IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

DRIVER DROWSINESS MONITORING SYSTEM USING YOLOV8

[1]P.Vijay Bhaskar Reddy, [2]S.Sai Rachana

Abstract: Drowsiness describes the state of being drowsy or sleepy. A person experiencing drowsiness may feel tired or sluggish and have difficulty staying awake. According to Central Road Research Institute (CRRI),40% of road accidents are caused due to drive drowsiness.Nowadays, more and more professions require long-term concentration. Drivers must keep a close eye on the road, so they can react to sudden events immediately. Driver fatigue often becomes a direct cause of many traffic accidents. Therefore , there is a need to develop the systems that will detect and notify a driver of her/him bad psychophysical condition, which could significantly reduce the number of fatigue-related car accidents. Based on that large dataset, we developed and evaluated a feature selection method based on the YOLO algorithm for the driver's state classification.

Index Terms **-driver safety, drowsiness, computer vision, yolo model, deep learning.**

I. INTRODUCTION

Driver safety is of utmost importance on the roads, and one significant threat to it is drowsiness while driving. Fatigue can impair a driver's ability to stay focused, react quickly, and make sound decisions, leading to an increased risk of accidents. To address this issue, computer vision and deep learning models, such as YOLO (You Only Look Once), have emerged as powerful tools. By leveraging computer vision techniques and the YOLO model, it becomes possible to detect signs of drowsiness in real-time using a camera mounted inside the vehicle. This technology can monitor the driver's facial expressions, eye movements, and other behavioral cues, providing timely alerts and interventions to prevent accidents caused by drowsy driving. By employing computer vision and the YOLO model, we can greatly enhance driver safety by detecting and addressing drowsiness effectively, potentially saving lives on the road.

News facts and statistics related to drowsy driving and the use of computer vision and the YOLO model for driver safety are as follows:According to the National Highway Traffic Safety Administration (NHTSA), drowsy driving is responsible for an estimated 100,000 crashes and 1,550 fatalities in the United States each year.A study conducted by the AAA Foundation for Traffic Safety revealed that drivers who sleep less than seven hours per night are significantly more likely to be involved in drowsy driving accidents.The Centers for Disease Control and Prevention (CDC) reports that being awake for 18 hours or more can have a similar impact on cognitive function as having a blood alcohol concentration (BAC) level of 0.05%, which is nearing the legal limit for intoxication in many countries.Computer vision technology combined with the YOLO model has shown promising results in drowsiness detection. The YOLO model enables real-time object detection and tracking, making it suitable for monitoring driver behavior and identifying signs of drowsiness.Researchers at Stanford University developed a computer vision-based drowsiness detection system called "Driver Monitoring System" (DMS) that utilizes the YOLO model. The system analyzes facial landmarks, eye movements, and head poses to detect signs of fatigue and issue timely alerts to the driver.A study published in the Journal of Safety Research found that implementing a computer vision-based drowsiness detection system in commercial vehicles could potentially reduce fatigue-related accidents by up to 86%.The integration of computer vision and the YOLO model in advanced driver assistance systems (ADAS) has gained significant attention from automotive manufacturers. Companies like Tesla, Volvo, and Mercedes-Benz are exploring the use of these technologies to enhance driver safety and reduce the risks associated with drowsy driving.These facts and statistics highlight the severity of the issue of drowsy driving and the potential of computer vision and the YOLO model to mitigate this problem and improve driver safety on the roads.

II. LITERATURE REVIEW

Drowsiness Detection System Utilizing Physiological Signals.Authors: Trupti K. Dange, T. S. Yengatiwar.2013.
Summary: This paper discusses a drowsiness detection system that utilizes physiological signals such as EOG (Electrooculogram), ECG (Electrocardiogram), EEG (Electroencephalogram), and HRV (Heart Rate Variability). The system detects changes in physiological parameters associated with drowsiness, such as decreased blood pressure, heart rate, and body temperature. It employs SVM (Support Vector Machine) as a classification algorithm for drowsiness detection. The paper also mentions other methods such as EEG-based fatigue detection, wavelet analysis of HRV, pulse sensor method, wearable drowsiness detection system, wireless wearables method, and hybrid approaches utilizing physiological features.
Drowsiness Detection with OpenCV (Using Eye Aspect Ratio).Author: Adrian Rosebrock.2017.
Summary: This paper presents a real-time algorithm for detecting eye blinks in video sequences using OpenCV. It utilizes facial landmark detection to estimate the eye aspect ratio (EAR), which characterizes the eye opening state. The paper discusses various methods for automatically detecting eye blinks, including motion estimation and decision-making based on eyelid coverage. The proposed algorithm uses SVM for classification and outperforms threshold-based methods. The paper highlights the robustness of modern facial landmark detectors in handling variations in head orientation, illumination, and facial expressions.
Real Time Driver Fatigue Detection Based on SVM Algorithm.Authors: Burcu Kir Savas, Yasar Becerkli.2018.
Summary: This paper proposes a real-time driver fatigue detection system based on SVM (Support Vector Machine) algorithm. The system extracts features from video recordings, including PERCLOS (Percentage of Eye Closure), yawn count, mouth opening, eye blink count, and head detection. SVM is used for classification, distinguishing between tired and non-tired drivers. The study involves training the system with a dataset and evaluating its performance using real-time video recordings. The accuracy of the fatigue detection system is reported to be up to 97.93%.
Driver drowsiness detection using ANN image processing.Authors: T. Vesselenyi, S. Moca, A. Rus, T. Mitran, B. Tătaru.2017.
Summary: This paper explores the development of a driver drowsiness detection system based on EEG (Electroencephalography), EOG (Electrooculography), and image processing methods. EEG is used to monitor brain activity, while EOG tracks eye movements. The paper discusses the use of sensors and electrodes for signal acquisition, as well as advancements in materials and MEMS (Microelectromechanical Systems) technology. The eye state (closed or opened) is also analyzed through image classification. Artificial neural networks, including deep learning techniques, are employed for classification purposes. The paper mentions the use of Deep Belief Networks, Restricted Boltzmann Machines, and Deep Autoencoders for image classification in drowsiness detection.

III. PROPOSED METHODOLOGY

In this project we are proposing driver drowsiness monitoring system with more accuracy and speed. Using a novel dataset of 5446 images of 2 different classes as awake and drowsy for training and testing our model. The proposed system achieves a highest accuracy of 91.1 %. In this model we have used YOLOV8 to train the dataset and after training we can use this model to detect and recognize whether the driver is experiencing drowsiness or not. When the system detects the driver feeling drowsy then a alarm sound will be generated, and the driver will get a alert and he can keep awake. YOLO has several advantages over other object detection algorithms. It is extremely fast, capable of processing images in real-time, making it suitable for applications that require quick responses. YOLO also has good generalization capabilities and can detect a wide variety of object classes. YOLO algorithm is typically trained using a large dataset with annotated bounding boxes and class labels. During the training process, the model learns to optimize the bounding box predictions and class probabilities based on the provided ground truth annotations. To train the YOLOV8 model we are using a dataset from Roboflow with a large set of images to get better prediction result.

The YOLO (You Only Look Once) algorithm is an object detection algorithm used in computer vision and deep learning. It was first introduced by Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi in 2015. YOLO is known for its real-time object detection capabilities and has been widely adopted in various applications, including autonomous vehicles, surveillance systems, and robotics. The main idea behind YOLO is to treat object detection as a regression problem. Instead of using a sliding window or region proposal-based approach, YOLO divides the input image into a grid and predicts bounding boxes and class probabilities directly from the grid cells.

YOLOv8: YOLOv8 is the latest version of YOLO by Ultralytics. As a cutting-edge, state-of-the-art (SOTA) model, YOLOv8 builds on the success of previous versions, introducing new features and improvements for enhanced performance, flexibility, and efficiency. YOLOv8 supports a full range of vision AI tasks, including detection, segmentation, pose estimation, tracking, and classification. This versatility allows users to leverage YOLOv8's capabilities across diverse applications and domains.

Enhancements in YOLOV8:

The YOLOV8 is similar to other versions of YOLO with some special enhancements:

Anchor free detections

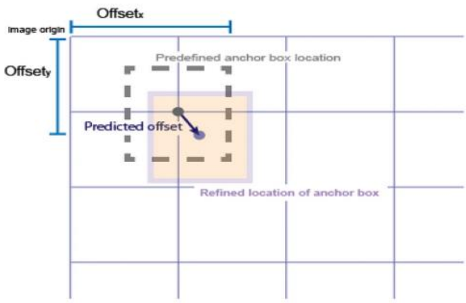

Fig 1. Anchor free detections

Anchor-free detection is when an object detection model directly predicts the center of an object instead of the offset from a known anchor box. Anchor boxes are a pre-defined set of boxes with specific heights and widths, used to detect object classes with the desired scale and aspect ratio. They are chosen based on the size of objects in the training dataset and are tiled across the image during detection. The network outputs probability and attributes like background, IoU, and offsets for each tiled box, which are used to adjust the anchor boxes. Multiple anchor boxes can be defined for different object sizes, serving as fixed starting points for boundary box guesses.

Working of YOLOV8 Algorithm

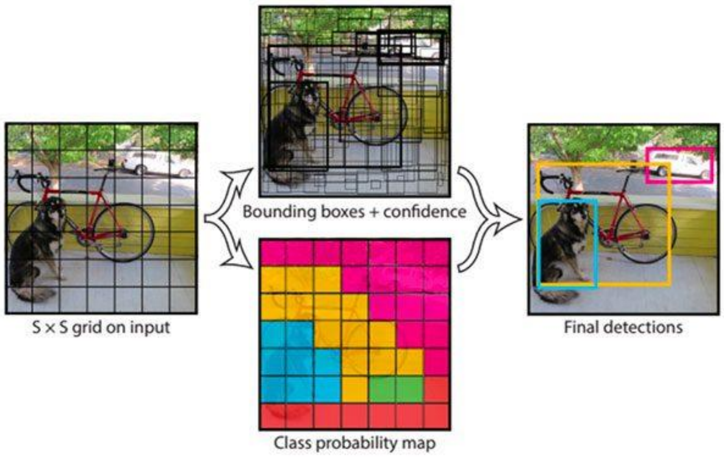

Fig 2. Working of YOLO Algorithm

Input Image: The algorithm takes an input image and resizes it to a fixed size suitable for processing. This size is usually determined based on the network architecture used.

Grid Division: The image is divided into an S x S grid, where each grid cell is responsible for predicting objects present in that cell.

Bounding Box Prediction: Within each grid cell, YOLO predicts multiple bounding boxes. Each bounding box is defined by five attributes: (x, y, w, h, confidence). The (x, y) coordinates represent the center of the bounding box relative to the grid cell, while w and h represent the width and height of the box. The confidence score indicates how confident the algorithm is that the box contains an object.

Class Prediction: Along with the bounding box predictions, YOLO also predicts the probabilities of different classes for each box. The number of class probabilities depends on the dataset being used. These class probabilities represent the likelihood of each class being present in the bounding box.

Confidence Thresholding: YOLO applies a confidence threshold to filter out low-confidence predictions. Bounding boxes with confidence scores below the threshold are discarded as false positives.

Non-Maximum Suppression (NMS): To eliminate duplicate detections and improve accuracy, YOLO applies non-maximum suppression. NMS removes redundant bounding boxes that have significant overlap and keeps only the most confident one. The overlap threshold for suppression is typically determined by a predefined Intersection over Union (IoU) value.

Final Output: The output of the YOLO algorithm is a set of bounding boxes, each associated with a class label and confidence score. These bounding boxes represent the detected objects in the input image.

Streamlit is an open-source Python library used for building and deploying data-driven web applications. It simplifies the process of creating interactive and user-friendly interfaces for data analysis, machine learning, and visualization. Streamlit allows developers and data scientists to focus on the core functionality of their applications without worrying about the underlying web development aspects. Streamlit is widely used by data scientists, machine learning engineers, and developers to create interactive dashboards, data exploration tools, and machine learning prototypes. Its simplicity, rapid development workflow, and intuitive interface make it a popular choice for building data-driven applications.

The actual implementation of the system goes as follows.First the dataset if collected from roboflow platform which is preprocessed and read to train dataset.It is the loaded into google colab platform and by using ultralytics library we import yolo and yolo pretrained model.We train on the custom dataset i.e drowsy and awake categories.Then a model is saved and linked with the streamlit interface which looks like in the Fig 2.

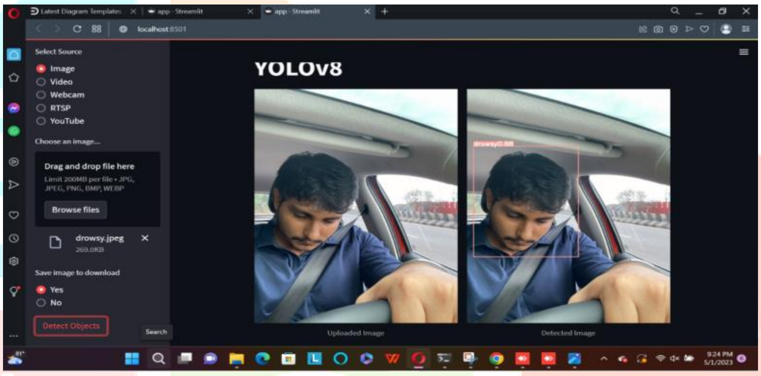

Fig 2. Streamlit webpage

IV. CONCLUSION

In this project, we have used YOLO(You Look Only Once)V8 object detection system to train dataset and after training we can use this model to detect and monitor the driver whether he is drowsy or in awaken state .If the driver is feeling drowsy then an alarm sound will be generated This model has successfully detected both classes (drowsy and awake) as mentioned in the dataset and successfully detected and monitored the driver state. Our accuracy is 91.1%. This model is fast and accurate than other KNN-algorithm based models as it detects objects in a single shot rather than two stage detection.

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