Helmet and Number Plate Detection Using Yolov3 Algorithm

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Abstract

Existing safety helmet detection approaches rely on object identification methodology with high recognition speeds to meet real-time exposure needs, but they can't identify small things with obstacles accurately. As a result, based on the attention process, we offer a helmet detection method (AT-YOLO). Because of its speed and precision, the YOLOv3 target identification method is frequently utilized in industry, however it does have certain drawbacks, such as accuracy loss in unbalanced datasets. To improve the YOLOv3 target detection method and preprocess the data set, the YOLOv3 target detection uses a Gaussian fuzzy data augmentation method. The YOLOv3 confidence level is enhanced by 95 to 96 through efficient pre-processing without affecting the YOLOv3 detection speed. Due to valuable feature fusion, the processed images give improvement in image localization, which is more in line with the production constraint of recognition accuracy and speed.

KeyWords: Helmet, YOLOv3, Deep Learning, CNN, RNN.

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Introduction

Intelligent monitoring has emerged as most important applications of computer vision in recent years. Object detection, as a hotspot of computer vision, offers a plethora of possibilities for intelligent surveillance. In early research, classical features are mostly used in object detection algorithms. Traditional picture recognition approaches, like the Gaussian mixture model [1], can distinguish foreground from background. A hand-designed feature extractor, Histogram of Oriented Gradient(HOG) [2] is used by researchers in the field of pedestrian detection to extract contour information. After that, a classifier like support vector machine(SVM) [3] is utilized to recognise pedestrians based on the collected attributes. The hand-designed feature extractor is complicated to utilize in actual application due to its defective characteristics and weak generalization capabilities.

Deep Learning (DL) has a technological guarantee thanks to the advancement of massively parallel computer technology, and it also gives valuablesolutions for data concealing, image classification, object identification, image retrieval, picture inpainting, and many other applications. DL is currently used in the most cutting-edge detection techniques. In the area of target detection, the use of DL has become commonplace. Regions with CNN features (R-CNN) [4] and its upgraded versions Faster R-CNN [6] and Fast R-CNN [5] are examples of algorithms. R-CNN [7] uses a DL model to remove image attributes and create region proposals with a sliding window at start, but it has a lot of recurring calculations. Fast R-CNN uses the SPP module to provide fixed-size output while integrating the regression and classification of bounding boxes into a network to diminishfrequent calculations [8]. R-CNN inputs picture features into Region Proposal Networks (RPN) at a faster rate [9].

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The RPN be able to accept feature maps of several size, object candidate box confidenceand output coordinate information, and then categorize the object candidate boxes. In two-stage object detection model like Faster R-CNN, area classification and selection should be done step by step. With the advancement of deep learning, factors such as the number of candidate boxes, the difficulty of basic network, the difficulty of classification, and regression sub-networks affect two-stage detection algorithms and the quantity of calculation continues to rise. In the algorithm, YOLO skips the candidate box extraction stage and instead uses an end-to-end deep convolutional network to perform candidate box classification, feature extraction, and regression.

Safety helmet wearing detection is an important practical application in object identification that is intimately tied to our production and daily lives. It has been the subject of extensive research by a number of academics. The authors in [10] retrieved the features of helmet and worker from the image and used a cascade to determine if the worker was wearing a helmet. Based on pedestrian detection results, Li et al. [11] used head positioning, colour space transformation, and colour feature recognition to recognise people wearing helmets. To improve feature resolution in helmet detection, Wu et al. [12] applied the upgraded YOLO-Dense backbone. To detect wearing helmets, authors in [13] employed Single Shot multi-box Detector (SSD) [14]. However, current helmet detection systems have drawbacks, like limited generalisation capacity for multi-scene detectionand low detection accuracy for small items. The author in [15] employed the enhanced Faster-RCNN technique to detect helmet wearing after using the K-means++ clustering algorithm to cluster the helmet's size in the image.

However, the one-stage detector has a faster detection speed among the present helmet-wearing detection algorithms, but its detection accuracy for dense and small targets is low, and its generalisation capacity of diverse scenes is pathetic. Due to the enormous computation amount and sluggish detection speed of the two-stage detector, it is impossible to congregate the real-time necessities of helmet detection. To address the aforementioned issues, we present an AT-YOLO model for helmet identification.

Literature Review

The safety helmet has been utilised in many forms of manufacturing sites as an effective protective gear, but because audit and oversight are not in position, accidents occur by not taking the helmet. Thus, the recognition of detection of helmet wearing is vital for security of workers' lives at the production site. The target detection algorithm [16], [17] is extensively utilized in helmet detection. The R-CNN algorithm based on candidate regions [18]–[21] requires the generation of candidate regions first, followed by regression and classification processes on the candidate regions; the next is the SSD algorithm [17] and You Only Look Once (YOLO) [23]–[26], which utilizes only one CNN network to estimate the location and category of different targets. YOLO achieves real-time detection speed but not exactness when compared to the R-CNN algorithm. Motorcyclists wearing or not wearing helmets were also detected using the faster R-CNN. Although the helmet detection in [29], [30], and [31] uses deep learning, the classic background subtraction is still utilised in the motorbike identification step to retrieve the foreground target, which will be very poor in a busy scenario.

Authors in [32] proposed YOLOv2 [31] and YOLOv3 [23], [32] to increase the accurateness of YOLO while keeping the speed benefit, particularly for the recognition of small items. Silva et al. [33] extracted picture characteristics using the Circle Hough Transform (CHT) and HOG descriptors then classified the target using a multilayer perceptron machine. This technique functions well for single-worn recognition, but ineffective for multi-worn recognition and cannot be used on photos with many people. Deep learning-based target identification approaches have advanced significantly in recent years, and they may be split into two types: one and two-stage detection algorithms with and without region suggestion, respectively.

YOLOv2 [27] employs the Darknet-19 backbone network, which is based on the VGG16 [28] model design approach. The 3 3 convolution and 2 2 maximum pooling layers are mostly used in the network. The feature map's height and breadth are cut in half and its number of channels is doubled after going through the pooling layer. YOLOv2 retains its advantage in terms of speed. Though, its backbone network is not profoundsufficient, more abstract picture semantic elements are difficult to perceive, and the bounding box forecasted by each

grid cell is too small, making it ineffective in predicting targets with large-scale changes.
The feature extraction network in the YOLOv3 network is Darknet53 [29]; there is only one convolutional layer in YOLOv3, most of which are 3*3 convolutions; the pooling layer is cancelled in YOLOv3; and the output feature map size can be restricted by step size of the convolutional layer. Based on the idea of a "pyramid feature map" (FPN), YOLOv3 employs small and large feature maps to identify large things and huge objects, respectively [30].

Table 1. In this Table representing few latest research advantage and disadvantage

Year's	Author's Name	Techniques	Advantages	Disadvantage
2019	Lokesh Allamki	mAP, OCR, Yolo,ALPR	Since every piece of software and library we utilized was open source, it was both versatile and affordable.	Using more open source software so that efficient customization is not accurate as requirements.
2022	Vijay Khare	Yolo-V3	YOLO can successfully list a particular object in an image.	YOLO is not appropriate for all items when there are numerous objects in an individual cell.
2021	Qingyang Zhou	AT-Yolo	We integrate the most effective training approach to boost network efficiency without raising inference costs.	To enhance the efficiency and precision of a video's object recognition, we will not able to the integrate the correlation of time series.
2020	Rui Geng	Yolo-V3	For processing like feature engineering, multi-resolution detection, and expanding the amount of anchor points, we can enhance algorithms like YOLOv3 or Faster RCNN.	Target detection criteria can no longer be met by the direct usage of YOLOv3 in a production environment.
2020	Anjana George	Darknet-53, CNN, YOLOv3	We have completely automated this procedure. The process will guarantee that complexity and time will be reduced.	Usually, the warning is manually inserted after the whole video file has been thoroughly screened. When done manually, identifying objectionable material in video sequences will take time.
2019	Fan Wu	YOLO V3, Densenet, CNN	This YOLO-Densebackbone convolutional neural network is created by replacing the foundation of a YOLO V3 system for feature extraction with the benefit of Densenet in hyperparameters and technical expense.	The initial network's issues with imprecise detection and overlapped bounding boxes are resolved.

Methodology

Accuracy and speed are required during real-time helmet and number-plate detection. For this, the You Only Look Once (YOLO) model based on DNN is used. YOLO is an algorithm for real-time object detection and recognition technology which is state-of-the-art.
YOLOv3 is a significant improvement over earlier YOLO versions in terms of speed and accuracy. It provides predictions using just one network appraisal, as opposed to systems like R-CNN that require thousands for a single image. As a result, it is 1000 times faster than R-CNN and 100 times faster than Fast R-CNN.
Custom Object identification is the art of finding various instances of a specific class in an images and videos, such as animals, humans, and others. Using pretrained custom object detection models, the Previous Object Detection API makes this simple to detect objects. However, these models detect a number of objects that are of no interest to us, So, it becomes necessity for custom object detector to discover the required classes.
Three objects must be recognized in order to accomplish whether user wear helmet and have number plate or not recognition and extraction. The different classes are – No Helmet, Helmet, and License Plate.
Weiner filtering method used for picture deblurring, image enhancement with segmentation, YOLO V3 for ROI, and CNN for Optical Character Reader were among the techniques, algorithms, and methodologies used in the proposed project's implementation.

A. Image Deblur

When any vehicle is recorded on a security camera, it moves in a planar motion. As a result, a fuzzy image is produced. As a result, the Weiner Filter is applied to deblur images. Take the car moving in a plane parallel to the i-axis. The following equation converts the amplitude recorded at pixel position (i,j) to an coherent image f(i,j) that could have been formed under perfect situations.

In perspective of an idealized image f(i,j), the blurred image h(i.j) is equivalent to

$$h(i,j) = \frac{1}{i_T}\Sigma_{k=0}^{i_O-1} f(i-k,j) \quad (1)$$

Where, i = 0, 1, ……………………, L - 1

i_O = The overall pixels captured by the camera with their brightness level.

L = It is used to denote the number of pixels present in a single row of a given image.

DFT of image h(i,j) is

$$\hat{H}(x,y) = \frac{1}{i_O}\sum_{k=0}^{i_O-1} \frac{1}{L^2}\sum_{l=0}^{L-1}\sum_{t=0}^{L-1} f(1-k,t)\, e^{-j\left(\frac{2\pi xl}{L}+\frac{2\pi yl}{L}\right)} \quad (2)$$

$$h(i,j) = \frac{1}{i_O}\Sigma_{k=0}^{i_O-1}\, e^{-j\left(\frac{2\pi xk}{L}\right)} \quad (3)$$

The Weiner Filter, whose equation is, is used to recover blurred images is as follows-

$$\hat{O}(x,y) = \frac{\frac{1}{i_O}\frac{Sin\left(\frac{\pi x\, i_O}{L}\right)}{Sin\left(\frac{\pi x}{L}\right)} e^{j\frac{\pi x}{L}(i_O-1)}}{\frac{1}{i_O^2}\frac{Sin^2\left(\frac{\pi x\, i_O}{L}\right)}{Sin^2\left(\frac{\pi x}{L}\right)}+\tau} \quad (4)$$

B. Helmet Detection

The various photos of each class with their corresponding annotated yolo supported text files are fed in YOLOv3 model, which is used to train for specific classes. The model is loaded with the weights obtained after completion of training. After that, a photo is offered as an input. All three training classes are detected by the model. This offers us information on the individual who is riding a motorcycle. If the rider is wearing a helmet or not, we can just gather the other class information on the rider.The license plate can be extracted using this method.

Fig. 1. Helmet Detection in Real-Time using YoloV3

C. Number Plate Detection

The majority of license plates have contrasting background and foreground colors. To properly perform the license plate localization, the proposed model must be trained using YOLO's custom weights. An ALPR system's ability to recognize and locate vehicle license plates is crucial. Here, YOLOv3 custom object detection algorithm is used, and includes significant design enhancements. There are a total of fifty-three convolutional layers in the proposed model. YOLO was previously not really very good at identifying small objects, however due to use of multi-scale predictions, YOLOv3 executes much well.

Convolutional neural networks YOLO are a completely convolutional network because it only uses convolutional layers (FCN). Darknet-53 has a more complicated architecture than other feature extractors. It uses a batch normalisation layer with a Leaky ReLU activation function after each of its fifty-three convolutional layers, as the name suggests. Then feature maps are downscaled via a convolutional layer having stride 2. This avoids the erosion of low-level attributes that pooling is known to cause.

The You Look Only Once(yolo) algorithm is utilised for custom object detection which is one among the fastest object detection algorithms available. It is an excellent choice for real-time object detection. This algorithm is used to detect the object's location, as well as the predicted class labels and the presence of every occurrence of objects in the image.

The Yolo V3's bounding box prediction is shown in Fig.2. Scores are assigned to each bounding box depending upon that class with which it may be linked. Here, we perform prediction on an image which contain onlysingle type of class from our list of classes which is number plate. Figure 3 shows the Yolo methodology of using a matrix-based technique to divide a picture into different regions and discover a Region of Interest (ROI). Yolo is illustrated in Fig. 4 marking different ROI options without using any filters. As illustrated in Fig. 4, here threshold value is fixed at 0.94 to filter just the most likely ROI.

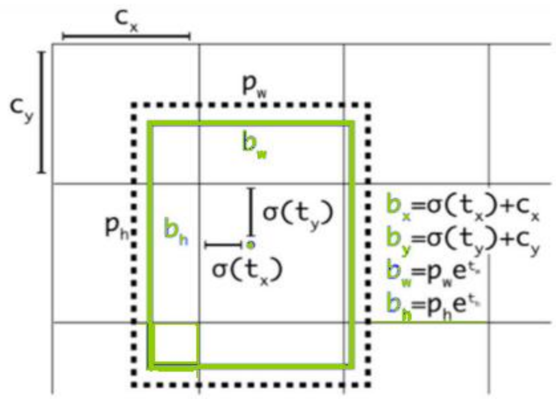

Fig. 2. Prediction of Different Bounding Boxes

Fig. 3. Yolov3 Grid Filtering

Fig. 4. YoloV3 Prediction

Fig. 5. YoloV3 Number Plate Detection

Fig. 6. Car's Number Plate Enhanced Image

D. License Plate Recognition

As once image has been trimmed from the desired area, it must be boosted using image processing method before displaying to the user and saving it in the database. Every character's image input format is just a 28 X 28 pixel-based picture.

CNNs make a comparison of input picture pixel wise or group wise of boxes. Convolutional neural networks are much preferable at sighted similitude than the whole picture comparison patterns because they compete for rough attribute contests in relatively comparable places in two images. Every attribute is a two-dimensional array of values that the predictive model uses to compare with other characteristics that contest common characteristics of the pictures. Simply multiplying each and every pixel of the image in the characteristic through the rate of corresponding pixel in the picture to evaluate the match of a characteristics to an image spot. Convolutions neural networks (CNN) are the result of this process of convolution. For the process of classification, different characteristics are taken from different areas of the image. The technique is repeated to compare the convolution, padding out the characteristic among each probable image patch. Every convolution layer's output is taken and used to create a new 2-Dimensional array depending on where every patch appears in the image. The very next phase is to replicate the convolution procedure N times in total, with a distinct convolution layer with each of the characteristics.

As a result, we have a collection of filtered

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photographs, one each for the filters. This entire array of convolution procedures can be thought of as a unique processing stage. Pooling is just a response enhancement method used by convolutional neural networks. Pooling is a method for reducing the size of large photographs while preserving the most important information. The ReLU is a modest but significant layers in this technique. If a negative number appears, replace it with Zero (0). This keeps the CNN scientifically healthy by preventing learnt standards from becoming trapped near 0 or exploding all the way to infinity.

Result

The Region of Interest (ROI) required for farther dealing out the picture that had to be supplied in the image enhancement function was successfully detected by the proposed model. 28 was chosen as the batch size. For speedier training, subdivisions were reduced to 16. There was just one class in the license plate detecting phase, as well as the filter size was fixed to 18. The initial weights for training were previously trained weight file from the darknet-53 convolutional layers.

Fig. 7. Car's Number Plate Detection using YoloV3

The above figure represents the Detection of Number Plate in Maruti Suzuki Car and locates its location using YoloV3.

Table 2. Tabulation of AP with average IOU each class

Epochs	Helmet	Plate	Avg IOU
1000	97.02	98.25	78.89
2000	98.34	98.69	84.56
3000	99	98.54	86.55
4000	98.17	98.89	77.68
5000	98.18	98.13	77.5
6000	98.63	98.73	75.69
7000	98.47	98.58	78.36
8000	98.3	98.45	79.62
9000	98.1	98.47	76.63
10000	98.31	98.53	80.6

For three classes, Table 2 displays the average IOU and average accuracy (AP) obtained by all iteration. We can choose the epoch with the greatest average IOU from Table 2 since it has the most overlap among the ground truthand the anticipated bounding box. For 64 batches with 8 subdivisions, the mean precision (mAP) is 97.9%, with an average training loss of 0.0829 for three classes. Table 3 shows the experiment's confusion matrix, while Table 4 shows recall, the precision, and F1-score tabulation. Table4 shows that the algorithm correctly identified 135 of the 137 non-helmeted motorcyclists as non-helmeted, while the other two were correctly identified as helmeted. In both situations, the recall rate is greater than 90%, indicating a low risk of false positives.

Table 3. The confusion matrix obtained from the experiments

	With helmet	Without helmet
With helmet	80	13
Without helmet	5	145

Table 4. Precision, recall and FI-score generated from the confusion matrix

	Precision (%)	Recall (%)	FI-Score (%)
With helmet	98.5	93.56	94.54
Without helmet	97.1	98.87	96.77
Weighted avg.	97	97.45	95.92

Conclusion

The YOLO helmet wearing detection model is proposed in this research. The modelling capacity of the network on the dependencies between distinct points in the image is strengthened by incorporating the attention mechanism into the YOLOv3 to substantially develop the model's feature demonstration ability and take out accurate features. Simultaneously, we combine the optimal training technique to improve network performance while lowering inference costs. We created a dataset and ran several assessment tests on it to check the performance of these proposed strategies. The experimental outcomes suggest that the strategies presented in this research develop the YOLO network's performance, making it an outstanding key for the helmet-wearing recognition method in real-world circumstances.

References

Chen Z, Ellis T. Self-adaptive Gaussian mixture model for urban traffic monitoring system[C]// IEEE International Conference on Computer Vision Workshops. IEEE, 2011:1771-1772.

DalalN,Triggs B. Histograms of Oriented Gradients for Human Detection[C]// 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR 2005, IEEE, 2005:886-893.

Burges CJC. A Tutorial on Support Vector Machines for Pattern Recognition[J]. Data Mining and Knowledge Discovery, 1998, 2(2):121-167.

Girshick R, Donahue J, Darrell T, et al. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation[C]// IEEE Conference on Computer Vision & Pattern Recognition. IEEE Computer Society, 2014:580-587.

Girshick R. Fast R-CNN [C]// Proc of IEEE International Conference on Computer Vision, 2015:1440-1448.

Ren S, He K, Girshick R, et al. Faster R-CNN: towards real-time object detection with region proposal networks [C]// Proceedings of the 2015 advances in Neural Information Processing Systems. Palais des Congrès de Montréal, Montréal CANADA, 2015:91-99.

R. Girshick, J. Donahue, T. Darrell and J. Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation,” in Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition, Columbus, Ohio, USA, pp. 580–587, 2014.

R. Girshick, “Fast R-CNN,” in Proc. of the IEEE Int. Conf. on Computer Vision, Santiago, Chile, pp. 1440–1448, 2015.

S. Ren, K. He, R. Girshick and J. Sun, “Faster R-CNN: Towards real-time object detection with region proposal networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.

B.E. Mneymneh, M. Abbas and H. Khoury, “Automated hardhat detection for construction safety applications,” Procedia Engineering, vol. 196, pp. 895–902, 2017.

K. Li, X. Zhao, J. Bian and M. Tan, “Automatic safety helmet wearing detection,” arXiv preprint, 2018. https://arxiv.org/abs/1802.00264.

F. Wu, G. Jin, M. Gao, Z. He and Y. Yang, “Helmet detection based on improved YOLOV3 deep model,” In 2019 IEEE 16th Int. Conf. on Networking, Sensing and Control, Banff, Canada, pp. 363–368, 2019.

X. Long, W. Cui and Z. Zheng, “Safety helmet wearing detection based on deep learning,” In 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conf., Beijing, China, pp. 2495–2499, 2019.

W. Liu, D. Anguelov, D. Erhan, C. Szegedy, A. C. Berg et al., “SSD: Single shot multibox detector,” In European Conf. on Computer Vision, Cham: Springer, pp. 21–37, 2016.

S. Chen, W. Tang, T. Ji, H. Zhu, W. Wang et al., “Detection of safety helmet wearing based on improved Faster R-CNN,” In 2020 Int. Joint Conf. on Neural Networks, Glasgow, UK, pp. 1–7, 2020.

GirshickRoss,DonahueJeff,DarrellTrevor,Malik Jitendra. Region- Based Convolutional Networks for Accurate Object Detection and Segmentation.[J]. IEEE transactions on pattern analysis and machine intelligence,2016,38(1).

HaodongPan,JueJiang,Guangfeng Chen. TDFSSD: Top-Down Feature Fusion Single Shot MultiBox Detector[J]. Signal Processing: Image Communication,2020,89.

Hao Ye,Geoffrey Ye Li,Biing-Hwang Juang. Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems.[J]. IEEE Wireless Commun. Letters,2018,7(1).

Ionut C. Duta,BogdanIonescu,KiyoharuAizawa,NicuSebe. Simple, Efficient and Effective Encodings of Local Deep Features for Video Action Recognition[P]. International Conference on Multimedia Retrieval,2017.

Hao Zhai. Research on Image Recognition Based on Deep Learning Technology[A]. Proceedings of 2016 4th International Conference on Advanced Materials and Information Technology Processing(AMITP 2016)[C]. Computer Science and Electronic Technology International Society,2016:5.

WangpengHe,ZheHuang,ZhifeiWei,ChengLi,Baolong Guo. TFYOLO: An Improved Incremental Network for Real-Time Object Detection[J]. Applied Sciences,2019,9(16).

Peng Q, Luo W, Hong G, et al. Pedestrian detection for transformer substation based on gaussian mixture model and YOLO[C]//2016 8th international conference on intelligent human-machine systems and cybernetics (IHMSC). IEEE, 2016, 2: 562-565.

Choi J, Chun D, Kim H, et al. Gaussian yolov3: An accurate and fast object detector using localization uncertainty for autonomous driving[C]//Proceedings of the IEEE International Conference on Computer Vision, 2019: 502-511.

Wu Y, Meng Z, Palaiahnakote S, et al. Compressing YOLO Network by Compressive Sensing[C]//2017 4th IAPR Asian Conference on Pattern Recognition (ACPR). IEEE, 2017: 19-24.

Molchanov V V, Vishnyakov B V, Vizilter Y V, et al. Pedestrian detection in video surveillance using fully convolutional YOLO neural network[C]//Automated Visual Inspection and Machine Vision II. International Society for Optics and Photonics, 2017, 10334: 103340Q.

Morera A´,Sa´nchez A´, Moreno A B, et al. SSD vs. YOLO for detection of outdoor urban advertising panels under multiple variabilities[J]. Sensors, 2020, 20(16): 4587.

J. Redmon and A. Farhadi, “YOLO9000: Better, faster, stronger,” in Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition, Honolulu, Hawaii, USA, pp. 7263–7271, 2017.

K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” arXiv preprint, 2014. https://arxiv.org/abs/1409.1556.

J. Redmon and A. Farhadi, “Yolov3: An incremental improvement,” arXiv preprint, 2018. https:// arxiv.org/abs/1804.02767.

K. He, X. Zhang, S. Re and J. Sun, “Deep residual learning for image recognition,” in Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition, Las Vegas, Nevada, pp. 770–778, 2016.

Laroca R, Zanlorensi L A, Gonc¸alves G R, et al. An efficient and layoutindependent automatic license plate recognition system based on the YOLO detector[J]. arXiv preprint arXiv:1909.01754, 2019.

Redmon J, Farhadi A. Yolov3: An incremental improvement[J]. arXiv preprint arXiv:1804.02767, 2018.

Chen F, Ma J. An empirical identification method of Gaussian blur parameter for image deblurring[J]. IEEE Transactions on signal processing, 2009, 57(7): 2467-2478.

Jamtsho, Yonten, PanomkhawnRiyamongkol, and RattapoomWaranusast. "Real-time license plate detection for non-helmeted motorcyclist using YOLO." Ict Express 7, no. 1 (2021): 104-109.

Gnanaprakash, V., N. Kanthimathi, and N. Saranya. "Automatic number plate recognition using deep learning." In IOP Conference Series: Materials Science and Engineering, vol. 1084, no. 1, p. 012027. IOP Publishing, 2021.

Shashidhar, R., A.S. Manjunath, R. Santhosh Kumar, M. Roopa, and S.B. Puneeth. "Vehicle Number Plate Detection and Recognition using YOLO-V3 and OCR Method." In 2021 IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC), pp. 1-5. IEEE, 2021.

Kadam, Sushant, Rushikesh Hirve, Nikhil Kawle, and Payal Shah. "Automatic detection of bikers with no helmet and number plate detection." In 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-5. IEEE, 2021.

Saeed, Maham, Muhammad Gufran Khan, Adil Zulfiqar, and Muhammad Tahir Bhatti. "Development of ANPR Framework for Pakistani Vehicle Number Plates Using Object Detection and OCR." Complexity 2021 (2021).

Setiyono, Budi, Dyah Ayu Amini, and Dwi Ratna Sulistyaningrum. "Number plate recognition on vehicle using YOLO-Darknet." In Journal of Physics: Conference Series, vol. 1821, no. 1, p. 012049. IOP Publishing, 2021.

Chang, Il-Sik, and Gooman Park. "Improved Method of License Plate Detection and Recognition using Synthetic Number Plate." Journal of Broadcast Engineering 26, no. 4 (2021): 453-462.

Kadam, Sushant, Rushikesh Hirve, Nikhil Kawle, and Payal Shah. "Automatic detection of bikers with no helmet and number plate detection." In 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-5. IEEE, 2021.

Prajwal, M.J., K.B. Tejas, V. Varshad, Mahesh M. Murgod, and R. Shashidhar. "Detection of non-helmet riders and extraction of license plate number using Yolo v2 and OCR method." International Journal of Innovative Technology and Exploring Engineering (IJITEE) 9, no. 2 (2019): 5167-5172.

Khan, Fahad A., Nitin Nagori, and Ameya Naik. "Helmet and number plate detection of motorcyclists using deep learning and advanced machine vision techniques." In 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA), pp. 714-717. IEEE, 2020.

Maheshwari, Vanshika, and Abhitosh Rajput. "Using the OCR Method with Yolo V2 to Detect Non-Helmeted Riders and Get License Plate Numbers." (2022).

Agrahari, Ashutosh, and Dhananjay Singh. "Smart city transportation technologies: automatic no-helmet penalizing system." In Blockchain technology for smart cities, pp. 115-132. Springer, Singapore, 2020.

Saini, Divyansh, Vedashree Arundekar, K. V. Priya, and Divya Jennifer D'Souza. "Identification of Helmets on Motorcyclists and Seatbelt on Four-Wheeler Drivers." In Recent Advances in Artificial Intelligence and Data Engineering, pp. 99-107. Springer, Singapore, 2022.

Saumya, Apoorva, V. Gayathri, K. Venkateswaran, Sarthak Kale, and N. Sridhar. "Machine learning based surveillance system for detection of bike riders without helmet and triple rides." In 2020 International Conference on Smart Electronics and Communication (ICOSEC), pp. 347-352. IEEE, 2020.

KM, Arya, and Ajith KK. "A Review on Deep Learning Based Helmet Detection." In Proceedings of the International Conference on Systems, Energy & Environment (ICSEE). 2021.

Jayasree, M. "Traffic Violation Proctoring System: Helmet and Triple Riding Detection." (2021).

Pillai, Arjun, Kajal Chourasia, Bhavya Agarwal, and Robin Singh Balyan. "Neural Network Based Traffic Monitoring using UAVs."