SEATBELT DETECTION IN TRAFFIC SYSTEM USING AN IMPROVED YOLOv5

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ABSTRACT: Seat belt is essential for avoiding fatalities and serious injuries in car accidents. Due to the challenge of identifying vehicles in images of a traffic scene that are affected by complicated illumination, the typical seat belt identification algorithm has low accuracy for determining the driver's seatbelt status. We proposed seat belt detection in a traffic management system utilizing an improved YOLOv5 algorithm developed by combining YOLOv5 with brightness augmentation. This procedure is used to improve existing algorithms for seat belt detection. The framework incorporates image enhancement, region proposal generation, depth feature extraction, target recognition, and detection into a convolutional neural network model, which significantly boosts training efficiency and detection accuracy. To examine the performance of the upgraded YOLOv5 detection algorithm, a benchmark dataset known as the Yawning Detection Dataset was gathered. The examination focuses on identifying the state of a safety belt between two classes: "seatbelt" and "non-seatbelt". The results demonstrate a high level of accuracy, with a mean average precision (*m*AP) of 96%, Precision of 99%, Recall of 99%, and a true positive score of 95.7%, indicating the system's effectiveness in identifying the safety belt status.

KEYWORDS: *Seatbelt Detection; YOLOv5; Convolutional Neural Network; and Yawning Detection Dataset*

1.0 INTRODUCTION

An intelligent transport system (ITS) is a sophisticated application that offers cutting-edge transport and traffic management capabilities. These technologies include alerting emergency personnel in the event of an accident, employing cameras to police traffic laws, and displaying signs that indicate speed limit changes based on conditions. The technologies used in intelligent transportation systems range from fundamental management systems like car navigation through traffic signal control systems, container management systems, variable message signs, automatic number plate recognition, and speed cameras, among others [1].

In addition, seat belt detection is an essential component of any Intelligent Transportation System. Wearing a seat belt is one of the most fundamental safety precautions as a seat belt protects humans from injury. For example, a sudden stop or a high-speed accident might directly endanger both the driver and the passengers. Consequently, to prevent such injuries, public safety officials require all drivers and passengers to wear seat belts, which act as a barrier and reduce fatalities [2]. Seat belt warning systems are also required to urge drivers to use their seat belts as accidents can happen to them at any time. Furthermore, failure to comply with the road safety code is critical as it can be dangerous to human life. It has been a concern that cars cannot meet the safety criteria if users have set the seat belt for themselves, resulting in more significant casualties and damage during accidents. In addition, it also positions children in more danger since the law requires them to always wear seatbelts [3].

Unfortunately, due to the existence of occlusions, cluttered backdrops, traffic density fluctuations, and the speed of detection, the typical technique for seat belt detection from surveillance footage becomes extremely difficult. The existing algorithms for such systems aren't particularly well matured, because of the complicated background and lighting, thus most of the results were poor. Besides, some of the algorithms required a longer time for seat belt recognition during the classification of images [4], [5]. In response, a novel method for detecting seat belts from surveillance films has been proposed, which employs a model based on YOLOv5 for effective detection in terms of speed and accuracy. To enhance the traffic images in the dataset, we applied a brightness augmentation algorithm prior. Seat belt detection can help prevent injuries in the event of a crash and additionally, for legal purposes, seat belt detection can help provide evidence of a driver's negligence in the event of a crash. The goal of this research is to reduce the error positive of the seat belt prediction with the aim of achieving more accurate detection in Intelligent Transport Systems.

2.0 LITERATURE STUDIES

The use of sensing, analysis, control, and communications technology to ground transportation in order to increase safety, mobility, and efficiency is known as intelligent transportation systems. An intelligent transportation system is made up of various applications that collect and communicate information to reduce congestion, improve traffic management, reduce environmental impact, and boost the advantages of transportation for commercial users and the public in general. Wearing a safety belt is absolutely essential for preventing fatalities and minimizing the severity of injuries [6]. It has been calculated that 3287 people die every day as a result of accidents, according to the research done by Khohli and Chadha [7]. A further claim made by Leland et al. [8] is that 1.35 million fatalities caused by car accidents are thought to occur annually. The capacity of car occupants to control the safety belt system through the use of a "seatbelt warning stopper" or by tightening the belt behind their backs presents another significant obstacle. The automatic identification and application of safety belt laws have consequently become more and more intriguing [9]. In order to satisfy the global demand of traffic safety authorities for automatic safety belt identification solutions that are not entirely reliant on onboard sensors, academics have focused their emphasis on the development of computer vision algorithms. Unfortunately, according to Zou et al. [10], existing object detection algorithms confront difficulties with regard to speed, accuracy, and environmental fluctuations.

Besides, by considering safe driving, a number of detection algorithms more specifically fall under deep learning categories have been applied for seat-belt detection by various researchers. Deep learning is a subset of machine learning in which neural networks are used to convey input values and output values via connections, matching the information processing of real biological nervous systems, which are made up of several layers of the perceptron. In order to understand the characteristics and classify the pattern, the input data would be organized into a hierarchy. The most common deep learning algorithm that has been applied widely towards seat-belt detection for various purposes is the convolutional neural network (CNN) and You Only Look Once (YOLO).

Table 1: Summary of Previous Studies

Author	*Method*	*Category of Algorithm*	*Result*
[11]	Convolutional Neural Network (CNN) & Support Vector Machine (SVM)	CNN	*Detection Rate 92.1%*
[12]	Multi-box object detector (SSD), Convolutional Neural Network (CNN), and Fisher Vector (FV)	CNN	*Accuracy 91.9%*
[13]	Convolutional Neural Network (CNN)	CNN	*Precision 0.63*
[14]	Convolutional Neural Network (CNN) and AlexNet	CNN	*Accuracy 90+%*
[15]	Convolutional Neural Network	CNN	*Accuracy 91.45%*
[3]	Convolutional Neural Network	CNN	*Precision 0.89*
[16]	YOLO	YOLO	*Accuracy 93%*
[17]	YOLO-DFAN	YOLO	*Accuracy Increased 5%*
[9]	YOLOv5 and ResNet34	YOLO	*Accuracy 97.2%*
[2]	*Tiny-YOLO*	*YOLO*	*Precision 0.9+*

The research was focused on performing seatbelt detection for complicated road backgrounds. On the other hand, [12] applied a near-infrared (NIR) and color (RGB) surveillance camera system pointed at the vehicle's windshield to investigate various strategies for detecting front-seat passenger seat belt violations. These authors employ object detectors, such as the single shot multi-box object detector (SSD), and picture classifiers, such as the convolutional neural network (CNN) and Fisher vector (FV), to identify seat belt usage. Moreover, [13] proposed a new convolutional neural network (CNN) architecture for 2D driver/passenger position estimation and seat belt detection. Compared to prior general posture estimate techniques, the new architecture is more agile and thus better suited for in-vehicle monitoring applications.

The new design, known as NADS-Net, uses a feature pyramid network (FPN) backbone with numerous detection heads to obtain the best performance for activities involving the detection of the driver/passenger condition. Besides conducting the experiments offline, the author [14] proposed his solution in real-time detection. Sensors are configured to detect the weather and contribute to increasing the detection's accuracy. A pre-trained model is given the responsibility of detecting a specific weather condition when it is discovered. Consequently, it is to see if it's possible to split up a large deep-learning model that can identify automobile seatbelts into smaller models, each of which can recognize a different weather scenario. As a result, each meteorological situation is represented by a single specialized model, AlexNet, a Deep Convolutional Neural Network (CNN) model. Moreover, (Ramakrishna et al., 2021b) have proposed Convolutional neural networks as a way to determine whether or not the driver is fastened to a seat belt. ConvNet automatically collects features from photos using filters or kernels without human intervention in order to classify the output images in this study. The least amount of preprocessing is needed in ConvNet compared to other classification techniques.

The Seatbelt dataset, which includes both standard and non-standard data, is used to build and train ConvNet initially. Alternatively, [3] was conduct a series of experiment using different preprocessing and deep learning approaches under the baseline model which is Convolutional Neural Network. To help the responsible authorities determine whether the drivers of the vehicles going through the entrance have fastened their seatbelts, the suggested approach can be used in any organizational setup. The number plate recognition module logs the car's license plate if a seat belt is not found in the vehicle. The relevant authorities might utilize this record to take any additional steps that are required. The organization's administrators may then monitor all the cars that enter the property and make sure that the drivers and occupants of the shotgun seats are all buckled up. Consequently, the YOLO family algorithm based on CNN architecture has also been receiving much attention by the research community. Recently, YOLO has been applied as the seat belt detection algorithm as it has more flexibility such as in choosing the series of inner combination methods like preprocessing and more specifically improvement of accuracy rate. For example, [16] has considered seat belt identification model based on the YOLO neural network was suggested by the author to determine whether the driver's seat belt was fastened.

The main components of belt detection and corner detection were used as the two steps in the solution. These actions enable the system to detect the circumstance in which the seat belt is secured behind a person. The main portion of the belt was identified as the first item, and the belt corner was identified as the second object, using tiny-YOLO. The model divides belt fastness into three categories: incorrect belt fastening, incorrect belt fastening, and belt fastening behind the back. Furthermore, [17] has proposed You Only Look Once (YOLO) dependency fusing attention network (DFAN) detection and is enhanced based on the thin network YOLOv4-tiny.

The author employs atrous spatial pyramid pooling network, DFAN, and path aggregation network (PANet) to replace the feature pyramid network (FPN) of the original network in order to make three significant improvements to the baseline network in response to the difficulty of extracting the features of an object with a low effective pixel ratio, which is an object with a low ratio of the actual area of the detection anchor area in the YOLOv4-tiny network. In addition, [9] proposed a brand-new method for occupant detection and seatbelt status monitoring is proposed. It is based on deep learning models. Using the YOLOv5s network, the windscreen is initially identified in this technique. Deep learning-based algorithms are then used to detect the presence of a passenger and the driver's seat belt rule infringement.

To achieve this, a combination of the 34-layer ResNet34 residual neural network with a power mean transformation layer and either temporal or spatial pyramid pooling layers is used. Meanwhile, [2]has proposed the YOLO neural network-based model was used by the author to perform detection to determine whether the driver's seatbelt is fastened. The first item was identified as the belt's main component using tiny-YOLO, and the second item as the belt's corner. The suggested model divides belt fastness into two groups: either the belt is not properly fastened, or it is not fastened correctly. The author of this study asserted that You Only Look Once (YOLO) will enable precise seatbelt recognition while presenting the extensive seatbelt dataset that was compiled from multiple sources. The entire previously proposed method, however, faces several difficulties, including managing constant lighting changes while the car is moving, the possibility of color similarities between the safety belt and the passengers' clothing, blurriness in images due to vibration and bumpy roads, and occlusion caused by objects like hands, hair, and clothing [8]. Subsequently, this has influenced the detection difficulties and directly affected the accuracy rate. Hence, there is room for improvement, more specifically in increasing accuracies via enhancement algorithms.

3.0 THE PROPOSED IMPROVED YOLOv5

Figure 1 illustrates the suggested model that is involved in seat belt detection. The YOLOv5 base model serves as the foundation for the suggested model. These base model designs were enhanced to make it possible to adopt the brightness augmentation function, and these function theories formulate the result of the ambient brightness function and the object reflection function as follows:

$$S(x,y) = R(x,y).L(x,y) \qquad (1)$$

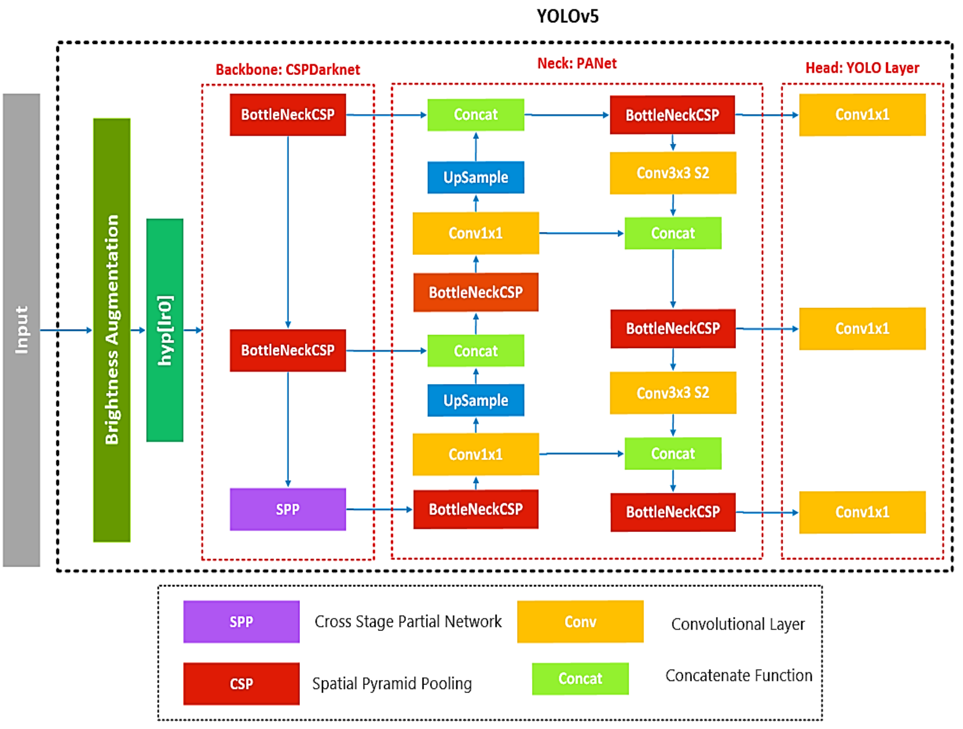

Figure 1: The Proposed Yolov5 Enhancement Model

where *S(x,y)* is the image enhanced, L*(x,y)* is the ambient brightness function, *R(x,y)* is the object reflection function, and *(x,y)* is the coordinates of the image pixel coordinates. The model then produced the improved picture R(x,y) when L(x,y) was calculated from the enhanced image S(x,y) during the image enhancement process. In practical situations, uneven outside lighting or shadows from towering structures or trees might lead to poor image quality. To circumvent this, the input photos are first transformed into a series of frames, with detection procedures set to occur at each individual frame using the YOLOv5 model. Brightness data enhancement, image size processing, and adaptive anchor box computation are all included in the input end. By combining four photos, brightness data improvement has improved the backdrop and the quantity of small items in the dataset.

The image size processing evenly adjusts original photos of various lengths and widths to a standard size while adding minimal black borders. In order to determine the most appropriate anchor box value, the adaptive anchor box computation compares the output predicted boxes with the actual boxes based on the beginning anchor boxes, calculates the gap, and then updates it in reverse.

The YOLOv5 model, which consists of four parts: the end of the Input, Backbone, Neck, and Prediction, receives the extracted frames for the detection process. The Backbone consists of the Focus, CSP, and Spatial Pyramid Pooling (SPP) structures. There are 45 layers in all the convolution. Since slicing operations are the principal usage of the Focus structure, feature extraction is considered sufficient. Using the CSPNet network's structure as a guide, two CSP structures were created for the YOLOv5 network: CSP1_x is located in the Backbone, while CSP2_x is positioned in the Neck. SPP maximises the pooling of the input graph using the convolution kernel $(k = \{1 \times 1, 5 \times 5, 9 \times 9, 13 \times 13\})$, and then splices the generated feature graphs of various scales. The SPP module has a substantial impact on feature extraction efficiency. The Feature Pyramid Network and Path Aggregation Network (FPN and PAN) make up the two components of the Neck module. To enhance the ability of feature extraction, the FPN fuses data by top-down up-sampling whereas the PAN sends data in a bottom-up pyramid. Non-maximum inhibition (nms) and Bounding Box Loss (a regression loss function) are included in the prediction. The loss function used by YOLOv5 is called GIOU_Loss. GIOU_Loss can address the issue of non-overlapping bounding boxes in comparison to IOU_Loss. In order to increase the likelihood of identifying the ideal detection box, YOlOv5 employs weighted in nms.

4.0 EXPERIMENTS AND RESULTS

4.1 Data Source

The proposed seatbelt detection model has been evaluated using a benchmarked dataset known as the Yawning Detection Dataset [18]. This dataset comprises various images separated into traffic, seatbelt, and non-seatbelt labels. Since the dataset comprises several real images and is publicly available, several researchers have evaluated their proposed solution using this dataset. However, some duplication images have been eliminated during the evaluation stages. The distribution of the dataset is as follows:

4.2 Performance Metrics

Based on previous studies, most of the researchers evaluated their proposed detection model based on precision, recall and mAP. The proposed detection model has also been evaluated using similar performance metrics as follows:

Precision:

$$Precision\ (P)\ =\ (TP)\ /\ (TP + FP)\quad (2)$$

Recall:

$$Recall\ (R) = (TP)\ /\ (TP+FN)\quad (3)$$

Mean Average Precision:

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \quad (4)$$

False negative (FN) and False positive (FP) refers to incorrect prediction made by the detection models. FN represents a case where the class seatbelt is identified incorrectly while FP represents a case where the class non-seatbelt is identified incorrectly. True negative (TN) and true positive (TP) refers to correct prediction made by the detection models. TN represents a case where the class seatbelt is identified correctly while TP represents a case where the class non-seatbelt is identified correctly.

4.3 Proposed Work Performance Evaluation

A series of evaluations via distinct metrics have been conducted against the improved YOLOv5 proposed detection model using a Yawning Detection Dataset benchmark dataset.

Table 2: Result of Precision, Recall and mAP Using Training Set

Class	Labels	*P*	*R*	*mAP*
Seatbelt	226	86%	89.5%	90.5%
Non-seatbelt	64	99%	96.9%	98.9%
Average		92%	89.5%	94.7%

Referring to Table 2, in training stage, the average result for precision, recall and *mAP* is 92%, 89.5% and 94.7% respectively.

Moreover, further evaluation has been conducted against the proposed method using seen and unseen images using testing set. The outcomes shown in Figures 4.1 represent a high level of efficiency, especially for the "person" class (also known as non-seatbelt) at 99.5%, "seatbelt" class at 92.6%, and *mAP* of 96%. Furthermore, out of 71 seatbelt images class, the proposed model can predict 68 images correctly while 3 images as false negative. The graphical results for precision, recall, mAP, and F1 score are shown in Figures 2 to Figure 5.

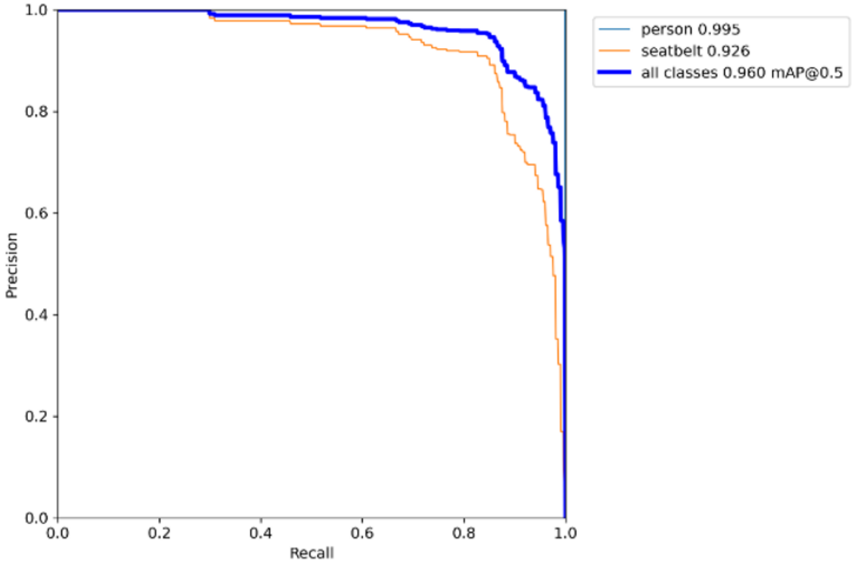

Figure 2: Result of Precision-Recall Curve (*mAP*)

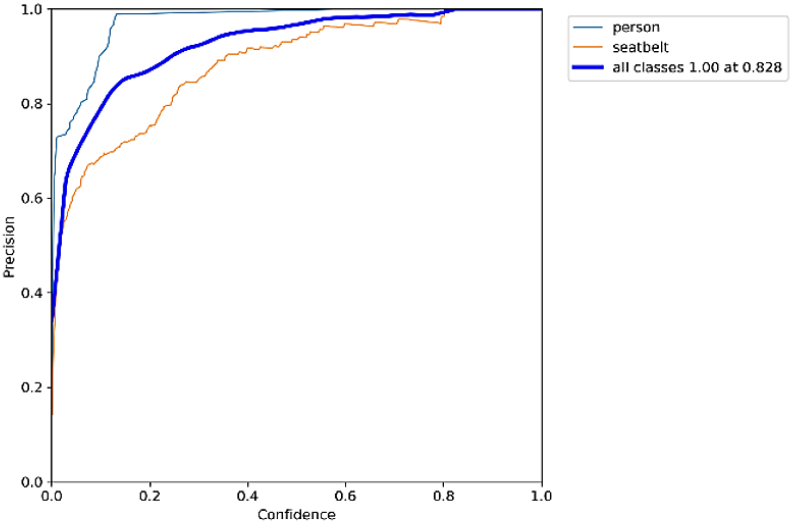

Figure 3: Result of Precision Curve

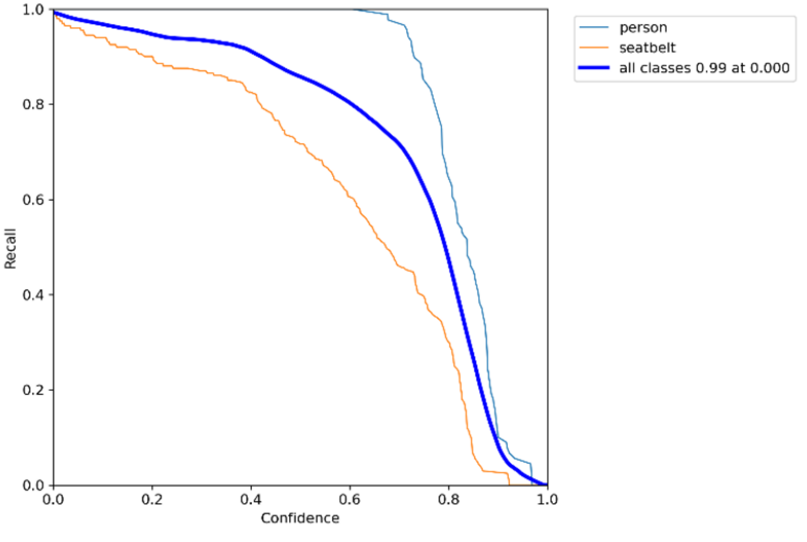

Figure 4: Result of Recall Curve

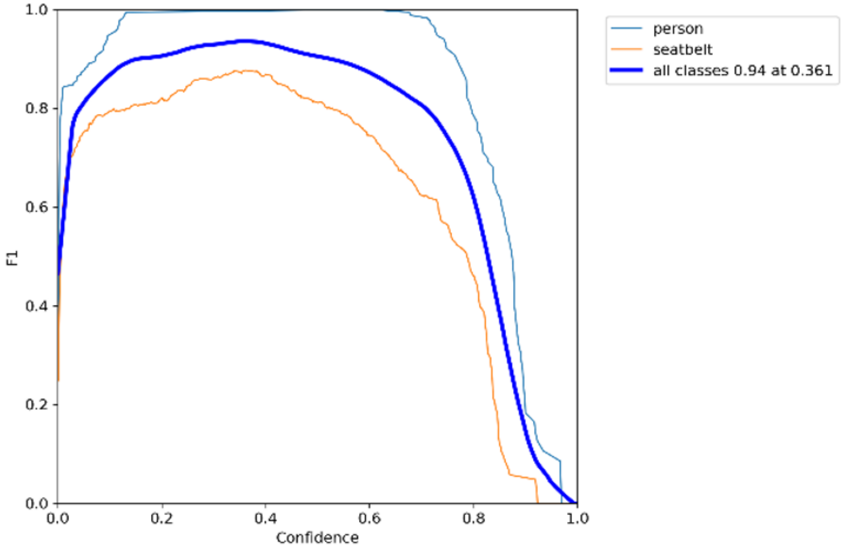

Figure 5: Result of F1

4.4 Previous Work Performance Comparison

A comparison of the outcomes of the evaluated relevant research was done to further highlight the superiority of the suggested study, and the results are provided in Table 3.

Table 3: Previous Work Comparison

Author	Methods	Result
[19]	CNN	Precision 63.58%
[20]	CNN + Alex Net	True Positive 92%
[6]	CNN based	Precision 86.88% Recall 96.36%
[2]	Tiny-YOLO	Precision 90%
Proposed Model	Improved YOLOv5	*mAP* 96% Precision 99% Recall 99% True Positive 95.7%

The output of the proposed model surpasses every previously examined object detection model, as shown by the findings in Table 3. The suggested concept, however, illustrates the useful benefits of safety belt detection.

5.0 CONCLUSION AND FUTURE WORK

The current study looked towards identifying a vehicle's seatbelt using an improved YOLOv5 algorithm. The Yawning Detection Dataset, a benchmark dataset, was used to build the model and assess its performance. The dataset consists of several photos that were split into classes for people wearing seatbelts and those who weren't (also known as non-seatbelt classes). The results of the present study showed a better level of effectiveness during the model training process compared to previous pertinent studies that were analyzed. The investigational study successfully met a mean average precision (mAP) threshold of 0.50 with a mean average precision (mAP) of 96%. Additionally, it received a true positive score of 95.7% and a recall score of 99% within the model. The proposed model is capable of accurately differentiating between the buckled and unbuckled states of a seat belt. Nonetheless, it is advised that future studies focus more on enhancing models' capacity to precisely detect the presence of seat belts under circumstances characterized by high levels of illumination to progress the field. Examining recent iterations of the YOLO algorithms, which have shown higher levels of precision and resilience in comparison to alternative object detection algorithms used in comparable research endeavors, is one potential strategy for resolving the issues related to lighting conditions.

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