Enhancing Road Safety through Drowsiness Detection in Advanced Driver Assistance Systems Using Artificial Intelligence

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Abstract –
Advanced Driver Assistance Systems (ADAS) have changed how we drive by adding safety features. Since drowsy driving is a major cause of car accidents, ADAS must identify it. Drowsiness detection in ADAS utilising AI can accurately detect early indicators of tiredness, such as changes in driving behaviour, head motions, and eye movements. AI enabled systems can effectively notify drivers to take a break, pull over, or take other safety precautions. In this paper we are discussing the implementation of Artificial Intelligence in drowsiness detection for the enhancement of road safety.

Keywords – ADAS, Drowsiness Detection, Artificial Intelligence, Object Detection, Yolov5

I. INTRODUCTION

Modern vehicles are increasingly equipped with advanced driver assistance systems (ADAS), which provide drivers with tools to enhance safety and prevent accidents. A crucial component of ADAS is drowsiness detection system, which can warn drivers when they are becoming fatigued and at risk of falling unconscious behind the wheel. Drowsiness is a significant issue for drivers, as it can impair their reaction times, judgement, and decision-making skills, resulting in severe accidents. Traditional techniques for detecting drowsiness, such as monitoring pulse rate or tracing eye movements, have limitations in terms of accuracy and efficacy. To enhance drowsiness detection, researchers have turned to artificial intelligence (AI) techniques. AI-based drowsiness detection systems can accurately detect when a driver is becoming drowsy by analyzing data from multiple sensors, such as cameras and accelerometers.AI-based systems can also utilize machine learning algorithms to learn from the driver's behavior and increase detection accuracy over time. In addition, deep learning algorithms can analyze facial expressions to detect signals of fatigue that are difficult to observe with conventional methods. The combination of AI and ADAS has the potential to substantially reduce accidents caused by drowsiness. AI-based drowsiness detection systems can enhance road safety and save lives by alerting drivers when they are becoming sleepy and at risk of falling unconscious. In this paper, we are focusing on the implementation of AI by using object detection algorithms in detecting drowsiness in order enhance safety on the road.

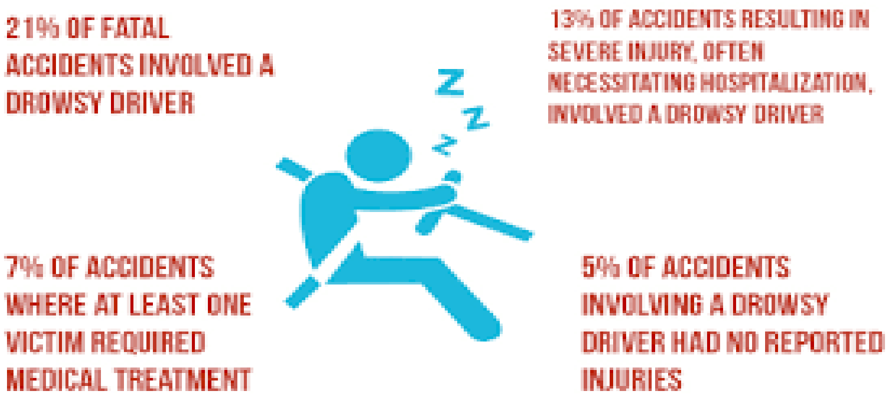

Fig. 1. Accidents caused by drowsy drivers [& Layne, PLLC]

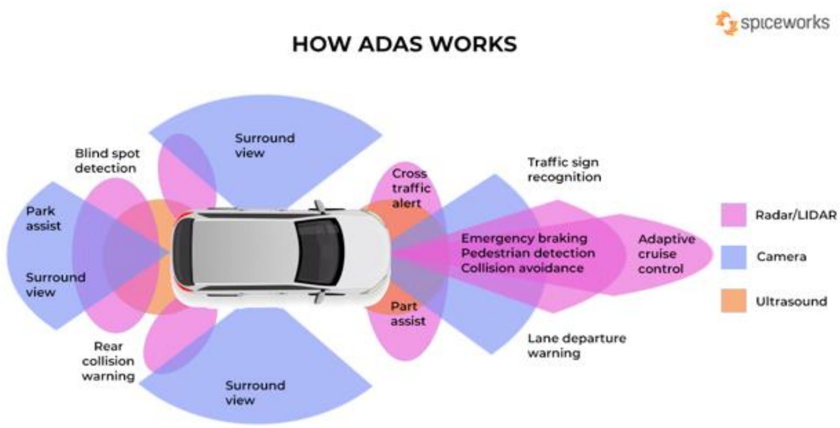

Fig. 2. Working of ADAS System ["What Is ADAS (Advanced Driver Assistance Systems)? Meaning, Working, Types, Importance, and Applications - Spiceworks"]

II. LITERATURE REVIEW

Human error causes 94%–96% of automobile accidents, according to the NHTSA. in 2016. At least 90% of automotive crashes are triggered by human error, according to many studies. 20% of drivers have passed out while driving in the last year, and 40% have done so at least once [1]. Advanced Driver Assistance Systems (ADAS) remove human error in vehicle operation. Driver performance is improved by ADAS systems' advanced technology. ADAS uses a variety of technologies for sensors to detect the vehicle's surroundings and inform the driver about them or take action. The driver's eyesight, sensibility, and decision-making are enhanced by ADAS sensors. Are you night-sighted? RADAR can. Before reversing, can you echolocate a youngster behind your car? However, SONAR sensors can. Do you have 360-degree vision? cameras and LiDAR technology can. Always aware of your latitude and longitude? Your car may get this and other data from numerous sets of global positioning satellites [2]. AI, image processing, and IoT are frequently utilised to improve road safety since they autonomously acquire and assess data without human mistake. [3]. Deep Learning has completed the revolution of object recognition, a key area in computer vision. Automobiles, robotics, and industry have been impacted by deep learning. Computer vision's object recognition or classification approach detects an object instance or class in a digital picture, such as face or individual detection [4].Single-stage detectors from YOLO to RefineDet[5]. R-CNN to the latest mask R-CNN object detection models. The YOLO-v5 method sends training data via the data injector and improves it. The data processor can conduct scaling, colour space modification, and mosaic enhancement [6].

III. METHODOLOGY

The process for creating an AI-based drowsiness detection model is as follows:

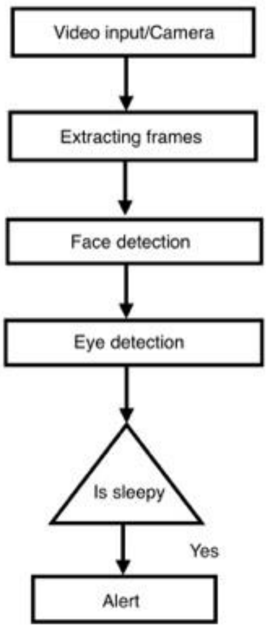

Fig. 3. Drowsiness detection flowchart

A. Data Collection : Collecting data is the initial phase in creating an artificial intelligence-based drowsiness detection system. In our research, we collected 200 high resolution images taken in different lighting conditions.

B. Data Pre-processing : The second stage is data pre-processing, which includes labelling images, changing their orientation, cropping the image, applying grayscale, etc. We have utilised roboflow, a tool for image labelling. It is a free instrument that accelerates the image labelling process.

Fig. 4. Dataset used in the study

C. Selection of object detection algorithm : Object detection is a computer vision technique that enables the identification and localization of objects within an image or video. With this type of identification and localization, object detection can be used to accurately label and count objects in a scene, as well as determine and monitor their precise locations. Consider an image containing two animals and a person, for instance. Object detection enables us to simultaneously classify and locate instances of the detected objects within an image. Multiple object detection algorithms exist, including region-based convolutional neural networks (R-CNN), faster R-CNN, single shot detectors (SSD), and you only look once (YOLO). We utilised the YOLOv5 object detection model in our research due to its rapid computation and processing speed, particularly in real time.

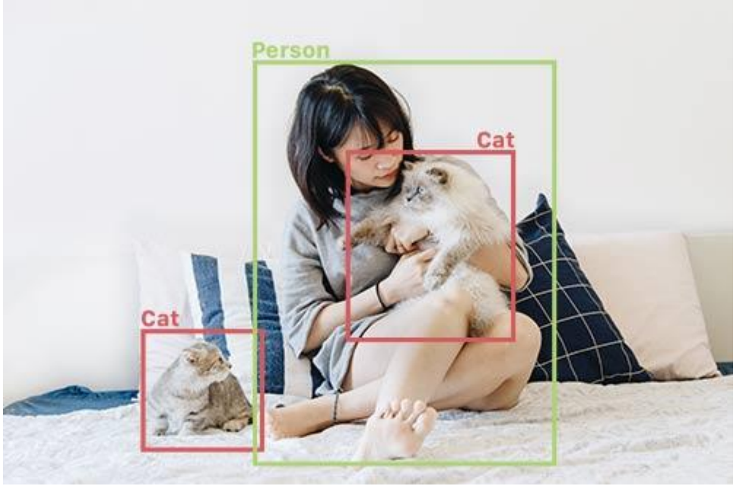

Fig. 5. Object detection
["Object Detection Guide | Fritz AI." *Object Detection Guide | Fritz AI*, www.fritz.ai/object-detection.]

D. *Model Training:* Training the model is the most important aspect of developing AI for drowsiness detection. To train the model, several parameters must be determined. The batch size and image size come first, followed by the epoch values and model weight. We utilized a 320x320 image with 16 batches and 300 epochs. The Yolo model is available in multiple sizes; we chose a small one for our research.

E. *Model Evaluation:* The model generates multiple metrics, such as the f1 curve, confusion matrix, recall curve, etc., after successful training. To evaluate the performance of the model, the f1 curve, mean average precision (mAP), and recall values were utilized. In addition, we evaluated the model using photographs, videos, and a live camera feed.

IV. Implementation

A. *Developing drowsiness detection using YOLOv5 involves the following implementation steps:*

1. *Installing and importing dependencies :* The first step is to import and install dependencies such as PyTorch, Numpy, Matplotlib, and CV2, and then use the git command to clone the model. After integrating dependencies, the requirements.txt file from the Yolov5 repository was installed.

2. *Loading the model* : The Yolov5 model from the Ultralytics repository was imported into a variable using the torch.hub.load command.

3. *Making initial detections :* To verify that the model has been accurately loaded, we performed some preliminary OpenCV detections on photos and through the web camera. The model could distinguish objects such as automobiles, buses, people, etc.

4. *Labelling of images :* For supervised machine learning, labelled data are essential. We utilised roboflow, an open-source software for image labelling that made the process of image labelling quicker and more accurate.

5. *Training on custom dataset :* Our custom dataset of 100 awake and 100 drowsy images was utilised to train the model. The sizes of the image and batch were 320 and 16, respectively. Yolov5s was trained for approximately 24 hours with over 300 epochs

6. *Loading the final model :* After training the model, we loaded it and conducted detections on images of drowsy and awake individuals. We also utilised CV2 to create webcam-based detections.

B. Challenges faced during implementation phase

1. *Deciding the appropriate dataset size :* Choosing the optimal dataset size is a difficult task. Training on an insufficiently-sized dataset will not produce the intended results. Nevertheless, training on a large dataset, such as 4000 images, will require significant time and resources. Furthermore, training on a large dataset necessitates a robust CPU and GPU.

2. *Configuring the train command :* Train command requires multiple parameters, including image size, batch size, epoch value, etc. Choosing the ideal values requires effort. In addition, the folder structure of YOLOv5 is not straightforward, and it is sometimes necessary to search for the correct path to the dataset.yaml file, which is essential for effectively executing the train command.

3. *Exiting from web camera window :* Although using open cv to access a web camera is straightforward. However, exiting the launched window does not always work. Additionally, the live camera feed will become obstructed if your CPU and GPU are underpowered.

V. RESULTS

The dataset used in training consists of 200 images captured under different lighting conditions and labelled "awake" or "drowsy." This dataset is intended for use in drowsiness detection-related machine learning applications. The dataset could be utilised for training and evaluating machine learning models that can distinguish between conscious and drowsy states based on visual signals from images. The dataset could be analysed further to ascertain how illumination affects the accuracy of drowsiness detection systems. Mean average precision (mAP), precision, recall, and the model's f1 score are utilised to evaluate the model's performance. These metrics provide an approximation of the model's performance under various conditions.

Metrics	Results
mAP	99.5%
precision	99.4%
recall	95.0%

Fig. 6. Metrics of our model

mAP calculates the average precision (AP) for every class and then takes the mean across all classes. The AP is a measure of how well the model retrieves pertinent search results. A mAP score of 99.5% indicates that our model performs exceptionally well on the task we evaluated it for. Precision is defined as the ratio of true positives to the sum of true positives and false positives. In other terms, it quantifies the proportion of accurate positive predictions made by the model. A precision of 99.4% indicates that our model has an exceptionally low rate of false positives, i.e., it makes very few erroneous positive predictions. Recall is the ratio of true positives to the sum of true positives and false negatives, or Recall = TP / (TP + FN). In other terms, it assesses the proportion of positive instances correctly identified by the model. A recall of 95% indicates that our model can accurately identify 95% of the positive instances in the dataset.

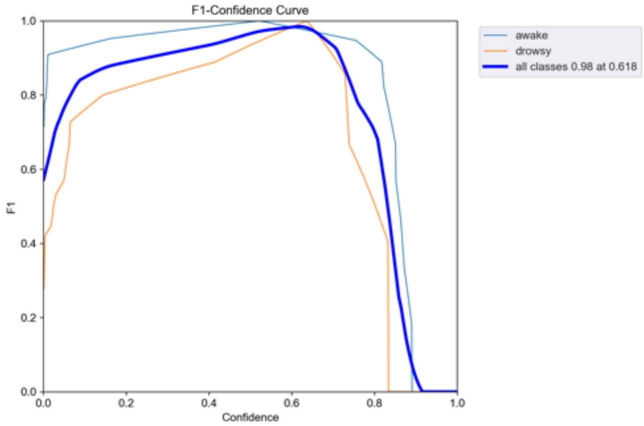

Fig. 7. F1 Curve of drowsiness detection model

An F1 curve is a plot of the F1 score for a binary classification model as a function of the classification threshold. The threshold represents the probability score above which the model classifies a sample as positive, and below which the sample is
classified as negative. In a multi-class classification problem, the F1 curve can be computed for each class, and it plots the F1 score for that class as a function of the classification threshold. The phrase "all classes 0.98 at 0.618" suggests that the F1 score for all classes in the multi-class classification problem is 0.98 at a classification threshold of 0.618. This means that the model has high precision and recall for all classes at this particular threshold value.

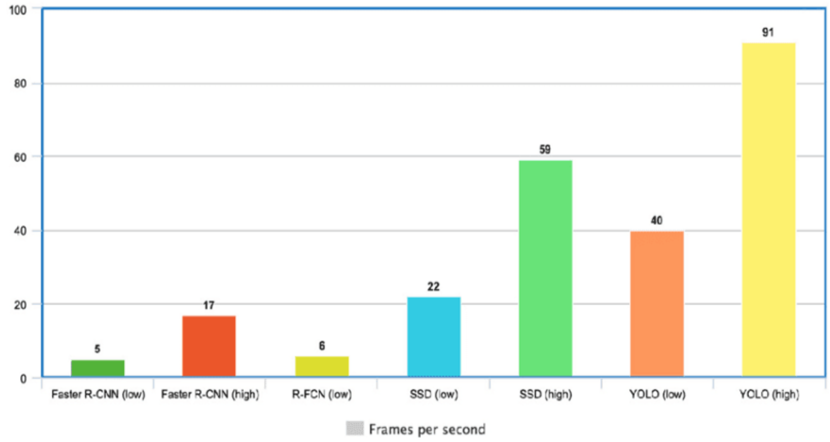

Fig. 8. Comparison of object detection algorithms framespersecond https://www.datacamp.com/blog/yolo-object-detection-explained

Frames per second (FPS) is a crucial metric for drowsiness detection in automobiles because it impacts the accuracy and responsiveness of the object detection system used to monitor the driver's behaviour. Object detection systems for drowsiness detection typically analyse video footage from a camera mounted on the dashboard or steering wheel of the vehicle using computer vision algorithms. These algorithms use real-time video processing to detect and monitor the driver's facial features, such as their eyes and mouth, as well as to detect signs of drowsiness such as drooping eyelids or yawning. The greater the FPS, the greater the frequency with which the object detection system can capture and analyse images of the driver's visage. This improves the accuracy and reliability of drowsiness detection, as the system is now able to detect even subtle changes in the driver's facial expressions that indicate lethargy. If the FPS is too low, however, the object detection system may overlook crucial details or movements of the driver's visage, resulting in inaccurate or delayed detection of drowsiness. This can be hazardous because it may cause accidents or other road safety hazards. YOLO is incredibly quick due to the absence of complex pipelines. It can compute 45 frames per second (FPS) of images. Moreover, YOLO achieves more than twice the mean Average Precision (mAP) of other real-time systems, making it an excellent candidate for real-time processing. With 91 frames per second, YOLO is far superior to other object detectors, as shown in the Fig. 8.

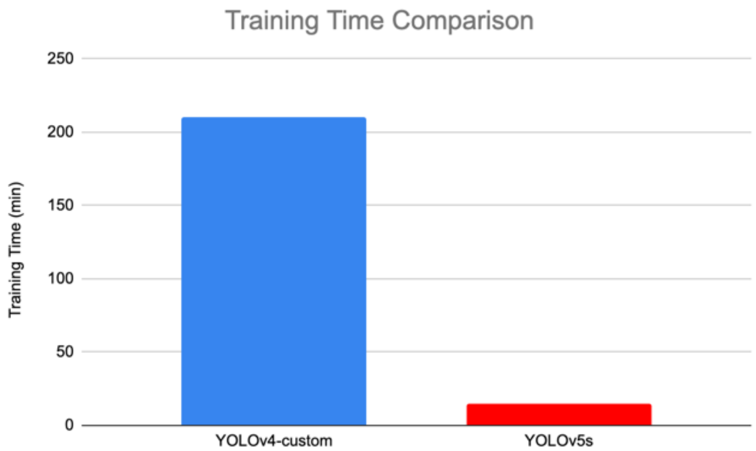

Fig. 9. Training time comparison

One of the most significant enhancements to the YOLOv5 architecture is the addition of the Focus layer, represented by a single layer, which replaces the first three layers of YOLOv3. This integration decreased the number of layers and parameters and increased both forward and reverse speed without significantly affecting the mAP.

Fig. 10. Model results on validation images

In object detection tasks, a bounding box with a score of 0.9 for the awake class and a red colour suggests the model is confident that it has detected a "awake" class object in the image. The score indicates the degree of trust in the model's prediction, with a score of 0.9 indicating a high level of confidence. The colour of the bounding box can be used to indicate the class of the detected object; in this case, red indicates the "awake" class. Our machine learning model's drowsiness detection accuracy is extremely high, based on the metrics . The following is a concise summary of what these metrics indicate: Mean average precision (mAP) of 99.5% is a common evaluation metric for object detection models that evaluates the average precision across various levels of recall. A mAP of 99.5% indicates that our model can detect drowsiness with high precision and recall. Precision of 99.4%: Precision is the proportion of true positives (i.e., correctly identified instances of lethargy) among all positive instances. A precision of 99.4% indicates that our model rarely misidentifies non-drowsy instances as drowsy, or that it has a very low rate of false positives. Recall of 95.0%: Recall assesses the proportion of true positives among all actual positive instances (whether identified correctly or erroneously). A recall of 95.0% indicates that our model correctly identifies the majority of drowsy instances and has a low rate of erroneous negatives, i.e., it overlooks actual drowsy instances only rarely. These metrics indicate that our model detects drowsiness with a high level of precision and recall. These high performance values may be beneficial in real-world settings where detecting fatigue is crucial for safety, such as in transportation and heavy machinery operation. However, it is essential to bear in mind that the performance of the model can vary depending on the specific use case and dataset, and it is always recommended to evaluate the model's performance in a variety of scenarios before deploying it in real-world applications. Depending on the specific implementation and configuration, faster R-CNN has attained a mean average precision (mAP) of up to 42.1%. This is less than the mAP of 99.5% which we have achieved with our model, indicating that your model may outperform Faster R-CNN in terms of overall detection accuracy.

Algorithms	Speed	Accuracy	Ease of Implementation
Faster RCNN	Bad	Good	Bad
SSD	Good	Good	Bad
Yolo	Good	Good	Good

Fig. 11. Comparison table of object detection algorithms

Single Shot Detector (SSD) and You Only Look Once (YOLO) are significantly faster than the Faster R CNN algorithm. Faster R CNN is based on two shot detectors, which requires two image analysis stages. In addition, Faster R CNN can only produce 7 frames per second on a single GPU, which is less than the other algorithms. In terms of precision, the algorithms perform comparably. However, in terms of implementation simplicity, YOLO is superior to the other two. YOLO can be implemented with significantly less code and is simpler to implement than the other two algorithms.

VI. CONCLUSION

Using artificial intelligence (AI) to detect drowsiness in advanced driver assistance systems (ADAS) has the potential to significantly enhance road safety. Using object detection models such as YOLOv5, which can accurately detect and localise key features of the face and eyes that are indicative of drowsiness, is a promising method for detecting drowsiness. YOLOv5's high precision and recall rates indicate that it is a promising model for detecting drowsiness in ADAS. It is essential to note, however, that the efficacy of any AI-based system for drowsiness detection will depend on a number of factors, including the quality and diversity of the dataset, the system's design and configuration on which the model is being trained, and the deployment context. Therefore, ongoing research and collaboration between researchers, industry partners, and regulatory bodies will be required to guarantee that these systems are safe, effective, and dependable. Overall, the use of AI and object detection models such as YOLOv5 for drowsiness detection has the potential to substantially enhance road safety by alerting drivers who are at risk of falling asleep behind the wheel. Although there are still numerous obstacles to surmount, the rapid development of AI technology and the rising demand for safer and more efficient transportation systems make this an intriguing area of research and innovation.

VII. REFERENCES

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