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RESEARCH ARTICLE

YOLO-VEHICLE: REALTIME VEHICLE LICENCE PLATE DETECTION AND CHARACTER RECOGNITION USING YOLOV7 NETWORK

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Abstract –The demand for a secure lifestyle and travel is increasing due to the rapid development of technology. Since the turn of the century, the number of road vehicles has risen dramatically. The rapid growth of the vehicular sector makes tracking individual vehicles increasingly difficult. In this work, a novel proposed YOLO-VEHICLE has been introduced to detect the licence plate in the highway using Yolov7 network. Initially, a CCTV camera captures the input highway traffic video. The collected video is converted into frames. The frames are detected the license plate using the YOLOv7 network. The detected Licence plates (LP) are segmented for partitions a digital image into discrete groups of pixels using U-Net. Finally, the segmented LP recognizing the character for clear view. The simulation outcomes show the performance is assessed by using the accuracy reached by the proposed YOLO-VEHICLE method, as well as its accuracy (ACU), precision (PRE), recall (RCL), and F1 score (F1S). According to the results, the proposed network accuracy was 99.59 %. In the comparison, the YOLOv7 network improves the overall accuracy of the YOLOv3, YOLOv4, and YOLOv5 is 95.14%, 96.32%, and 97.36% respectively. The YOLO-VEHICLE approach improves the overall accuracy of 13.37%, 2.13%, 14.03% better than edge intelligence-based enhanced YOLOv4, Faster R-CNN, and recognition system respectively.

Keywords *– Vehicle, Licence plate, Deep learning, YOLOv7, U-Net.*

1. INTRODUCTION

The dramatic growth in vehicular traffic on the highways drives a significant need for traffic monitoring and management technologies [1]. Manual monitoring of cars traveling at high speeds is almost impossible in this case. There will be a waste of manpower and time [2,3]. Even if it is operated manually, it will result in great problems and blunders. There are currently ways for tracking cars and number plates using ML techniques [4,5]. These methods fail in real time owing to the complications of background processing. As a result, there is an urgent need to construct an automated system that would help in tracking the autos by tracing their license plate in the most effective method [6].

Figure 1. License plate location on sample image

They are used to recognize license plates for security purposes on school campuses, public parking lots, and in urban traffic [7]. In present ALPR systems, camera image and RFID card solutions are employed independently or together [8,9]. However, these methods do not achieve the requisite high precision. In order for the images collected by the vehicles to be processed, they must be sufficient in brightness, intensity, and clarity when they are moving at high speeds [10,11]. Furthermore, the angle from which the images are collected is essential. The most complicated aspect is that each country has an own standard for printing number plates [12]. The YOLO model was developed as a result to expedite the process of recognising an object and pinpointing its location in an image. When YOLO-based techniques like YOLOv3, YOLOv4, and YOLOv5 are created, the YOLO continues to deliver higher performance in terms of processing time and accuracy [13]. The primary goal of the study is to identify and recognize LP with greater ACU.

The main contribution is followed as:

- In this work, a novel YOLO-VEHICLE has been presented to detect the licence plate in the highway using Yolov7 network.
- Initially, a CCTV camera captures the input highway traffic video. The collected video is converted into frames.
- The frames are detected the license plate using the YOLOv7 network. The detected Licence plates (LP) are segmented for partitions a digital image into discrete groups of pixels using U-Net.
- Finally, the segmented LP recognizing the character for clear view.

The following portions of this work will be arranged as follows: Literature review will describe in section 2, section 3 will detail the YOLO-VEHICLE approach, section 4 will go over the findings and analysis, and section 5 will examine the conclusions.

2. LITERATURE SURVEY

Recently, researchers demonstrated many DL and ML-based algorithms aimed largely at improving the accuracy of identifying automobile license plates. In this part provides an overview of some new and advanced techniques.

In 2022, Wan, S., et al., [14] suggested using video pre-processing based on edge computing to get rid of the extra frames. A video is divided into super frame segments of interest using a mix of multi-modal linear features and STIP-based motion detection to remove unnecessary video frames. The experimental findings demonstrate great robustness and precise key frames. On the UA-DETRAC dataset, the optimised YOLOv3 result the other models in terms of detection accuracy.

In 2021, Liu, B., et al., [15] suggested a DRL to investigate the possibilities of traffic video data in enhancing ramp metering effectiveness. From the traffic video frames, the locations of the vehicles are retrieved and then transformed into position matrices. A existing strategy that results in shorter travel times and increased traffic flows downstream of the merging region is evaluated and compared with the tests based on real- world traffic data.

In 2019, Masmoudi, M., et al., [16] design a video-based object recognition, specifically those that can be used with autonomous vehicles. Both the ML and DL algorithms use SVM, YOLO, and SSD. When making short driving judgments, the YOLO model and SSD are more accurate due to their high capacity to recognize objects in real time; however, the SVM performs badly and its speed does not ensure real-time reaction.

In 2023, Chen, C., et al., [17] suggested an edge intelligence-based enhanced YOLOv4 vehicle detection to enhance vehicle detection performance using ECA and HRNet, and DeepLabv3+ image segmentation enhances segmentation precision by combining the original backbone network with MobileNetv2. The outcome demonstrates that the suggested strategy may raise the accuracy of vehicle detection from 82.03% to 86.22% and raise the quality of the image segmentation model from 73.32% to 75.63%.

In 2021, Saidani, T. and Touati, Y.E., [18] suggested a system based on the Faster R-CNN, has been enhanced by adding an adaptive attention network for license plate segmentation in order to extract the digits and letters of identification. To train and test the suggested system, a dataset of Arabic nations was constructed. The suggested model dataset achieved 98.65% recall and 97.46% accuracy.

In 2021, Habeeb, D., et al., [19] developed an Arabic and Latin alphabet LP recognition system that detects, segments, and recognizes car plate numbers using a DL. The test was conducted under a variety of meteorological conditions, including fog, varied contrasts, dirt, different colors, and distortion issues. On Iraqi and Malaysian datasets, the recommended approach has an average recognition rate of 85.56% and 88.86%, respectively.

In 2021, Onesimu, J.A., et al., [20] designed a three-step technique to identify the LP, segment the characters, and character recognition. The suggested model automatically refreshes the database with information about the cars that enter and depart the parking space. It has been tested in a variety of situations, including fuzzy images, varying camera distances, and day and night conditions. The findings show that the recommended technique has 91.1%, 96.7%, and 98.8% ACU for LP detection, segmentation, and identification, respectively.

According to the above related work, various deep learning and machine learning techniques focus on vehicle LP detection. Additionally, existing techniques are more time-consuming, and less accuracy. Therefore, the proposed method used to detect the licence plate in the highway using Yolov7 network.

3. YOLO-VEHICLE

In this section, a novel YOLO-VEHICLE has been proposed to detect the licence plate in the highway using Yolov7 network. Initially, a CCTV camera captures the input highway traffic video. The collected video is converted into frames. The frames are detected the license plate using the YOLOv7 network. The detected Licence plates (LP) are segmented for partitions a digital image into discrete groups of pixels using U-Net. Finally, the segmented LP recognizing the character for clear view. Figure 1 depicts the entire flow of the YOLO-VEHICLE approach.

3.1. Image acquication

The truck on the highway is found using the logistic vehicle detection approach, as shown in Figure 2. The road area is divided into a remote region and a proximal area depending on where the camera was installed. The CCTV cameras' real-time highway videos are first collected, and the videos that have been acquired are then turned into frames. The highway route is being travelled by a variety of vehicles, including cars, trucks, buses, motorbikes, bicycles, etc. The sample frames for each recording setting are shown in Figure 3.

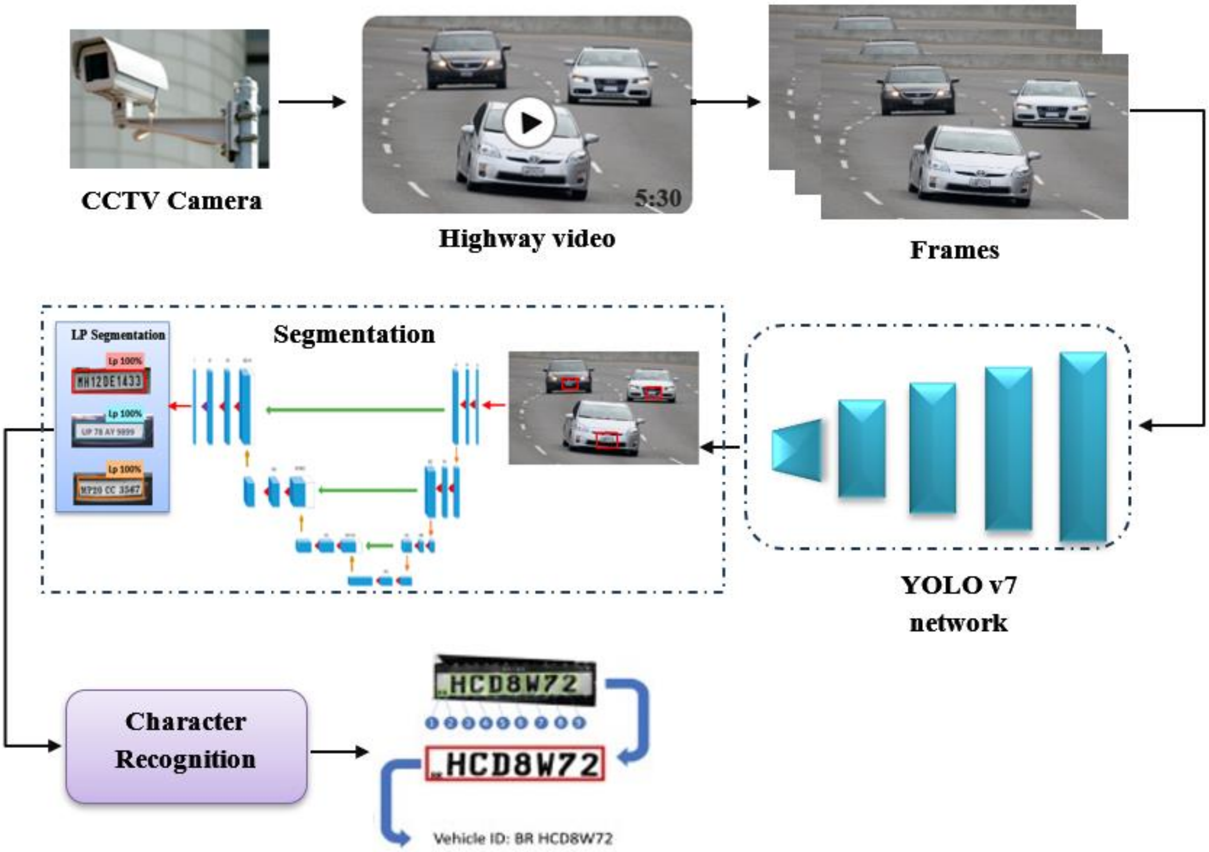


Figure 2. The overall workflow of YOLO-VEHICLE

Figure 3. Different video frames from various recording scenario

3.2. Detection via Yolov7

In this part, YOLOv7 discusses an LP detection technique on the roadway. In terms of real-time applications, such as immediate segmentation and posture estimation, YOLOv7 is the most recent version it offers the best performance and efficiency. YOLOv7's architecture varies from prior object identification algorithms in several areas, including Compound Model Scaling and E-ELAN. The main output does the final detection, whereas the neck mostly generates feature pyramids. The backbone eliminates features from the input images. There are also several architectural modifications to YOLOv7, including the enlarged E-ELAN, a set of freebies that include planned and reparametrized convolutions, compound scaling, coarseness and fineness for auxiliary loss and lead loss, respectively.Architecture of YOLOv7 network shown in Figure 4.

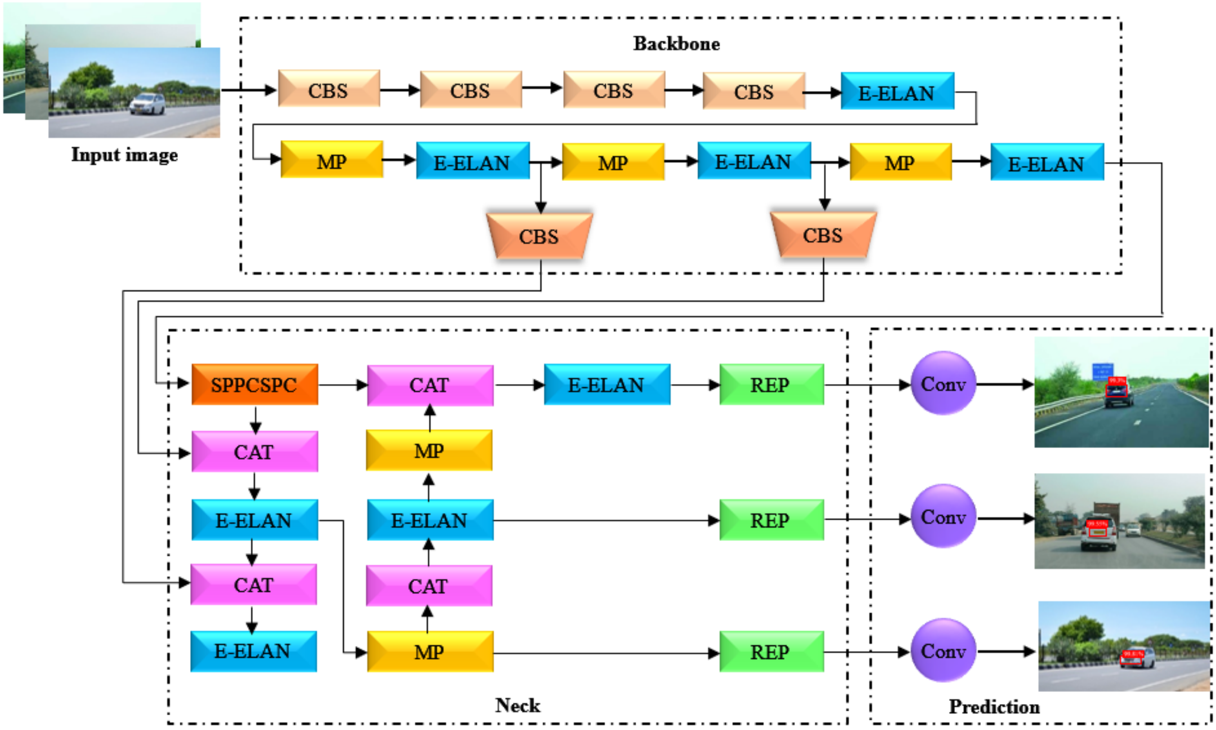


Figure 4. Architecture of YOLOv7 network

E-ELAN:

The prior Efficient Layer Aggregation Network (ELAN) design will employ a deeper resolution guiding gradient path. Regular ELAN has the disadvantage of being unable to handle large computational blocks, being destroyed by its gradient path, and using parameters to their maximum capacity. YOLOv7 Seven solves this problem by extending, rearranging, and merging cardinality.

YOLOv7 compound model scaling:

The primary goal of model scaling is to change key model properties in order to create models that are suitable for a wide range of application needs. Conventional approaches that employ concatenation-based designs must take numerous scaling parameters into account at the same time since they cannot be studied independently. For example, raising the model depth will affect the ratio of input to output channels in a transition layer, perhaps leading to the model consuming less hardware. As a result, YOLOv7 supports compound scaling in concatenation-based models. The compound scaling approach preserves the model's original level properties, resulting in the optimal design. Finally, it identifies the LP in the given road images.

3.3. Segmentation via U-Net

U-Net is used in this layer to segment the frames. To comprehend what is provided in an image at the pixel level, segmentation is used. It offers detailed information about the image as well as the vehicle's shapes and limitations. The result of image segmentation is a mask, each element of which denotes the class that a given pixel belongs to. This approach can be used to control traffic systems and has shown encouraging results using real imagery. According to Figure 3 shows the up-sampling (decoding) and down-sampling (encoding) paths that make up U-Net. The down sampling pipeline is made up of five convolutional blocks. The number of feature mappings is raised from 1 to 1024 in each block by employing two convolutional layers with filter sizes of 3×3, one stride in each direction, and rectifier activation. Except for the last block, down sampling is performed using max pooling with step size 2x2, which reduces the size of the feature map from 240x240 to 15x15. The filter size for this layer is 3x3 and the steps are 2x2. Two convolutional layers are removed from the number of feature maps generated by merging the deconvolutional feature map with the feature map from the encoding pass of each up-sampling block. Unlike the original U-Net architecture, all convolutional layers in the down sampling and up sampling passes use zero padding to preserve the output dimension. Finally, employing a 1×1 convolutional layer, just two feature maps remain, representing the foreground and background segmentations, respectively.

A skip connection is also included by the U-Net architecture to transport output from the encoder to the decoder. Concatenated feature maps are propagated to subsequent layers by joining these feature maps with the results of the up-sampling procedure. The network can recover the spatial characteristics lost during pooling operations to the skip connections. Finally, it segments the detected LP using U-Net.

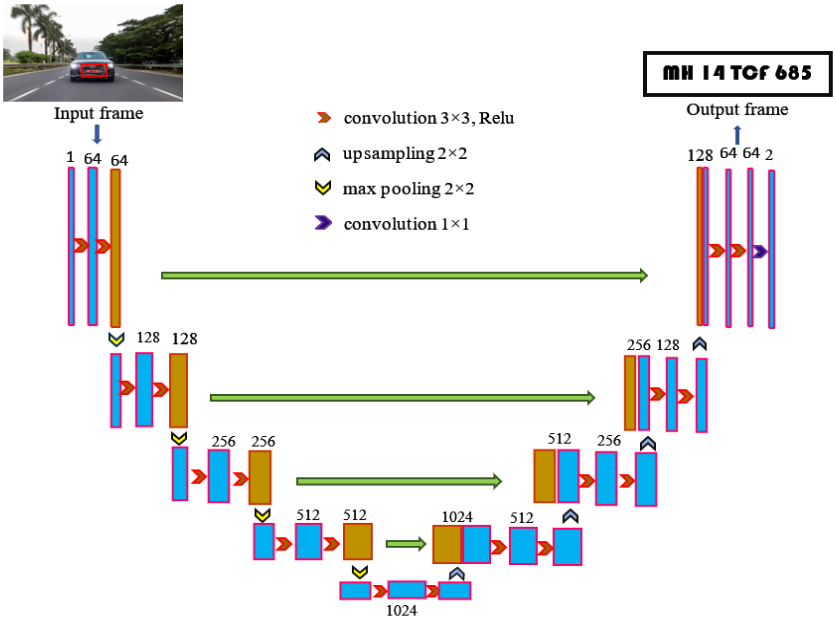


Figure 5. Architecture of U-Net

3.4. Number Plate Recognition

The final stage is to recognize the segmented characters. The segmented characters to vary in size and thickness. Characters may be broken, slanted, or affected by noise. This section covers character recognition methods.

The simplest basic method for character recognition is Template Matching. It uses a cross-correlation technique to compare or assess the extracted character's similarity to the template character set. The character that best matches one of the template set's options is chosen. Because changes in lighting conditions have a direct influence on the gray level intensities in the produced image, these methods are frequently used for binary images.

The Template Matching Technique is used to discern segmented characters, and the returned characters are compared to the templates by scanning each column individually. The character with the greatest correlation value is the most closely matched. However, Template Matching can only identify characters that are not broken, skewed, have no font modifications, and have been scaled to a certain size.

Over 1200 photos with dimensions of 250 pixels wide, collected under a variety of situations and hues, had a 100% extraction rate and an acceptable 90% identification rate. Over 1300 license plate image with a specified aspect ratio of 640 × 480 pixels are used under real-time settings. The extraction rate is around 99.59% efficient, with a processing time of 1.2 seconds at 10 frames per second.

4. RESULT AND DISCUSSION

The experimental setup for the YOLO-VEHICLE approach was constructed using MATLAB 2020b, as well as the results of the experiments. The suggested technique was evaluated on the obtained dataset using several parameters such as ACU, PRE, RCL, and F1S. specificity, precision, F1 score, recall, and accuracy.

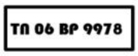
Input	Detection	Segmentation	Character Recognition
			MH 12 HL 8674
			PO C 2081
			TN 06 BP 9978

Figure 6. Simulation analysis of YOLO-VEHICLE

Figure 4 illustrate the simulation analysis of YOLO-VEHICLE. In column 1 shows the input vehicle images, column 2 displays the LP detection using YOLO network, column 3 displays the segmented LP using U-Net, finally, the segmented LP number are recognized the character as show in column 4.

4.1. Performance analysis

The YOLO-VEHICLE method is assessed in this part through experiment findings. The performance of proposed LP detection system is evaluated using statistical parameters such as ACU, PRE, RCL, and F1S.

$$ACU = \frac{(TP+FP)}{(TP+TN+FN+FP)} \tag{1}$$

$$PRE = \frac{TP}{TP+FP} \tag{2}$$

$$SPL = \frac{TP}{TP+FN} \tag{3}$$

$$F1S = 2\left(\frac{Precision*Recall}{Precision+Recall}\right) \tag{4}$$

The proposed YOLO-VEHICLE network achieves great accuracy in both training and testing. Performance is evaluated using the YOLO-VEHICLE method's accuracy, as well as its ACU, PRE, RCL, and F1S. The results showed that the YOLO-VEHICLE approach was 99.59% accurate.

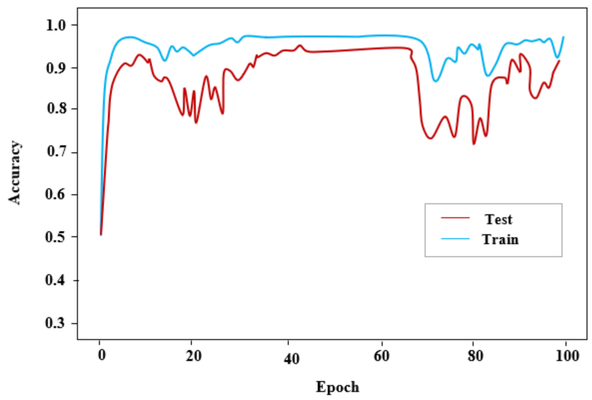


Figure 7. Accuracy graph of proposed YOLO-VEHICLE method

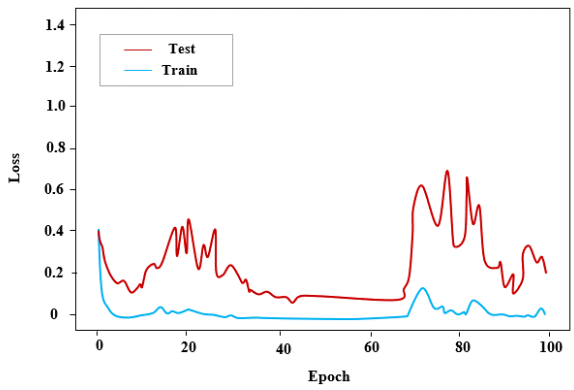


Figure 8. Loss graph of proposed YOLO-VEHICLE method

Figure 5 shows that the YOLO-VEHICLE model has outstanding training and testing accuracy, with a loss displayed in Figure 6. The YOLO-VEHICLE model achieves a performance of 99.59% in terms of ACU, PRE, RCL, and F1S. It clearly illustrates how to enhance detection ACU using a YOLOv7 network.

4.2. Comparative analysis

In a comparative study, the YOLOv7 technique is compared against three different approaches. Table 1 compares the overall efficacy of DL to previous methodologies. The YOLOv7 model is contrasted with various DL techniques, such as YOLOv3, YOLOv4, and YOLOv5. The performance of the DL approach was evaluated using a variety of measures, including ACU, PRE, RCL, and F1S.

Table 1. Comparison between Deep learning networks

Networks	ACU	PRE	RCL	FIS
YOLOv3	95.14	94.72	93.82	93.42
YOLOv4	96.32	94.38	92.46	90.51
YOLOv5	97.36	95.47	94.36	89.76
YOLOv7 (ours)	99.59	97.05	95.49	94.36

Figure 7 shows that the YOLOv7 network increases the overall ACE of the YOLOv3, YOLOv4, and YOLOv5 by 95.14%, 96.32%, and 97.36%. The YOLOv7 enhances the overall precision of the YOLOv3, YOLOv4, and YOLOv5 by 94.72%, 94.38%, and 95.47%. The YOLOv7 network improves the overall REL of the YOLOv3, YOLOv4, and YOLOv5 is 93.82%, 92.46%, and 94.36%. The YOLOv7 network improves the overall F1 score of the YOLOv3, YOLOv4, and YOLOv5 is 93.42%, 90.51%, and 89.76% respectively.

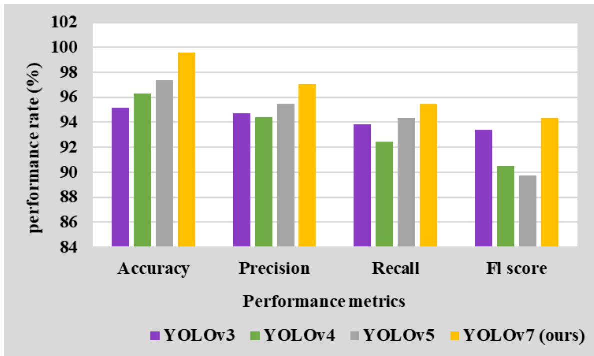


Figure 9. Comparison analysis of existing deep learning models

Table 2. ACE comparison amid the YOLO-VEHICLE and existing models

Authors	Methods	ACE (%)
Chen, C., et al., [17]	Edge intelligence-based enhanced YOLOv4	86.22
Saidani, T., [18]	Faster R-CNN	97.46
Habeeb, D., [19]	Recognition system	85.56
Proposed	YOLO-VEHICLE	99.59

Table 2 illustrate that traditional network such as edge intelligence-based enhanced YOLOv4, Faster R-CNN, and recognition system are less accurate than the YOLO-VEHICLE method. The YOLO-VEHICLE technique has an exceptional accuracy rate of 99.59%. The YOLO-VEHICLE technique enhances overall accuracy by 13.37%, 2.13%, and 14.03% compared to edge intelligence-based improved YOLOv4, Faster R-CNN, and recognition system, respectively. According to the above comparison, the YOLO-VEHICLE model is more accurate than other models.

5. CONCLUSION

In this work, a proposed YOLO-VEHICLE to detect the licence plate in the highway using Yolov7 network. Initially, a CCTV camera captures the input highway traffic video. The collected video is converted into frames. The frames are detected the license plate using the YOLOv7 network. The detected Licence plates (LP) are segmented for partitions a digital image into discrete groups of pixels using U-Net. Finally, the segmented LP recognizing the character for clear view. Performance is assessed by using the accuracy reached by the proposed YOLO-VEHICLE method, as well as its ACU, PRE, RCL, and F1S. According to the results, the YOLO-VEHICLE accuracy was 99.59% of ACU. In the comparison, the proposed YOLOv7 network increases the overall accuracy of the YOLOv3, YOLOv4, and YOLOv5 by 95.14 percent, 96.32%, and 97.36%, respectively. The YOLO-VEHICLE approach improves the overall accuracy of 13.37%, 2.13%, 14.03% better than edge intelligence-based enhanced YOLOv4, Faster R-CNN, and recognition system respectively. In the future, we will try to find district road vehicle speed with more accurate result using advanced YOLO network.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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