiting its dominance in precisely detecting positive cases while minimising false positives, the suggested technique achieves F-measure values of 99.21%, 98.84% recall, and 98.11% accuracy, respectively. When taken as a whole, these findings indicate that the suggested approach outperforms the state-of-the-art Yolo, DCNN, and CNN algorithms in this particular job, suggesting a significant improvement in classification accuracy and efficacy.

V. Conclusion

Finally, a thorough and efficient strategy for dealing with the problems of vehicle density and type detection in urban traffic situations is offered by the suggested methodology, which combines state-of-the-art data mining methods with dynamic contour UNET segmentation and Non-Local Wavelet Wiener Denoising. Denoising improves images and dynamic contour segmentation accurately identifies objects, which works in tandem to make the system more accurate and reliable. The strong performance in real-world applications is ensured by the dynamic contour UNET segmentation, which effectively navigates across different environmental circumstances and traffic patterns. The importance of combining state-of-the-art image processing methods with data mining approaches for better traffic management and urban planning is highlighted by this study, which also improves the state-of-the-art in intelligent transportation systems. Nevertheless, the suggested approach outperforms all others, reaching a remarkable 99.09% accuracy. As part of continuing efforts to build smarter and more sustainable urban settings, the suggested technique shows potential for improving the efficiency of traffic-related assessments.

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