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Weighted Score-Level Feature Fusion and Bio-Inspired Image Enhancement Resulting in Nighttime Vehicle Detection

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ABSTRACT: In this study, a successful nighttime vehicle identification system is demonstrated that fuses a weighted feature fusion technique with a novel bio-inspired picture enhancing method. We create a nighttime picture enhancement technique by simulating the adaptive feedback from horizontal cells and the center-surround antagonistic receptive fields of bipolar cells, which is inspired by the retinal mechanism in real visual processing. In order to train the support vector machine classifiers, we also extract features from the convolution neural network, the histogram of oriented gradient, and the local binary pattern. By fusing the score vectors of each feature with the learned weights, these features are created. We generate precise zones of interest during detection by fusing object proposals with vehicle taillight detection. The proposed bio-inspired image enhancement technique adds effectively to vehicle identification, according to experimental findings. Our vehicle detection approach outperforms several cutting-edge methods with a 95.95% detection rate at 0.0575 false positives per image. Our suggested approach can handle a variety of situations, including those with occlusions, blurred areas, and vehicles of varying types and sizes. Moreover, several automobiles and vehicles in different locations can be detected.

KEYWORDS: Feature extraction, Vehicles, Vehicle detection, ROI (Region of interest), Image enhancement, Brightness, Biomedical imaging, Support vector machines.

I. INTRODUCTION

In recent years, the identification of vehicles at night has grown in importance for intelligent transportation systems (ITS). It is also a foundational technology for autonomous and advanced driver assistance systems (ADAS) (ADS). Rear-end collisions, one of the most lethal traffic accidents, account for about 30% of all vehicle accidents. In this study, we concentrate on avoiding rear-end crashes by recognizing moving cars in front of the driver at night.

Modern object detectors have the ability to extract features from the original daytime photos. However, the contrast between the background and the object and the overall brightness are so low in nighttime photographs that some vehicle details (such as the edge, color, and shape elements of automobiles) appear hazy. So, in order to accurately detect vehicles, we should improve the contrast, brightness, and details of the nighttime photos prior to feature extraction. We present an efficient nighttime picture enhancement method that simulates several crucial elements of the retinal information processing mechanism, which is inspired by the mechanics of the biological visual system for processing retinal information. The most noticeable taillights are generally turned on by moving vehicles at night. Hence, the taillights are highly helpful for accurately isolating sections of interest (ROIs). The performance of existing detection techniques can be enhanced by creating a set of ROIs, such as object proposal approaches. In this study, we use the ROI extraction method that combines Edge Boxes with vehicle taillight detection.

It has been demonstrated that single feature-based detection techniques work well. These kinds of detection techniques could result in incorrect classifications, nevertheless, when dealing with more complicated scenarios. Thus, in order to complement the features of the convolutional neural network (CNN), we compute two widely used effective features: the histogram of oriented gradient (HOG) and the local binary pattern (LBP). We employ a variety of features, thus an important step is to blend them successfully. It has been claimed that score-level feature fusion is efficient. A score-level feature fusion strategy that combines the three features with weights learned from scores using a linear SVM is

developed after focusing on how to fully utilize each feature's complementary nature and the various capabilities of the same feature for different classes.

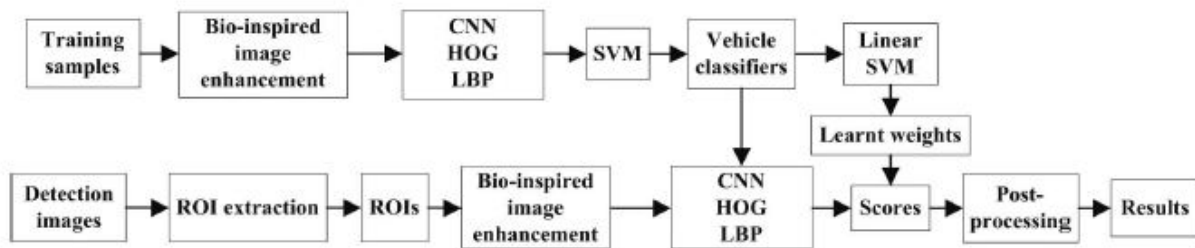


Fig. 1.1 Framework of the proposed nighttime vehicle detection method

Fig. 1 depicts the conceptual layout of the suggested nighttime vehicle detection method. Three complimentary features—CNN features, HOG features, and LBP—are then extracted from the enhanced images during the training stage after the original training samples have been upgraded using the suggested image enhancement approach. With LibSVM, three SVM classifiers are trained, and five-fold cross-validation is done using each distinct feature separately. Each classifier's score vectors are computed as well. Using a linear SVM, the scores are utilized to determine the weights of each feature for each distinct class (Lib Linear). Accurate ROIs are extracted from the input photos during the detection phase. The three attributes are then taken out of each increased ROI. The related features are then classified using the trained classifiers, and scores are computed. These scores are added to the learned weights to produce final score vectors for prediction. To ensure that each vehicle is encircled by a single window, post-processing (non maximum suppression) is then carried out.

The following are the contributions made by this work:

- (1) To improve the contrast, brightness, and details of nighttime photos, an innovative and efficient bio-inspired nighttime image enhancement method is provided. Modern techniques are less effective than our strategy.
- (2) To supplement CNN features, we extract HOG and LBP. To combine the three features, we use an efficient weighted score-level feature fusion based on learned weights and a linear SVM. Modern classifier ensemble methods use a new approach for learning weights and bias words.

1.1 Vehicle Detection

The use of automatic vehicle identification methods has received a lot of research in recent years. We only discuss a few of the most important vehicle detection techniques in this subsection because there are so many of them. Certain detection techniques extract the elements that can serve as a representation of certain vehicle qualities. A feature that was deemed to be a variation of HOG for object detection was retrieved by the Deformable Parts Model (DPM). A recent mapping of each DPM step to an equivalent CNN layer (Deep Pyramid DPM) surpassed several cutting-edge CNN-based techniques. The use of automatic vehicle identification methods has received a lot of research in recent years. We only discuss a few of the most important vehicle detection techniques in this subsection because there are so many of them. Certain detection techniques extract the elements that can serve as a representation of certain vehicle qualities. A feature that was deemed to be a variation of HOG for object detection was retrieved by the Deformable Parts Model (DPM). A recent mapping of each DPM step to an equivalent CNN layer (Deep Pyramid DPM) surpassed several cutting-edge CNN-based techniques. A Markov Random Field model that took into account the reflection intensity and suppressed map, as well as the image intensity to represent and detect cars, was used to discriminate light pixels from reflection pixels. In, nighttime vehicle recognition was accomplished by utilizing image processing methods to look for taillights. Unfortunately, due to the difficulty of reliably detecting vehicle lights in complicated settings, all techniques are susceptible to scenario fluctuations.

1.2 Nighttime Image Enhancement

The nighttime photos' poor contrast and brightness make it difficult to distinguish moving objects. Some straightforward algorithms for nighttime image enhancement were modified. For instance, the color information of the

nighttime photos was preserved in the traditional histogram equalization approach. Image-fusion techniques make up the majority of nighttime picture enhancement techniques. These techniques increased the illuminant regions in nighttime photographs using a number of methods to emphasize the foreground regions. The final improved image was created by combining the foreground portions that were highlighted with daytime backdrop photographs. Despite being reported, efficacy and robustness are inappropriate for our situation because there are no preceding daytime photographs. Without using daytime photos, Lin et al. concentrated on enhancing the multi-scale retinex (MSR) for nighttime image augmentation. They used a modified sigmoid function in place of the logarithm function. As a result, the MSR operation's output might directly represent a picture. The noise can be reduced and the original image's highlighted areas can be kept by merging the original image with the MSR image using the appropriate weights. In order to make the approach perform well in scenes of nighttime traffic, Kuang et al. created a new sigmoid function and weight function. Images with low visibility were also processed using the renowned MSR with color restoration (MSRCR). Noises may be greatly increased after the present nighttime picture improvement, which causes errors in the subsequent processing stage and insufficient local contrast enhancement.

1.3 Score-Level Feature Fusion

The standard and straightforward feature fusion strategy of concatenating one feature after another to create a new and huge feature vector—referred to as "concatenating" in this work—performed badly when there was a lot of redundant information among numerous features. It has also been extensively researched to combine several features at the score level by fusing all of the scores that each feature receives in order to produce the final scores for classification prediction. In order to merge two different types of features at the scoring stage, Chen et al. used the mean, max, and product operators. A weighted feature fusion technique based on Gaussian mixture models was proposed by Han et al (GMM). Each feature's weights were based on the maximum likelihood probability. Guermeur et al. integrated their suggested linear ensemble method (LEM) with two multi-class SVM classifiers (referred to as M-SVM+LEM in this study). In order to learn the weights of each classifier for each class, the classification results (i.e., scores) were post-processed and entered into an LEM technique, but the bias terms necessary to calibrate the scores were not learned. Santos et al. used a genetic algorithm (GA) to find the ideal weights for each classifier in order to combine the classifiers' scores (named GAFW in this work). To linearly integrate the score vectors of features for nighttime vehicle detection (referred to as "WSLF-ACC" in this work), Kuang et al. computed the average classification contribution as weights of each feature.

II. LITERATURE SURVEY

Automatically identifying and counting automobiles in unsupervised video taken on highways is an extremely difficult topic in computer vision, but it has many practical uses, such as monitoring activity at intersections to identify traffic jams and forecasting traffic to help with traffic control. It is frequently impractical to manually review the enormous amount of data that they produce. A novel method for identifying and counting cars in a daytime setting was developed by H.S. Mohana [23–25] ET. AL., employing real-time traffic flux and differential approaches. The traffic flux estimation is obtained by counting the background and object pixels in a frame. The fundamental concept is that the presence of a vehicle causes a change in the traffic flux density. In this study, a straightforward differential algorithm is created and put to the test using an application for vehicle recognition and counting. The implementation of the vehicle identification and counting technique will depend heavily on the traffic flux estimation. As video analysis has increased, real-time dynamic scene analysis has grown in importance. The technique created has a basic statistical foundation. In order to speed up computation, dynamic selection of images from the sequence is successfully implemented. Twenty various video sequences are used to test the devised technique, which is then carefully weighted with basic confidence metrics. An area of the backdrop that won't be impacted by traffic is used as a reference in order to make the design illumination invariant. Fixed threshold is used to distinguish between low, medium, and high traffic flux. There is a plot for traffic flux density that basically shows 1% flux density versus the number of frames in the picture and then shows how the flux changes depending on the size of the vehicles. It goes without saying that the amount of flux (white pixels) will increase or decrease depending on the size of the vehicle or item.

A system to assess traffic density using the cell transmission model was proposed by Laura Munoz ET. AL., [30]. This supports non-uniform cell lengths, uses cell densities as state variables in place of cell occupancies, and keeps the downstream edge of a modeled motorway segment congested. As irregular cell lengths can be included when using cell densities rather than cell occupancies, there is more freedom in how the highway can be divided. A system for real-time traffic monitoring was proposed by Tomas Rodriguez et al. [21]; the system is self-adaptive and capable of running

independently for extended periods of time, i.e. there are no hidden parameters that need to be changed. It works well in all kinds of weather and automatically chooses the right algorithm for day, night, and transitional times. The system can handle long broken shadows, shadows from parallel streets, and both rapid and gradual changes in illumination. Because the system is tolerant of temporal tracking errors and strict constraints are used to identify the vehicles, normal camera movements (such as wind vibrations) hardly have an impact on its performance. Also, they adequately handle big cars and obstructions and achieved respectable performance in congested areas. A thorough examination of the operational environment, efficient calibration and image rectification techniques, a unique segmentation strategy enhanced by a cutting-edge technique for the automatic selection of segmentation parameters, and detection and tracking strategy specifically tailored for traffic environments are all required. In recent research, the status of traffic congestion was automatically classified using the Hidden Markov model.

Another method for modeling the traffic flows in real-time is to use a static Support Vector Machine (SVM) technique. The SVM approach offers a tight real-time process and, as compared to the HMM approach, both training and testing procedures are made simpler. Sadly, similar to an HMM technique, the static SVM was unable to perform as intended on a video sequence containing background anomalies such a static shadow. In order to obtain good performance, the entire process required a sizable number of training samples. On the other hand, a traffic density estimating procedure can be complemented by a background modeling strategy, which has been frequently employed in the detection of shadows. However, it presents issues in adverse weather, rapidly changing lighting, and congested roads.

III. THEORETICAL BACKGROUND

3.1 PROBLEM IDENTIFICATION

They investigated the issue of feature sets for reliable visual object recognition, using a test case of linear SVM-based human detection. They examined current edge- and gradient-based descriptors and demonstrated experimentally that grids of HOG descriptors greatly outperform earlier feature sets for human detection. They investigated the impact of each computation stage on performance and came to the conclusion that fine-scale gradients, fine orientation binning, relatively coarse spatial binning, and high-quality local contrast normalization in overlapping descriptor blocks are all crucial for successful results.

DISADVANTAGES

It has been demonstrated that single feature-based detection techniques work well. These kinds of detection techniques could result in incorrect classifications, nevertheless, when dealing with more complicated scenarios.

3.2 PROBLEM SOLVING

The two steps of our suggested methodology are the training stage and the detecting stage. Three complimentary features—CNN features, HOG features, and LBP—are then extracted from the enhanced images during the training stage after the original training samples have been upgraded using the suggested image enhancement approach. With LibSVM, three SVM classifiers are trained, and five-fold cross-validation is done using each distinct feature separately. Each classifier's score vectors are computed as well. Using a linear SVM, the scores are utilized to determine the weights of each feature for each distinct class. Accurate ROIs are extracted from the input photos during the detection phase. The three attributes are then taken out of each increased ROI. The related features are then classified using the trained classifiers, and scores are computed. These scores are added to the learned weights to produce final score vectors for prediction. After then, post-processing is done to make sure each car has a single window around it.

The following are the contributions made by this work: The contrast, brightness, and details of nighttime photographs are enhanced using a cutting-edge and successful bio-inspired nighttime image enhancement technique. Modern techniques are less effective than our strategy. We extract HOG and LBP as a complement to CNN features, and then we merge the three features with an efficient weighted score-level feature fusion based on learned weights using a linear SVM. Modern classifier ensemble methods use a new approach for learning weights and bias words.

ADVANTAGES

The following are the advantages of our score-level feature fusion based on learned weights: Each classifier's complementary strengths (i.e., features) are completely utilized for the specific class. The weights of each class are distinct and are taught independently for the same classifier. In order to calibrate the initial scores, bias words are learned. Some score-level feature fusion algorithms ignore these factors. Multi-class detection jobs can benefit from the

usage of our suggested feature fusion technique. We only need to learn new weights and bias terms for new extra classes and features when dealing with more features and more classes because each classifier's weight and bias term are learned separately. We then total the new calibrated scores with the previous scores. Our feature fusion strategy can also escape the dimensionality curse because each feature is utilized to train a classifier and its dimensionality is kept constant. We discover that our system effectively detects automobiles from a variety of situations in varied numbers, types, locations, and sizes.

3.3 SYSTEM ARCHITECTURE

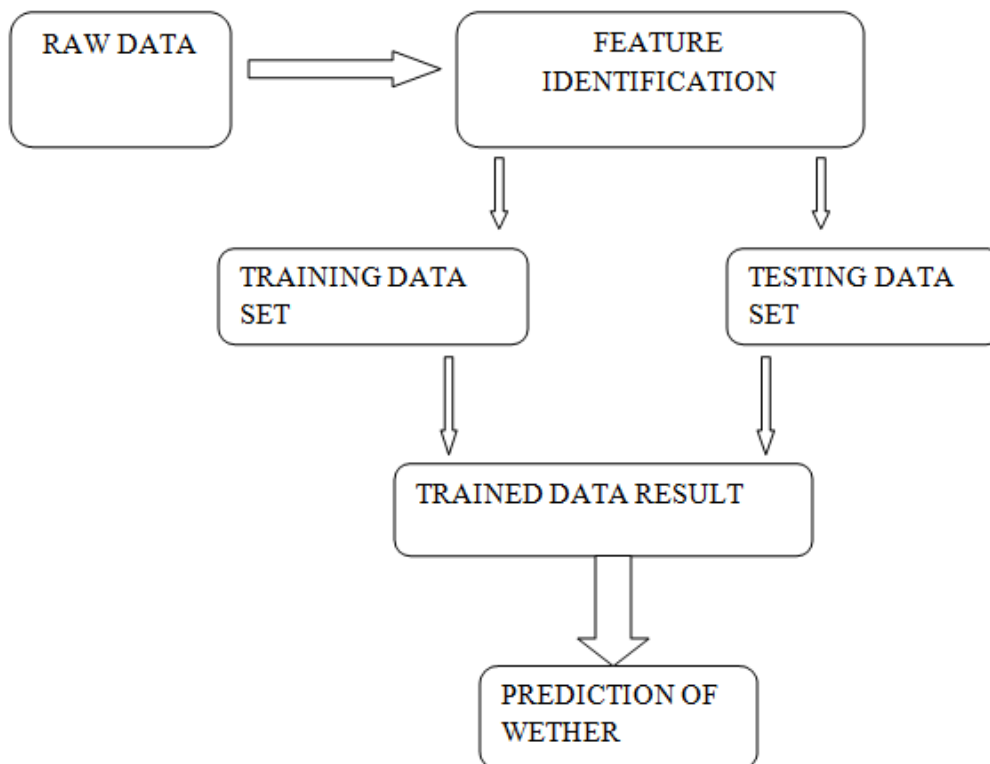


Figure 3.1 Architecture Design

The whole working process, from input selection through function close, is illustrated in Figure 3.1. After gathering the raw data from the dataset, preprocessing will identify the features from the input, and since training data has already been collected, comparing the testing data to it using a classification algorithm will reveal whether or not we can easily identify the lighting object in front of our car using this method.

IV. SYSTEM IMPLEMENTATION

4.1. IMAGE ACQUISITION

In the context of image processing, image acquisition can be roughly defined as the action of acquiring a picture from a source, typically a hardware-based source, in order to send it via subsequent processes. The initial stage in the workflow sequence for image processing is always picture capture because processing is impossible without an image. It can be crucial in some sectors to have a constant baseline from which to work, and the obtained image is entirely unprocessed and is the product of whatever apparatus was used to generate it. Test and reference images are purchased from open repositories.

4.2. PREPROCESSING

Frame extraction and grey image generation are suggested during the preprocessing stage. Rod and cone photoreceptor sampling is the first step in the retina's information processing mechanism. The retina's long-, medium-, and short-wavelength cone photoreceptors process the red (R), green (G), and blue (B) components of the incoming image, respectively.



Figure 4.1 input selection process

Figure 4.1's input video $I(x, y)$ is first sampled by three different types of cone photoreceptors and then transformed into images of the R, G, and B channels ($I_c(x, y), c(R, G, B)$). Then, the photoreceptors' three cone signals are collected by the horizontal cells (HCs).

4.3. ENHANCEMENT

The third phase involves improving the image. Nighttime picture enhancement is a crucial pre-processing step for vehicle detection at night. Our proposed bio-inspired nighttime picture improvement method is used instead of the ROI extraction framework for image enhancement. Then, the following procedures are used to identify the potential zones of vehicle taillights: (1) utilizing an empirical threshold to reduce noise and transform the RGB photos to intensity images (2) calculating the image sizes.

4.4. DETECTION

The detection of vehicles at night is the last step. Multi-class detection jobs can benefit from the usage of our suggested feature fusion technique. We simply need to learn new weights and bias terms for new additional classes and features and sum the new calibrated scores with the old scores when dealing with more features and more classes because each classifier's weight and bias term are learned individually.

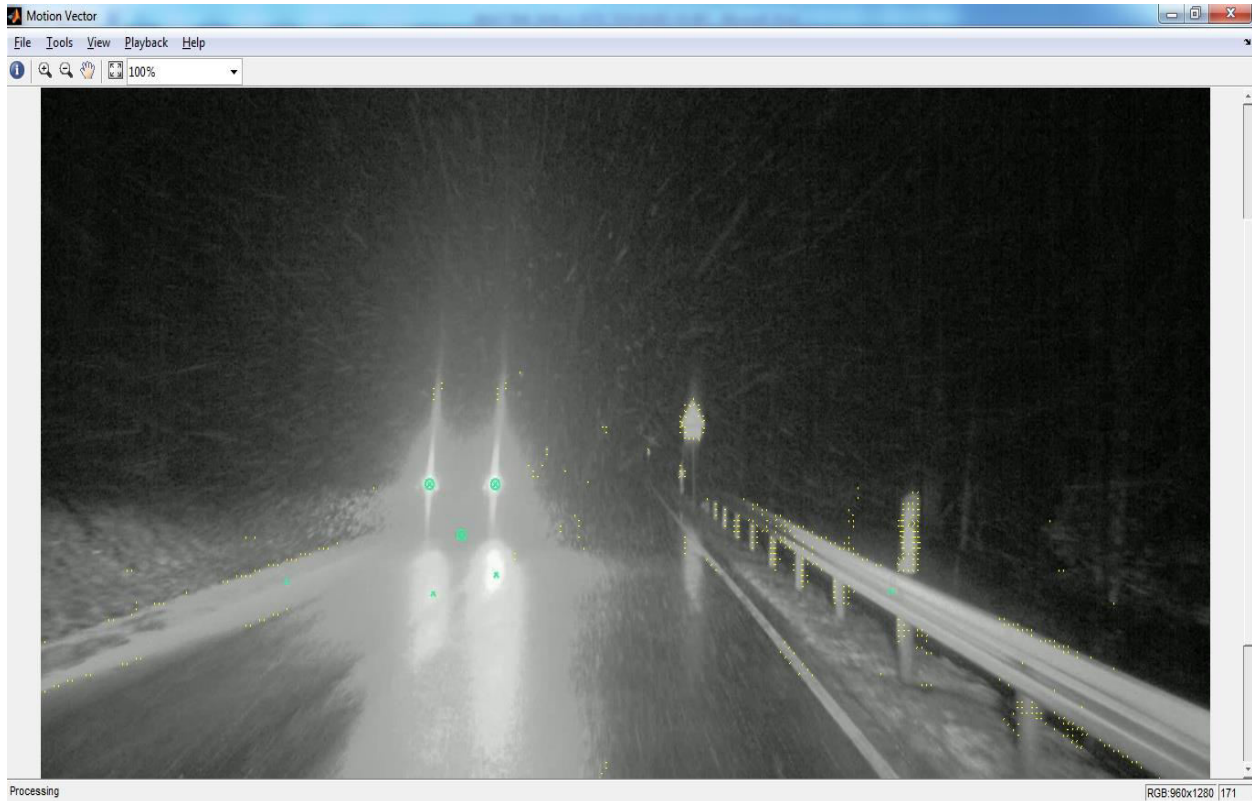


Figure 4.2 Detection based on motion vector detection

5. Validation of Feature Complementarity

In this study, we extract HOG and LBP to enhance CNN features. We contrasted the suggested fusion's miss rate vs. FPPI curves using just one feature. We verified the efficacy of our weighted feature fusion and the complementarity of the three characteristics. The variations in these comparisons relate to the features employed; picture enhancement, ROI extraction, and detection methodology are all used in the same way. CNN is superior to HOG and LBP, and the combination of CNN, HOG, and LBP is preferable to employing the three elements separately. These findings show that CNN is complemented by HOG and LBP, and our suggested fusion fully exploits this complementarity.

V RESULT AND DISCUSSION

Here, four various types of working from the input video are processed. Level 1 presents the input selection video that was described in the part before; the next section will address threshold-based detection, which will make the second level of detection process clearer. The above level 2 completed signifies in figure 5.1 that it will advance to level 3 after it receives a clear detection in comparison to the previous two levels.



Figure 5.1 threshold based detection process

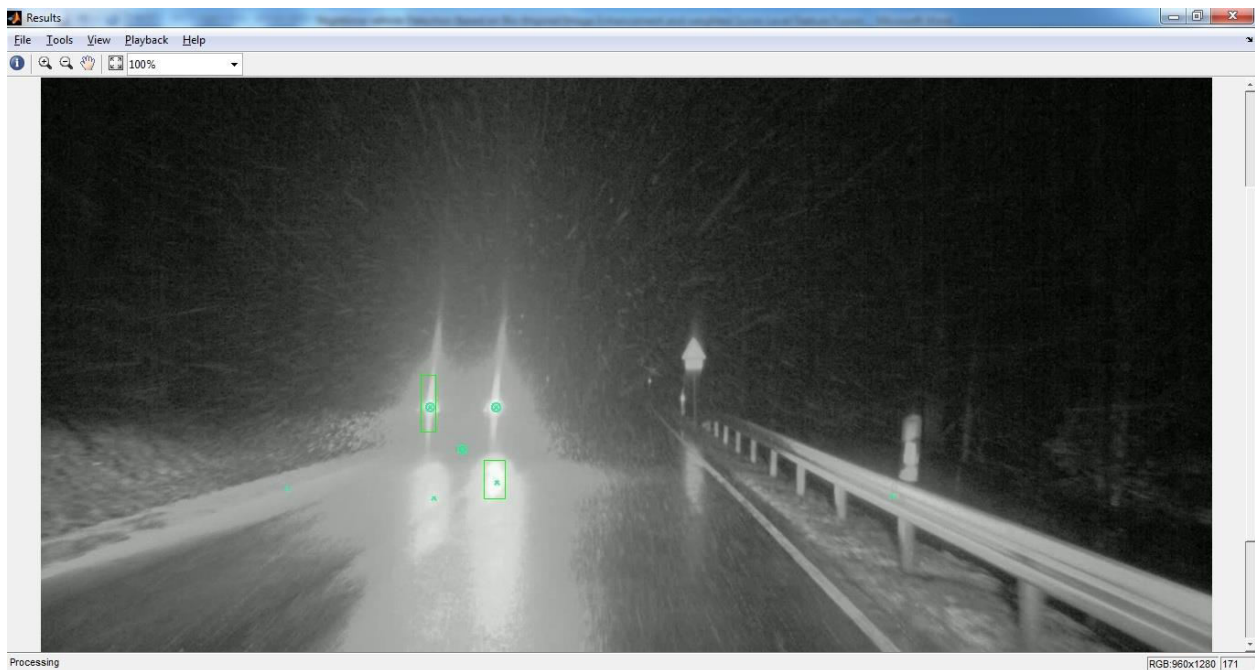


Figure 5.2 Detections the final level accurate opposite vehicle lighting and climate

The final stage of detection is depicted in the above picture, and it uses data from the previous working level. Final results will be compared in order to obtain ideal object lighting for nighttime detection in any environment. Will offer the prior method's best detection rate. This will facilitate locating front and rear car illumination via camera to detection and dashboard information.

VI. CONCLUSION & FUTURE WORK

6.1 CONCLUSION

In this study, a brand-new bio-inspired picture enhancing technique is combined with a weighted score-level feature fusion strategy to create a revolutionary nighttime vehicle recognition system. According to experimental findings, our method for nighttime picture enhancement may boost contrast and brightness while also preserving and improving object features. It also outperforms several state-of-the-art methods for nighttime image improvement in terms of improving vehicle detection. A new weighted score-level feature fusion approach is also used to integrate three complementary features linearly. In comparison to employing individual features and some cutting-edge feature fusion algorithms, this novel approach to feature fusion is more efficient. Also, "DPM," "CNN+SVM," and a recent method in are outperformed by our suggested vehicle detection method. Vehicles of all shapes and sizes can be reliably recognized in challenging circumstances. Yet, occasionally certain partially obscured and distant cars are overlooked. Moving forward, we'll concentrate on detecting obscured and distant vehicles while utilizing intrinsic channel features to speed up the detection process. Also, in order to validate and enhance the vehicle detection algorithm, we will need to create a larger and more complicated nighttime vehicle dataset.

6.2 FUTURE WORK

The submitted solutions and analysis findings in this challenge offer rich experiences, significant observations and insights, as well as possible future directions: In their submitted answers, all participants favored deep learning techniques. With the exception of Sub-challenge. Some teams decide to use hand-crafted low-light enhancement techniques as pre-processing, while other teams submit deep learning-based techniques since they are flexible and can be tweaked to perform better depending on the objective. Using semi-supervised learning and a reconstruction loss to direct the reconstruction of the complete image from the intermediate feature, the top two winners make efforts to explore the potential of unlabeled data. This tactic improves performance, demonstrating that it should receive more consideration in the future. The best options for the framework may vary depending on the tasks and methods utilized to solve the difficulties. The winner of our challenge adopts the cascade of enhancement and detection, while the loser chooses a one-step detection technique (without an implicit dehazing module). A sequential enhancement approach has been reported to be beneficial by some teams, including tfirst, in removing mixed degradation like underexposure, low-resolution blurring, and noise. Also, it reveals a viable route that merits more investigation.

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