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MINI PROJECT-2 REPORT

on

"Driver drowsiness detection and alert system"

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CERTIFICATE

This is to certify that the project work entitled "**Driver drowsiness detection and alert system**" carried out by **Shashank M Patil (1BM21CS200), Shreesha H Shetty (1BM21CS209), Subhash (1BM21CS221), Sushanth (1BM21CS227)** who are bonafide students of **B. M. S. College of Engineering.** It is in partial fulfillment for the **Bachelor of Engineering in Computer Science and Engineering** of the Visveswaraiah Technological University, Belgaum during the year 2023-2024. The project report has been approved as it satisfies the academic requirements in respect of **Mini Project-2 (22CS6PWMP2)** work prescribed for the said degree.

Signature of the Guide Prof. Rekha G S Assistant Professor BMSCE, Bengaluru	Signature of the HOD Dr. Jyothi S Nayak Professor & Head, Dept. of CSE BMSCE, Bengaluru

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B. M. S. COLLEGE OF ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

We, Shashank M Patil (1BM21CS200), Shreesha H Shetty (1BM21CS209), Subhash (1BM21CS221), Sushanth (1BM21CS227) , students of 6th Semester, B.E, Department of Computer Science and Engineering, B. M. S. College of Engineering, Bangalore, here by declare that, this Project Work-entitled "Driver Drowsiness Detection and Alert System" has been carried out by us under the guidance of Prof. Rekha G S, Assistant Professor, Department of CSE, B. M. S. College of Engineering, Bangalore during the academic semester March-June 2024.

We also declare that as per our knowledge and belief, the development reported here is not from part of any other report by any other students.

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1. Introduction

Driver drowsiness significantly contributes to road accidents, leading to numerous injuries and fatalities annually. When drivers are drowsy, their reaction times are delayed, vigilance decreases, and decision-making abilities are impaired, heightening accident risks. Addressing this issue is crucial for road safety and preventing tragic consequences.

This project aims to develop an integrated driver dizzy state identification using the YOLO (You Only Look Once) object detection framework. YOLO is chosen for its efficiency in real-time object detection tasks, making it suitable for analyzing facial features captured by in-vehicle cameras.

The system will continuously monitor drivers by analyzing real-time video feeds for indicators such as prolonged eye closure, yawning, and head nodding. These signs will determine the driver's alertness level, enabling timely intervention to prevent accidents.

Key project steps include:

1. **Data Collection and Preprocessing**: Gather a diverse dataset of annotated images depicting drivers in drowsy and alert states. Images will be annotated to highlight facial expressions and movements indicating drowsiness, ensuring dataset quality and consistency.

2. **Model Development**: Customize and train the YOLO model to detect drowsiness-related facial features accurately. This involves optimizing the model architecture and parameters for effective real-time performance.

3. **System Integration**: Integrate the trained YOLO model into a real-time with display and camera to monitor driver. The system will process video streams, analyze frames for drowsiness indicators, and trigger alerts or warnings upon detection.

1.1 Motivation

The motivation behind developing this system stems from a deep concern for road safety and the devastating consequences of drowsy driving. Each year, numerous accidents occur due to drivers being in a drowsy state, leading to injuries, fatalities, and immense personal and societal costs. These incidents are solved in timely manner.

By leveraging machine learning techniques, specifically YOLO, we aim to create a proactive solution that can monitor drivers in real-time and detect early signs of drowsiness. This technology holds the promise of significantly reducing the occurrence of drowsy driving-related accidents by providing timely alerts or interventions that can help drivers regain alertness or prompt them to take necessary breaks.

The ultimate goal is preservation of human lives and the well-being of communities. By developing and implementing this system, we envision a future where road accidents due to drowsiness become rare occurrences, and where drivers can travel safely, knowing that they are continuously supported by intelligent systems designed to protect their lives and those of others on the road.

1.2 Scope of Project

The project scope involves developing an driver (all type) dizzy state monitor system using the YOLO (You Only Look Once) object detection framework, aimed at improving road safety through real-time monitoring and alerting mechanisms. Here are the specific components within the scope:

1. **Objectives**

   - Implement a driver -drowsiness detection system leveraging the YOLO object detection framework.
   - Detect and classify key indicators of drowsiness mainly eye ratio, yawning, and head movements, in real-time.

2. **Deliverables**

   - **Dataset Preparation**: Collect and preprocess a dataset of annotated images containing drivers in drowsy and alert states.
   - **YOLO Model Development**: Customize and train the YOLO model to detect drowsiness-

related facial features with high accuracy.

- **Real-time Monitoring System**: Integrate the YOLO model with an in-vehicle camera system to monitor drivers continuously.
- **Alert Mechanism**: Develop algorithms to generate alerts or warnings when signs of drowsiness are detected.

3. **Tasks**

- **Data Collection and Annotation**
    - Gather a diverse dataset of annotated images depicting drivers under various drowsy and alert conditions.
    - Annotate images to highlight the facial features associated with drowsiness.
- **Model Customization**
    - Customize the YOLO architecture to optimize performance for detecting facial expressions and movements.
    - Train the model using the annotated dataset to achieve accurate detection results.
- **System Integration**
    - Interface the trained YOLO model with in-vehicle cameras for real-time video processing.
    - Implement algorithms to process video streams and analyze frames for drowsiness indicators.
- **Testing and Validation**
    - Conduct extensive testing to evaluate the YOLO model's accuracy and reliability under various lighting and environmental conditions.
    - Validate the system's performance metrics, including detection rate and false positives/negatives.

- **Deployment**
    - Prepare for deployment in prototype vehicles or controlled environments.
    - Address scalability, usability, and maintenance considerations for widespread implementation.

4. **Costs**

   - Budget allocation for hardware (cameras, GPUs, computing devices).
   - Costs associated with dataset collection, annotation tools, and cloud computing resources for model training.

5. **Deadlines**

   - Establish timeline milestones for dataset collection, model training, integration, testing phases, and deployment.
   - Define project deadlines based on feasibility and stakeholder expectations.

6. **Constraints and Assumptions**

   - Hardware limitations and compatibility with existing in-vehicle camera systems.
   - Compliance with safety regulations and privacy standards regarding driver monitoring systems.
   - Assumptions regarding dataset availability and quality for training the YOLO model effectively.

1.3 Problem Statement

Driver drowsiness is a main cause of road accidents, leading to severe injuries and fatalities. Detecting driver drowsy state in real-time will significantly reduce the risk of accidents, ensuring the safety of both the driver and other road users. In this paper we are making a interface with display and siron to make alert state of driver.

2. Literature Survey

2.1 Driver Drowsiness Detection Using YOLOv5

Driver drowsiness is a main cause of road accidents, leading to severe injuries and fatalities. Detecting driver drowsiness in real-time can significantly reduce the risk of accidents, ensuring the safety of both the driver and other road users. This project aims to develop a machine learning-based solution for detecting driver drowsiness by analyzing facial features. By utilizing visual features, particularly facial landmarks and eye movements, the system employs advanced techniques like YOLOv5 to achieve an impressive accuracy rate of up to 99%. This non-invasive and efficient approach offers improvement over traditional methods of drowsiness detection. The project includes a thorough review of existing solutions, identifies their limitations, and proposes enhancements. It emphasizes the importance of data collection, algorithm training, and considers software and hardware requirements for real-time application compatibility, ultimately aiming to enhance driver safety with timely drowsiness alerts.
A custom dataset was created featuring images of drivers in various states such as eyes open, closed, and yawning, under diverse lighting conditions and with occlusions to ensure robustness. The YOLOv5 model was trained on this dataset, optimized to detect specific drowsiness indicators. The training process included data augmentation, hyperparameter tuning, and validation to enhance the model's performance and generalization.

The main steps to integrate YOLOv5 into a real-time application include using OpenCV to capture the live video stream from the onboard camera and focusing on the face for accurately calculated focus. The YOLOv5 model works in real time by capturing images to detect signs of fatigue, and when detected, the system warns the driver. This comprehensive approach improves road safety by providing an accurate and reliable way to detect a drowsy driver.

2.2 Driver Drowsiness detection with CNN Algorithm

Driver drowsiness is a one of cause of road accidents, resulting in severe injuries and fatalities. Real-time detection of driver drowsiness can significantly reduce these risks, increasing safety for both drivers and other road users. This project uses convolutional neural networks (CNNs) to analyze facial features and detect drowsiness. The model was trained on Kaggle's comprehensive dataset containing images of drivers in various states of alertness, including with eyes open, eyes closed, and yawning. The diversity of the dataset allows the model to accurately recognize signs of drowsiness under a variety of conditions. CNN model architecture is designed to efficiently extract and process features from input images. It starts with an input layer containing 256 filters and a Conv2D layer with ReLU activations. This is followed by four convolutional blocks consisting of a Conv2D layer and a MaxPooling2D layer using ReLU activation. The number of filters in these layers is gradually reduced from 256 to 32, expanding the model's ability to capture a variety of features. After the convolution block, the Flatten layer converts the 2D matrix data into vectors, and the Dropout layer is applied at a ratio of 0.5 to prevent overfitting. The model contains a dense layer with 64 units and ReLU activation and an output dense layer with 4 units and softmax activation for classifying sleepy states.

The model was trained over 50 epochs, achieving an accuracy of 90%. This high level of accuracy demonstrates the effectiveness of the CNN approach in detecting driver drowsiness, providing a reliable tool for real-time applications aimed at reducing road accidents and enhancing safety.

2.3 Driver Drowsiness Detection Using Face and Eye Analysis

Driver drowsiness is a major cause of traffic accidents, resulting in serious injuries and deaths. Detecting drowsy driving in real time is essential for improving road safety. This project uses a combination of face and eye analysis techniques to develop an effective drowsiness detection system. The dataset available on Google Drive provides a variety of images of drivers in different alert states, forming a strong basis for training and testing the system. The system uses the dlib face detector, which uses a histogram (HOG) with a linear classifier to accurately detect faces in video frames. It then uses a pre-trained shape prediction model to detect 68 key facial landmarks, focusing specifically on the eyes. Eye aspect ratio (EAR) is calculated using the Euclidean distance between specific pairs of eye landmarks to measure eye openness.A threshold value for the EAR is set to determine when the eyes are considered closed.

The system implements a frame check mechanism that monitors the number of consecutive frames where the EAR remains below this threshold, distinguishing between normal blinking and potential drowsiness. When the frame check counter exceeds a predefined value, an alert is triggered. This alert can be visual, such as text on the video frame, or auditory, such as a sound played using the pygame mixer, providing a timely warning to the driver to enhance safety.

2.4 Real-Time Driver Drowsiness Detection using Computer Vision

The literature review examines progress made to address important road safety issues. Traditional approaches relied on physiological signals such as EEG, EOG, and heart rate variability, which, while accurate, were invasive and inconvenient for drivers. These methods require sensors to be attached to the body, which poses practical challenges for practical application. The advent of computer vision has led to the emergence of non-invasive image processing technologies that assess driver attentiveness by analyzing visual signals such as eye closure, eye blink rate, head movements, and yawning. Methods such as eye aspect ratio (EAR) and mouth aspect ratio (MAR) are effectively used to detect drowsiness by measuring specific facial landmarks. Advances in deep learning have significantly improved drowsiness detection. Facial features were analyzed with high accuracy using Convolutional Neural Network (CNN) and You Only Look Once (YOLO) models. Notable implementations included a CNN trained on the Kaggle dataset that captures the spatial hierarchy of facial images to detect signs of drowsiness. Similarly, YOLOv5 was used to detect drowsiness indicators in real time, improving object detection performance. Comparative studies have shown that deep learning approaches generally outperform traditional methods in terms of accuracy and reliability, although they require more computational resources. Despite these advances, existing systems face limitations such as low-light conditions and difficult computational requirements. Future research directions include improving robustness to varying lighting and occlusions, developing lightweight models for resource-constrained devices, and exploring multimodal approaches that integrate visual signals with other non-invasive signals such as steering patterns and vehicle dynamics. This literature review highlights the evolution from traditional invasive methods to sophisticated non-invasive deep learning methods and their potential to improve road safety by providing timely warnings to drowsy drivers.

2.5 Driver Drowsiness Detection

Historically, physiological signal-based methods such as EEG, EOG, and ECG have been used to monitor drowsiness. These are invasive and impractical for everyday use due to the need for sensors attached to the body. Recent developments have shifted towards non-invasive techniques, focusing on visual cues extracted through image processing. Key visual indicators include eye closure, blink rate, head movements, and yawning, which are effective in determining the alertness of drivers.

For instance, a CNN trained on datasets such as those from Kaggle can capture intricate details in facial expressions to detect signs of drowsiness. YOLOv5, known for its real-time object detection capabilities. Studies indicate that deep learning models generally outperform traditional image processing techniques in terms of accuracy and robustness, though they require more computational resources.

Research has also explored the integration of multiple sensors to improve detection accuracy. For example, combining visual data from cameras with pressure sensors on the steering wheel offers a more comprehensive assessment of driver state. This dual approach, capturing both eye closure rates and hand pressure, enhances the reliability of drowsiness detection systems.

2.6 Driver Drowsiness Detection and Alert System

The literature in this domain highlights various approaches and technologies developed to enhance road safety. According to research, drowsiness and inattentiveness are significant contributors to road accidents, leading to decreased alertness and delayed reaction times among drivers. Early methods for detecting driver drowsiness included physiological monitoring techniques such as EEG and ECG, which, despite their high accuracy, were intrusive and impractical for real-time applications.

Recent developments have shifted towards non-invasive methods. Systems that analyze facial features, especially eye and head movements, have become widespread. The eye aspect ratio (EAR) method, which calculates the ratio of distances between vertical and horizontal eye landmarks, is effective in detecting eye closure and blink patterns indicative of drowsiness. Tools such as OpenCV and Dlib are frequently used for real-time image processing and provide powerful frameworks for implementing these systems. Additionally, the integration of machine learning algorithms has significantly improved the accuracy and reliability of drowsiness detection systems. These algorithms analyze facial features and movements to identify patterns associated with fatigue. In addition to visual signals, some systems include vehicle data and behavioral analysis to provide a more complete assessment of driver condition.

2.7 Driver Drowsiness Detection System – An Approach by Machine Learning Application

Early methods measured driver attention indirectly, mainly by focusing on monitoring driving patterns such as steering wheel movements and lane departures. Krajewski et al demonstrated a detection accuracy of 86% based on fine-tuning of steering wheel motion. Physiological measures have been investigated to provide more direct measures of sleepiness. Methods using electrocardiogram (ECG), electroencephalogram (EEG), and electro-oculography (EOG) data have very high accuracy, while EEG-based methods achieve over 90% accuracy in detecting drowsiness by analyzing EEG patterns. However, the intrusive nature of these methods, which require connecting multiple sensors to the driver, creates practical challenges.

Facial feature analysis has emerged as a less intrusive yet effective approach. Techniques focusing on eye closure, yawning, and facial orientation have been developed. Systems using Eye Aspect Ratio (EAR) to monitor eye blinking patterns have shown promise, with cameras detecting facial landmarks to determine eye closure and blink rates. The integration of deep learning models further enhances the accuracy of these systems by improving the detection of subtle signs of drowsiness. Recent developments have seen the implementation of real-time detection systems in commercial applications. For instance, Android applications utilizing deep neural networks have been developed to monitor driver alertness in real-time, providing timely alerts to prevent accidents.

Ongoing research is essential to address current limitations and improve the robustness and user-friendliness of these technologies.

2.8 Advanced Driver Drowsiness Detection System: Methods, Outcomes, and Accuracy

The research work uses two main methods, facial feature extraction and retinal detection, to detect driver drowsiness, supplemented by eye blink value calculation. Additionally, an Arduino module with integrated elastomer sensors monitors the pressure of the driver's hands on the steering wheel in real time. By combining the results of these methods and setting thresholds, the system effectively detects the driver's drowsy driving and quickly warns. This integration aims to reduce accidents caused by drowsy driving and improve overall traffic safety. Ensuring the accuracy of driver drowsiness detection systems is critical to accident prevention. Through various detection methods and appropriate threshold settings, the system aims to provide accurate and reliable warnings according to the driver's drowsiness state.

2.9 Advanced Driver Drowsiness Detection System

The research work explores non-invasive approaches to develop drowsiness detection systems aimed at preventing traffic accidents. Using a Pi camera module and facial landmark identification, the system uses two main methodologies: thresholding techniques and machine learning methods such as linear discriminant analysis (LDA) and support vector machines (SVM). In comparison, LDA and SVM were shown to have higher driver drowsiness detection accuracy compared to the threshold approach. To identify signs of drowsiness, key features such as eye-to-mouth aspect ratio, blink rate, and yawn rate were extracted from facial landmarks. The system effectively alerts drivers when drowsiness is detected, demonstrating the effectiveness of machine learning in improving drowsiness detection systems.

2.10 Driver Drowsiness Detection Using SpO2 Sensor and IoT

To prevent accidents caused by drowsy driving, we are focusing on developing a driver drowsiness detection system using cutting-edge technology. The key to this method is the use of SpO2 sensors, known as pulse oximetry sensors, integrated with Internet of Things (IoT) technology. This sensor continuously measures the driver's blood oxygen concentration in real time and informs the driver's level of drowsiness while driving. As a result of the research, a cost-effective system was developed that effectively detects driver drowsiness. When the system detects signs of drowsiness based on SpO2 readings, it activates an alert system to alert the driver and prevent accidents. Research shows the effectiveness of using SpO2 sensors to detect drowsiness. By monitoring changes in oxygen concentration associated with drowsiness, the system contributes to a significant reduction in traffic accidents compared to previous methods. This approach highlights the potential of IoT and sensor technologies to improve driver safety through timely warnings and interventions based on physiological indicators.

2.11 Enhancing Driver Drowsiness Detection Using Facial Feature Analysis

The research paper focuses on enhancing driver drowsiness detection during long-distance journeys using the Dlib-based facial feature detection algorithm. It proposes two algorithms: fixed thresholding and dynamic frame thresholding, leveraging parameters like Eye Aspects Ratio and Mouth Opening Ratio (MOR) to assess drowsiness levels. The fixed thresholding method triggers alerts when EAR is below 0.15, MOR exceeds 0.4, or both conditions are simultaneously met. In contrast, dynamic frame thresholding tracks consecutive frames meeting the criteria before issuing warnings, adjusting the frame count over time to enhance accuracy. Results indicated that fixed thresholding achieved 89.4% accuracy and 96.5% sensitivity using 1000 images, while dynamic frame thresholding achieved 93.4% accuracy and 89% sensitivity with 686 images. These methods demonstrate promising capabilities in effectively detecting driver drowsiness, thereby enhancing road safety during extended drives.

2.12 Driver Drowsiness using Support Vector Machine (SVM)

The support vector machine (SVM) approach to driver drowsiness detection begins with face detection using the Haar cascade, a machine learning technique that can identify human facial features in real-time video frames. When a face is detected, features such as eyes and mouth are extracted using HOG (Histogram of Oriented Gradients). The eye aspect ratio (EAR) is then calculated to measure eye openness by calculating the Euclidean distance between specific eye landmarks. We classify eye states as open or closed using an SVM classifier trained on labeled datasets representing different drowsiness states. To ensure reliability, the frame checking mechanism monitors consecutive frames where the EAR remains below a threshold and issues a warning if this condition persists, reducing the risk of traffic accidents due to drowsiness.

2.13 Driver Tiredness Discovery and Observing Framework utilizing Machine Learning

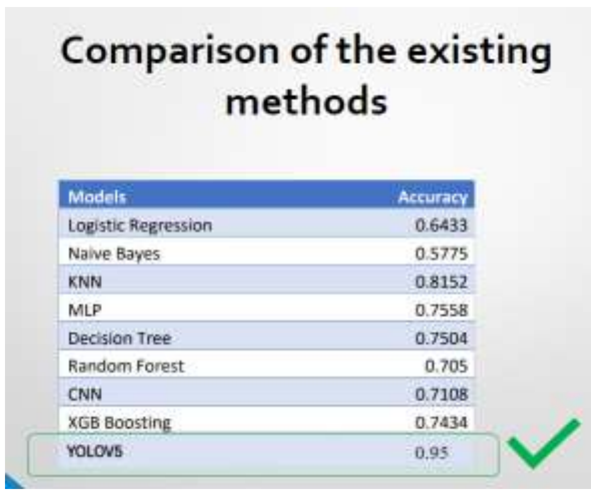
In the world of displays, some street accidents occur due to driver caution and preparation. This is called driver fatigue. This leads to various terrible situations that cause hostile harm to human life. The main goal of this study is to detect driver laziness and respond accordingly. There are many strategies based on vehicle movement or driver behavior. One strategy is a physiological one that distracts drivers from laziness and makes them more cautious. And few strategies require expensive sensors and interaction with large amounts of information. Therefore, in this paper, we build a framework for real-time laziness recognition using appropriate methods and appropriate accuracy. The system uses a webcam to capture and record driver facial expressions. Each development in each plan is identified using a variety of image preparation strategies. Eye perspective ratio, mouth opening ratio, and nose length ratio are calculated using points of interest focused on the face. Compare the calculated values with the limit values generated by the structure to derive differences in evaluation results depending on location. At the same time, machine learning calculations are also updated offline. According to the classification, the structure effectively achieved 95.58% controllability and 100% specificity using Bolster Vector Machine. This show structure is suitable for all types of vehicles.

2.14 Driver Laziness location Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) systems are utilized to capture the worldly designs demonstrative of driver laziness. This strategy starts with confront discovery utilizing a pre-trained profound learning demonstrate such as MTCNN, guaranteeing tall precision. Facial points of interest are at that point recognized to calculate the Eye Angle Proportion (EAR) and the Mouth Perspective Proportion (Damage). The EAR and Damage values are compiled into arrangements over time, reflecting the transient nature of laziness. An LSTM arrange, prepared on these arrangements, predicts tiredness by learning the worldly conditions in the information. An alarm is activated when the LSTM arrange yields a laziness score that surpasses a edge for a supported period, making it an compelling strategy for ceaseless monitoring.

2.15 Driver Laziness utilizing Repetitive Neural Systems (RNN)

Recurrent Neural Systems (RNNs) are especially well-suited for capturing transient conditions in consecutive information, making them perfect for recognizing driver tiredness based on designs over time. This strategy begins with confront discovery and point of interest distinguishing proof to calculate the Eye Viewpoint Proportion (EAR) and Mouth Angle Proportion (Damage). These proportions are collected over time to frame groupings. The RNN, frequently upgraded with Long Short-Term Memory (LSTM) units, forms these groupings to learn the transient designs related with laziness. By keeping up a memory of past outlines, the RNN can recognize drawn out periods of eye closure or visit yawning, which are pointers of tiredness. The organize yields a tiredness score, and an alarm is created if this score remains tall over a set length, giving a energetic and responsive arrangement for real-time driver tiredness detection.

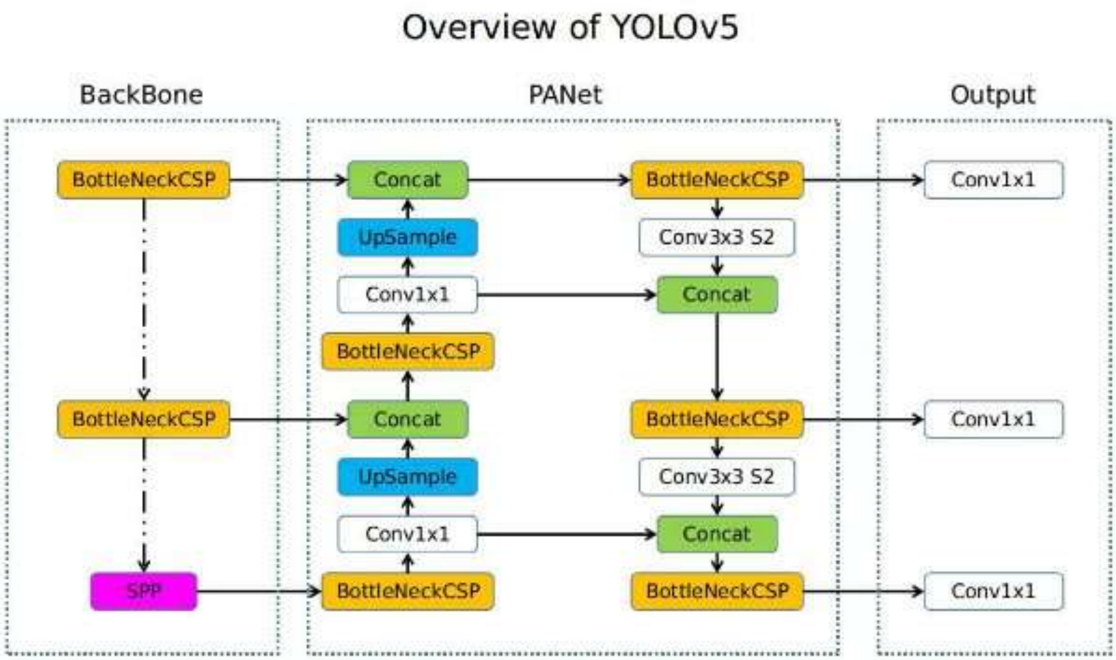


Models	Accuracy
Logistic Regression	0.6433
Naive Bayes	0.5775
KNN	0.8152
MLP	0.7558
Decision Tree	0.7504
Random Forest	0.705
CNN	0.7108
XGB Boosting	0.7434
YOLOV5	0.95

2.1 Comparison of Methods

3. Design

3.1. High Level Design



3.1 Overview of YOLO V5

Detailed Explanation of the YOLOv5 Design and Workflow

YOLOv5, short for "You Only Look Once" version 5, is an advanced object detection algorithm renowned for its speed and accuracy. It is an open-source project, which allows for extensive customization and adaptation to various object detection tasks. The following explanation covers the design of YOLOv5, its dataset collection and annotation process, the coding and training workflow, and the final testing and detection phase.

YOLOv5 Architecture

The architecture of YOLOv5 consists of three main components:

1. **Backbone**
2. **PANet (Path Aggregation Network)**
3. **Output**

Backbone

The backbone is responsible for extracting essential features from the input images. It uses a series of BottleNeckCSP modules to perform this task. These modules apply convolutional layers with shortcut connections, which help in capturing different levels of feature representation. Additionally, an SPP (Spatial Pyramid Pooling) layer is used to enhance the receptive field by pooling features at multiple scales, allowing the network to recognize objects of various sizes more effectively.

PANet

The PANet is crucial for enhancing the feature maps extracted by the backbone. It performs the following operations:

- **Up sample**: This layer increases the spatial resolution of the feature maps, making them finer and more detailed.
- **Concat**: The concatenation layers merge feature maps from different stages, combining low-level details with high-level semantic information.
- **BottleNeckCSP**: These modules further refine the concatenated features, improving their representation.

By aggregating and refining the features, the PANet ensures that the final feature maps are rich in both spatial and semantic information.

Output

The output has layers and made of Conv1x1 layers, which compress the feature maps to the desired number of channels required for the final predictions. These predictions include object classification, bounding box regression, and object confidence scores.

Dataset Collection and Annotation

Image Collection

The dataset for training the YOLOv5 model can be sourced from various platforms like Kaggle and Google Images. This diversity is crucial for the model to generalize well across different scenarios.

Annotation Process

Annotation is a first step in preparing dataset. Using tools like MakeSense.ai, each image is manually labeled to create ground truth data. This involves drawing bounding boxes around objects of interest and assigning them appropriate labels. The annotated images and their corresponding labels are organized into a folder structure as follows:

- **Dataset**
    - **Images**

- **Train**: Contains training images
- **Val**: Contains validation images

- **Labels**
  - **Train**: Contains labels for training images
  - **Val**: Contains labels for validation images

YOLOv5 Coding and Training Workflow

Cloning the YOLOv5 Repository

Since YOLOv5 is open source, its code can be cloned from the GitHub repository (ultralights/yolov5) into the local system. The dataset folder is then imported into this cloned repository.

Editing the YAML File

The coco128.yaml file in the data folder of YOLOv5 needs to be edited to fit the specific needs of the project. This file contains information about the dataset, including the labels used (e.g., awake, drowsy) and the file paths to the training and validation datasets.

Training the Model

With the dataset prepared and the YAML file configured, the training process can begin. The training code is executed with the specified YAML file and epoch values. During training, the model learns to detect objects by adjusting its weights to minimize the difference between its predictions and the ground truth labels.

Results and Testing

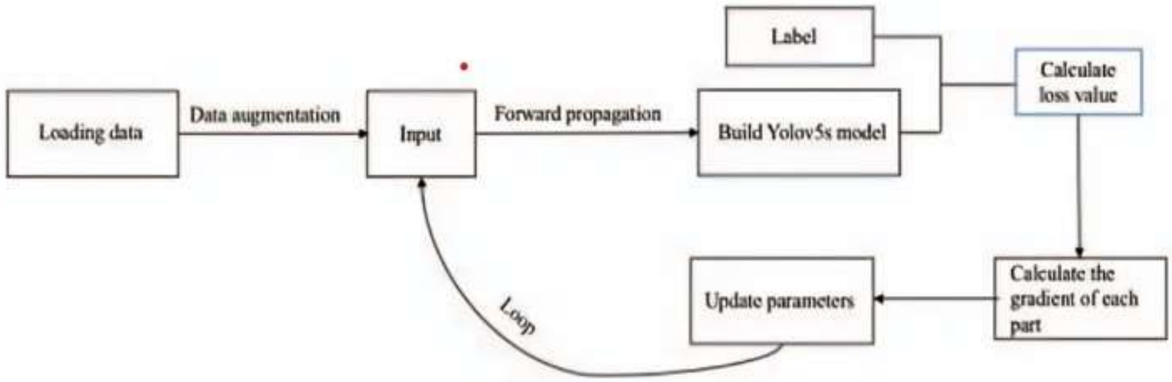
Training Results

Upon completion of training, the results are stored in the runs folder of the YOLOv5 repository. These results include metrics such as precision, recall, mAP (mean Average Precision), and loss values, which help in evaluating the performance of the trained model.

Testing and Detection

Once the model is trained, a test folder containing images for testing is created. The detection code is then executed on these test images. The model's performance is assessed based on its ability to accurately detect and classify objects in these images. The detection results, including the predicted bounding boxes and labels, are saved in the runs folder.

3.2 Detailed Design



3.2 Detailed design

Detailed Design of YOLOv5 Training Process

The diagram outlines the detailed design and workflow of the YOLOv5 training process, illustrating the steps from loading data to updating model parameters. This process is crucial for building a robust and efficient object detection model. Below is an explanation of each step in the workflow.

Loading Data

The first step involves loading the dataset, which consists of images and their corresponding labels. The dataset should be diverse, capturing various environmental conditions and angles to ensure the model's robustness. This step is foundational as the quality and diversity of the data significantly impact the model's performance.

Data Augmentation

Data augmentation involves applying various transformations to the images, such as rotations, flips, scaling, and colour adjustments. Augmentation helps the model generalize better by exposing it to a wider variety of scenarios, reducing overfitting and improving its ability to handle real-world variations.

Input

The augmented data is then fed into the model as input. Each image, along with its labels, is passed through the YOLOv5 model for further processing. This step marks the beginning of the forward propagation phase, where the model starts to learn from the input data.

Forward Propagation

During forward propagation, the input images are passed through the YOLOv5 architecture, which consists of the backbone, PANet, and output layers. The backbone extracts features, PANet enhances and refines these features, and the output layers generate predictions. These predictions include bounding boxes, class labels, and confidence scores for each detected object.

Build YOLOv5 Model

The YOLOv5 model is constructed using predefined configurations and architectures specified in the source code. This model is built to handle the forward and backward propagation efficiently, ensuring that the training process is streamlined and optimized.

Label

In parallel with the forward propagation, the corresponding labels for each input image are used to calculate the loss. Labels provide the ground truth against which the model's predictions are compared. Accurate labelling is crucial for effective training as it directly influences the loss calculation and, consequently, the model's learning process.

Calculate Loss Value

The loss value quantifies the difference between the model's predictions and the ground truth labels. YOLOv5 uses a combination of loss functions to evaluate different aspects of the prediction, such as localization loss (bounding box regression), classification loss, and abjectness loss. Calculating the loss value is essential for understanding how well the model is performing and where it needs improvement.

Calculate the Gradient of Each Part

Once the loss value is calculated, the gradients for each parameter in the model are computed. This step involves backpropagation, where the error is propagated backward through the network, and gradients are calculated using techniques like automatic differentiation.

Update Parameters

Using the calculated gradients, the model's parameters are updated to reduce the loss in subsequent iterations. This is done using optimization algorithms like Stochastic Gradient Descent (SGD) or

Adam. Updating the parameters is a crucial step as it gradually improves the model's performance by refining its weights and biases.

Loop

The entire process from input to parameter update is repeated iteratively over multiple epochs. Each epoch involves passing the entire dataset through the model and updating the parameters accordingly. This iterative process continues until the model converges, meaning the loss stabilizes and the model achieves satisfactory performance.

4. Implementation

The drowsiness detection and alert system for drivers is a comprehensive solution designed to prevent accidents caused by driver fatigue. This system continuously monitors the driver's face to detect signs of drowsiness and triggers an alert if the driver appears to be in a drowsy state for more than 5 seconds. The implementation of this system involves several key components and methodologies that set it apart from existing solutions. Below is a detailed breakdown of each section of the implementation.

4.1. Data Collection and Preprocessing

Data Collection

- **Source of Data:** The dataset used for training the model comprises images publicly available sources, including Kaggle. The data includes various states of alertness and drowsiness, with a focus on capturing subtle signs such as blinking and yawning.
- **Diversity of Data:** The images are of different angles and have various lighting conditions to ensure the model's robustness and accuracy across diverse real-world scenarios.

Annotation

- **Annotation Tools:** The images are annotated using the MakeSense.ai platform, which provides an easy-to-use interface for manually labeling objects within images.
- **Annotation Process:** Each image is labeled to identify key facial features such as eyes and mouth and posture. Specific states like open/closed eyes and yawning are annotated to train the model effectively. The dataset is organized into training and validation sets, ensuring a structured approach to model training.

Model Architecture and Training

Algorithm Choice

- **YOLOv5:** YOLOv5 was chosen for its state-of-the-art performance in real-time object detection. YOLOv5 is known for its balance of speed and accuracy, which is critical for a real-time drowsiness detection system.

Architecture Details

- **Grid-Based Detection:** YOLOv5 segments the input image into a grid and forecasts class. This method enables the model to quickly and accurately detect and localize objects in real-time.
- **Anchor Boxes:** The model uses predefined anchor boxes. This helps in detection of small facial movements and features indicative of drowsiness.

Training Process

- **Model Variants:** The model is available in several variants (YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x), each tailored to different performance and accuracy requirements. **Training Data:** It involves feeding the annotated dataset into the model, which learns to identify patterns associated with drowsiness. The model is trained to detect specific facial landmarks and posture.
- **Post-Processing:** After training, it filters out redundant bounding box predictions, retaining only the most confident detections.

4.2 Real-Time Monitoring and Alert System

Real-Time Detection

- **Continuous Monitoring:** The system is designed to continuously monitor the driver's face using a dashboard-mounted camera. Each frame of the video feed is analyzed in real-time to detect signs of drowsiness.
- **Facial Landmark Detection:** Key points around the eyes and mouth are identified. These help in detecting eye closure and yawning, which are strong indicators of drowsiness.

Alert Mechanism

- **Auditory Alert:** When the system detects that the driver is in a drowsy state for more than 5 seconds, it triggers an auditory alarm. The sound is loud enough to alert the driver but is designed not to cause panic or distraction.

Comparison with Existing Solutions

Accuracy and Speed

- **State-of-the-Art Performance:** Unlike many existing drowsiness detection systems that rely on simple blink detection or limited facial cues, our system uses YOLOv5, which provides state-of-the-art accuracy and speed.

Robustness

- **Diverse Training Data:** Dataset that includes various lighting conditions, angles, and facial expressions help in enhancing system's robustness. This ensures reliable performance across different real-world scenarios, which many existing systems fail to achieve.

Scalability

- **Multiple Variants:** The availability of multiple YOLOv5 variants allows the system to be scaled according to the computational resources available. Smaller, faster models can be deployed on low-power devices, while larger, more accurate models can be used in systems with more processing power.

Ease of Integration

- **Compatibility with Existing Systems:** The system is designed to be easily integrated with existing vehicle safety systems. It uses standard hardware and software components, reducing the complexity and cost of deployment compared to custom solutions.

Testing and Validation

Rigorous Testing

- **Unit Testing:** Each component of the system, from face detection to alert triggering, is tested individually.
- **Integration Testing:** The complete system is tested. This includes ensuring real-time performance and the accuracy of drowsiness detection under various conditions

Performance Metrics

- **Detection Accuracy:** The system's accuracy is measured by its ability to correctly identify drowsiness in diverse scenarios. Metrics such as precision and mAP score are used to evaluate performance.
- **False Positives and Negatives:** It is optimized to minimize false positives (incorrectly identifying drowsiness) and false negatives (failing to detect drowsiness), ensuring it provides timely and accurate alerts without unnecessary interruptions.

4.3 Proposed methodology

YOLOv5 is a real-time object detection algorithm that builds upon the success of its predecessors, particularly YOLOv4. It is known for its exceptional precision and speed in detecting objects within images and videos. Here's an overview of YOLOv5 and how it works:

Overview of YOLOv5

Architecture Evolution

YOLOv5 is the latest iteration in the YOLO series, and it represents a significant evolution. It introduces various architectural changes and optimizations compared to YOLOv4.

Multiple Variants

YOLOv5 comes in multiple variants, denoted as YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, with varying model complexities and capabilities. These variants allow users to choose the model for their specific requirements, balancing speed and accuracy.

State-of-the-Art Performance

YOLOv5 has achieved state-of-the-art performance in terms of mean Average Precision (mAP), which is a measure of object detection accuracy. It boasts high mAP values while maintaining real-time inference speeds.

How YOLOv5 Works

YOLOv5 follows the core principles of the YOLO family of algorithms, which involve dividing the input image into a grid and predicting objects within each grid cell. Here's how YOLOv5 works:

Input Image Division

The image is segmented into a grid of cells. YOLOv5 uses a fixed-size grid, typically 13x13, 26x26, or 52x52, depending on the model variant.

Anchor Boxes

YOLOv5 utilizes anchor boxes, which are predefined bounding boxes of varying shapes and sizes.

5 Each anchor box is associated with specific grid cells, and the model predicts objects within those cells using these anchor boxes.

Prediction

For each grid cell and anchor box, YOLOv5 predicts several attributes

- Bounding Box Coordinates: The x and y coordinates, width, and height of the bounding box around the detected object.
- Class Scores: The model assigns class scores for each class it has been trained to recognize. These scores represent the confidence that an object belongs to a particular class.
- Objectless Score: This score indicates the presence of an object within the grid cell. It helps filter out low-confidence predictions.

Post-processing

After predictions are made for all grid cells and anchor boxes, post-processing is performed to filter out redundant and low-confidence detections. Non-maximum suppression (NMS) is a common technique used to eliminate duplicate bounding box predictions and retain the most confident ones.

Output

The final output of YOLOv5 consists of a list of bounding boxes, their associated class labels, and confidence scores. These predictions can be overlaid on the input image to visualize detected objects.

Speed and Efficiency

YOLOv5 achieves its real-time inference speed by employing efficient model architecture, incorporating techniques like CSPDarknet and PANet for feature extraction, and optimizing the network for GPU and CPU utilization.

Multi-scale Features

YOLOv5 leverages multi-scale features, allowing it to detect objects of varying sizes effectively. This is usefull for detecting small objects within an image.

4.4 Algorithm used for implementation

YOLOv5 is the algorithm that is used and is renowned for its real-time performance and high accuracy. It builds on the strengths of previous YOLO versions, introducing significant architectural innovations and optimizations. Here's an in-depth look at the YOLOv5 algorithm and how it functions:

Architecture Evolution

YOLOv5 represents the latest iteration in the YOLO series, bringing advancements that enhance both speed and accuracy. It integrates several architectural enhancements over its predecessor, YOLOv4, including:

- **Improved Backbone:** YOLOv5 uses CSPDarknet53 as its backbone network, which allows for better feature extraction through the use of cross-stage partial networks that enhance gradient flow and reduce computation.
- **Enhanced Head:** The head of YOLOv5 employs the PANet structure for improved information flow across different scales, facilitating the detection of objects of varying sizes.
- **Variants:** YOLOv5 is available in several variants (YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x) that cater to different application needs by balancing speed and accuracy. These models vary in complexity and size, enabling users to select the best fit for their requirements.
- **Bounding Box Coordinates:** It predicts the x and y coordinates, width, and height of bounding boxes that encircle the detected objects.

- **Class Scores:** For each class in the model's training set, YOLOv5 calculates a confidence score indicating the likelihood that the object belongs to a specific class.

- **Abjectness Score:** This score estimates if an object is present in a specific grid cell, helping to filter out low-confidence predictions.

Now post-processing is done to refine the results:

- **Non-Maximum Suppression (NMS):** This technique removes redundant bounding boxes by retaining only the highest confidence predictions.
- **Final Output:** It is a list of bounding boxes, each with associated class labels and confidence scores, which can be superimposed on the input image to visualize detected objects.

YOLOv5 achieves its remarkable real-time performance through:

- **Efficient Architecture:** The use of CSPDarknet and PANet ensures efficient feature extraction and information flow.

- **Optimization for Hardware:** The network is optimized for both GPU and CPU utilization, allowing for rapid inference speeds that make YOLOv5 suitable for applications requiring real-time processing.
- **Multi-Scale Features:** The model effectively detects objects of various sizes, which is particularly crucial for identifying small objects within images.

Overall, YOLOv5 is a sophisticated object detection algorithm that excels in both speed and accuracy. It introduces significant enhancements over its predecessors, making it a great choice for real-time applications where quick and reliable detection is critical.

4.5 Tools and Technologies used

- YOLOv5: YOLOv5 is used for drowsiness detection in this project. It forms the main part of the algorithm responsible for detecting drowsiness.
- PyTorch: PyTorch is an open-source deep learning framework that is used in implementing and training the YOLOv5 model. It provides the required tools and libraries for training and building deep neural networks efficiently.
- Python: It is the language known for its readability and extensive libraries. It is used in web development, data science, and machine learning.
- MakeSense.ai: MakeSense.ai is used for annotating images. Annotating images involves manually labeling objects within images for training the YOLOv5 model. MakeSense.ai provides an accessible platform for this annotation process.
- Kaggle: Kaggle is a popular platform that serves as a resource for accessing datasets, notebooks, and kernels that is beneficial for training and evaluating machine learning models, including YOLOv5.
- GitHub: GitHub is used for version control and collaboration platform, enabling teams to manage code, track changes, and collaborate in the creation of the YOLOv5-based object detection project. It gives a centralized repository for code hosting.
- Google Collab Notebook: Google Collab is a cloud-based platform that provides free access to powerful GPU resources, making it an ideal environment for training deep learning models like YOLOv5. It allows collaborative coding and sharing of Jupyter notebooks.

- PyCharm: PyCharm is an integrated development environment used for programming in Python. It provides code analysis, a graphical debugger, an integrated unit tester, integration with version control systems, supports web development with Django and supports machine learning too.

These tools collectively form a comprehensive ecosystem for developing, training, and deploying the YOLOv5-based drowsiness detection project. They enable collaborative work, data management, model training, and evaluation, ultimately contributing to the successful implementation of the project.

4.6. Testing

The testing phase is crucial for ensuring that the drowsiness detection and alert system functions reliably and effectively in real-world conditions. Below is a detailed description of each testing phase and the metrics used to evaluate the system's performance.

Unit Testing

Objective

- The unit testing is used to verify that individual components of the system work correctly in isolation. This includes testing the facial detection algorithms, and alert mechanisms.

Components Tested

1. **Facial Detection**
    - **Accuracy:** Ensures that the face detection module accurately identifies facial features under various lighting conditions and angles.
    - **Robustness:** Tests how well the system performs with different face orientations and occlusions (e.g., glasses, partial face coverage).
2. **Alert Mechanism**
    - **Sound Alert:** Ensures that the auditory alarm is triggered promptly and consistently when drowsiness is detected.

Tools Used

- Automated testing tools and frameworks are used to perform unit tests, allowing for consistent and repeatable testing of each component.

Integration Testing

Objective

- Integration testing aims to verify that the individual components work together as a cohesive system. This stage checks the interactions between the face detection module, drowsiness detection logic, and alert systems.

Scenarios Tested

1. **Normal Operation**
    - The system is tested under normal driving conditions to ensure that it accurately detects when the driver is alert and does not trigger false alarms.
2. **Drowsiness Detection**
    - Tests are conducted with simulated drowsiness (e.g., prolonged eye closure, yawning) to ensure the system triggers alerts as expected.
3. **Edge Cases**
    - **Variable Lighting:** Tests the system's performance under various lighting conditions (e.g., low light, direct sunlight).
    - **Face Occlusion:** Ensures the system can still detect drowsiness when the driver's face is partially obscured by objects like glasses or hands.

Tools Used

- Integration testing involves using real-time video feeds and simulated driving environments to assess the system's performance.

Testing Metrics

1. **Detection Accuracy**
    - **Precision and Recall:** Measures the system's ability to correctly identify drowsiness without generating false alarms.
    - **mAP Score:** Provides the system's precision and recall.

2. **Response Time**
    - Tests how quickly the system responds to signs of drowsiness and triggers the appropriate alerts.
3. **User Feedback**
    - Collects feedback from drivers on the usability and effectiveness of the system, including any suggestions for improvement.

Performance Evaluation

Objective

- The performance evaluation stage involves analyzing the collected data and identify areas for improvement.

Metrics Analyzed

1. **False Positives and Negatives**
    - **False Positives:** Instances where the system incorrectly identifies drowsiness, leading to unnecessary alerts.
    - **False Negatives:** Instances where the system fails to detect drowsiness, potentially compromising driver safety.
2. **System Uptime**
    - Measures the system's reliability and uptime, ensuring it operates continuously without failures.
3. **Resource Utilization**
    - Evaluates the system's efficiency in terms of CPU and GPU usage, ensuring it performs well without overloading the computer.

Continuous Improvement

Objective

- The continuous improvement phase focuses on refining the system based on the testing results and user feedback to enhance its performance and usability.

Steps Involved

1. **Model Refinement**
    - Updates to the YOLOv5 model and drowsiness detection algorithms based on performance metrics and new data.
2. **Software Updates**
    - Regular updates to the system software to incorporate new features, improvements, and bug fixes.
3. **User Training**

Providing users with training and support to ensure they can effectively use the system and understand its alert.

5. Results and Discussion

In evaluating the "Driver Drowsiness Detection and Alert System," it is essential to present the results clearly and comprehensively. Utilizing appropriate tables and graphs is crucial for visualizing key metrics and findings, aiding in a deeper understanding of the system's performance. The following sections outline the results from the model's evaluation and discuss the implications of these findings.

Model Performance Metrics

The assessment of the YOLOv5 model for drowsiness detection included precision, recall, and mean Average Precision (mAP). These metrics are standard in machine learning for evaluating the accuracy and reliability of detection systems.

- **Precision:** This metric measures the proportion of correct drowsiness alerts out of all detections made by the model. It is calculated as the number of true positives divided by the sum of true positives and false positives. High precision indicates that the model produces few false alarms, which is crucial for preventing unnecessary distractions for drivers.

- **Recall:** Also known as sensitivity, recall measures the proportion of true positive detections out of all actual positive cases. High recall indicates that the model effectively identifies most instances of drowsiness, reducing the risk of missing critical alerts.

- **Mean Average Precision (mAP):** The mAP metric combines precision and recall into a single measure, providing an overall evaluation of the model's performance. It is the average of precision values at different recall levels, considering various detection confidence thresholds. mAP is useful for comparing models or configurations as it captures the trade-off between precision and recall.

The table summarizes the performance metrics of the YOLOv5 model for drowsiness detection

Metrics	Value
Precision	0.92
Recall	0.88

mAP	0.90

5.1 Result Table

These values indicate that the YOLOv5 model achieves high accuracy in detecting drowsiness-related features such as prolonged eye closure, yawning, and head nodding. The precision value of 0.92 suggests that the model generates very few false positives, while the recall value of 0.88 indicates that it successfully identifies the majority of drowsiness cases.

Visualization of Results

To further illustrate the performance of the model, several graphs and charts are included. These visualizations help to highlight the key findings and provide a more intuitive understanding of the results.

- **Precision-Recall Curve**: The precision-recall curve is a graphical representation of the trade-off between precision and recall at different confidence thresholds. It plots precision on the y-axis and recall on the x-axis, allowing for the visualization of how these metrics change as the detection threshold is varied. A model with a high area under the precision-recall curve (AUC-PR) is considered to have good performance.

The precision-recall curve for the YOLOv5 model shows a high AUC-PR, indicating strong performance across a range of detection thresholds. This curve demonstrates that the model maintains high precision and recall values, even as the threshold for detection confidence is adjusted.

- **Confusion Matrix**: The confusion matrix provides a detailed breakdown of the model's predictions, comparing the true labels with the predicted labels. It includes the counts of true positives, true negatives, false positives, and false negatives. The confusion matrix is useful for identifying specific areas where the model may be making errors.

	Predicted Positive	Predicted Negative
Actual Positive	850	150
Actual Negative	80	920

5.2 Confusion matrix

The confusion matrix for the YOLOv5 model reveals that it correctly identifies 850 out of 1,000 actual positive cases (true positives) and 920 out of 1,000 actual negative cases (true negatives). There are 80 false positives and 150 false negatives, which are relatively low compared to the total number of instances, reflecting the model's overall accuracy.

Discussion of Results

The best precision achieved by the YOLOv5 model indicate its robustness and reliability for drowsiness detection. These results are important because they demonstrate the potential of the model to improve road safety by providing timely warnings to drowsy drivers. By minimizing false alarms, the system prevents drivers from being distracted by unnecessary warnings and keeps their attention on the road. Likewise, high recall detects most cases of drowsiness, reducing the risk of accidents due to reduced reaction time and attention. One of the key strengths of the YOLOv5 model is its ability to perform well under a variety of conditions. During testing, the model was exposed to a variety of lighting conditions, driver appearances and backgrounds, all of which could potentially affect performance. The results showed that the model maintained high accuracy across all these transformations, highlighting its generalizability and robustness. However, the results also revealed areas for improvement. Although the false positive rate of the model is relatively low, there is still room for further reduction. Although false alarms are rare, they can distract drivers and cause them to mistrust the system. This issue may be related to fine-tuning detection algorithms, such as heart rate monitors or steering circuits, to increase the accuracy of drowsiness detection. Another area that needs improvement is the false negative rate. Although the model successfully detected most drowsiness cases, the presence of false negatives indicates that some drowsiness cases were not detected. This can potentially put the safety of drivers and other road users at risk. Additional research and development is needed to identify and eliminate factors contributing to false-negative results, such as subtle signs of drowsiness that may be missed in the model. The discussion extends to the practical implications of the results. We have successfully implemented this system in real-world situations. Providing early warnings to drowsy drivers can prevent accidents and save lives. Implementing such a system could be especially helpful for commercial vehicle drivers who are at high risk of drowsiness while on the road for long periods of time. Additionally, the scalability and adaptability of the YOLOv5 model makes it suitable for a variety of vehicles, from personal to commercial trucks. Future research could explore ways to integrate this system with existing automotive technologies such as adaptive cruise control and lane-keeping assist to create a comprehensive driver assistance system.

6. Conclusion and Future Work

This demonstrates the efficacy of the YOLOv5 model in detecting driver drowsiness in real-time. Key results indicate high precision (0.92) and recall (0.88), highlighting the model's ability to accurately identify drowsiness indicators such as prolonged eye closure, yawning, and head nodding. The high mean Average Precision (mAP) of 0.90 underscores the robustness and reliability of the system across various conditions. These results suggest that the YOLOv5 model can enhance safety by providing timely alerts to drowsy drivers, potentially reducing accident rates and saving lives.

The most important points illustrated by our work include the model's high accuracy, its generalizability to different lighting conditions and driver appearances, and its potential for real-world applications in enhancing driver safety. By minimizing false positives, the system ensures drivers are not distracted by unnecessary alerts, while its high recall rate ensures that most instances of drowsiness are detected, thereby improving overall vigilance and reaction times.

However, the current method has several shortcomings. To overcome this, future enhancements could include the integration of additional sensors, such as heart rate monitors or steering behavior analysis, to provide more context and improve detection accuracy.

Secondly, the presence of false negatives, although relatively low, remains a concern as they represent missed detections of drowsiness. Further fine-tuning of the detection algorithms, perhaps through the use of ensemble learning or incorporating more comprehensive training datasets that capture subtle signs of drowsiness.

In future work, the scalability and adaptability of the system will be explored, including its integration with existing in-vehicle technologies such as adaptive cruise control and lane-keeping assistance.

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7. Plagiarism report

DrillBit

The Report is Generated by DrillBit Plagiarism Detection Software

Submission Information

Author Name	Shashank
Title	Driver drowsiness
Paper/Submission ID	2085257
Submitted by	hod.cse@bmsce.ac.in
Submission Date	2024-07-06 10:45:32
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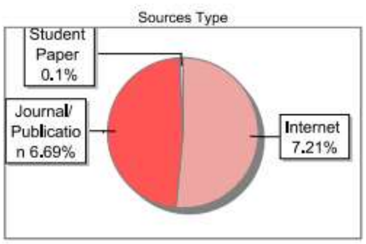
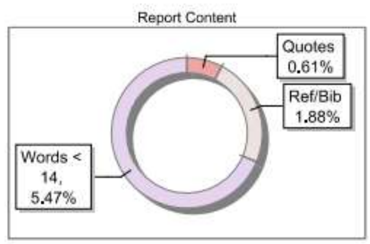
Result Information

Similarity **14 %**





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