



# Saferide: Ensuring Rider Safety By Detecting Helmets

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**Abstract:** This paper solves a real-world problem of rider safety by ensuring helmets are worn through the use of the machine-learning technology, YOLO v8, used for helmet detection. The goal is to develop a system that can accurately detect helmets in real-time video feeds. Starting from the high-resolution recording of video captures made from the camera on the rider, image processing is deployed to enhance the quality of the frames and make it easier for features to be identified. The real-time processing system efficiently detects whether the rider is wearing a helmet. Several processes are involved namely, collecting data, preparing images, choosing the correct architecture, and building up the model. Training the model is essential, and during this stage, the enhancement of the model by the addition of optional data augmentation can significantly help improve the model's performance and make it less sensitive to certain variations, like lighting and pose of the rider. The YOLO v8 model consists of very efficient layers that help with the quick identification of helmets on riders. This has been trained on a lot of data, and its performance has been reported regularly to find efficiency in classifying any object as a rider with/without a helmet. If a helmet is detected, the servo motor, in conjunction with the buzzer, will be activated to alert the rider. The feedback here is instantaneous and encourages them always to buckle up. This is a so-called proactive attempt to better rider safety with the addition of smart technology with the sole aim of proper wearing of helmets.

**Index Terms** - Rider Safety, Helmet Detection, YOLOv8, Machine Learning, Object Detection, Real-Time Processing, Buzzer Feedback, Servo Motor.

## I. INTRODUCTION

Rider safety [1] has long been a critical concern in the field of transportation, particularly for motorcyclists and cyclists who are at a higher risk of injury in the event of an accident. Among the most effective safety measures is the consistent use of helmets, which significantly reduce the risk of head injuries. However, ensuring that riders adhere to helmet-wearing regulations remains a challenge, especially in environments where enforcement may be limited or inconsistent. To address this issue, this research presents SafeRide, a proactive system designed to ensure rider safety through the detection of helmets using advanced machine-learning [2] techniques. The core of the SafeRide system is the use of YOLOv8 (You Only Look Once version 8) [3], a pre-trained object detection model, to identify helmets in real-time [4] video feeds. By leveraging high-resolution cameras and advanced image processing algorithms, SafeRide provides a reliable and scalable solution for detecting helmet usage on riders. The system's real-time processing capabilities ensure prompt detection, offering immediate feedback when a helmet is not detected, thereby encouraging the consistent use of helmets. Additionally, the system is designed to be both accurate and efficient, operating within the constraints of real-world conditions where factors like lighting, rider movement, and helmet style can introduce variability. This paper details the methodology employed in SafeRide [5], including data collection, preprocessing, model development, and evaluation. The research also explores the integration of Realtime feedback mechanisms, such as activating a servo motor and buzzer, to reinforce helmet usage immediately. By combining computer vision, machine learning, and hardware-based feedback, SafeRide represents a

significant step forward in promoting rider safety and enforcing helmet usage in an intuitive, non-intrusive manner.

## II. LITERATURE REVIEW

Improvements in the IoT-based smart helmet system aim at enhancing the safety of the riders. Key characteristics of the system include alcohol detection, accident detection, GPS-based location tracking, and emergency alert triggering. Similarly, sensor integration, such as the employment of accelerometers and gas detectors, expanded the function of smart helmets beyond manufacturing industries to mining industries. Some of the studies mentioned earlier introduce new designs and methodologies, for instance using SVM toward accident detection, Bluetooth connectivity, or solar-powered solutions to make them more functional and cost-effective [6]. This is as emphasized on their role towards accident prevention and safety enhancement. Studies have presented various methodologies, including sensor integration for alcohol detection, crash identification, and real-time alerts to emergency services via IoT frameworks [7]. The study uses YOLOv5 models at different complexities and obtained a high mAP of 94.7%, showing robust performance in helmet usage detection across quite diverse scenarios. Such results mean that the developed algorithm could be applied in safety-critical environments, providing a scalable and effective solution [8]. Based on existing machine vision techniques, this study proposes a system that uses KNN classification to detect motorcycle riders and evaluate the use of helmets. This addresses an important gap in automated safety monitoring. The research contributes to the overall discourse of enhancing safety of roads through the technology advancement of both vehicle and rider detection [9]. There is a need for innovative methods on safety monitoring for perambulatory workers by covering potential difficulties such as illumination sensitivity and the accuracy of pedestrian detection algorithms. Overall, this review underscores the importance of designing a robust safety helmet detection system in order to avoid risks in dangerous sites such as power substations [10].

At the same time, YOLOs highlight their real-time capability along with the failure of overlapping bounding boxes and wrong detections. YOLO models generally can be summarized in the following terms. Here, the authors propose integration of Dense Net into the architecture of YOLO V3 for enhanced feature extraction and overall detection performance regarding safety helmets from existing models' drawbacks [11]. It encompasses the most common human detection methods, such as Histogram of Oriented Gradients (HOG) and feature extraction, widely applied in video surveillance and autonomous systems. It also points out helmet detection as one of the most critical measures of safety in construction, thereby requiring innovative approaches that come with the use of colour information and geometric transforms such as the Circle Hough Transform (CHT) [12]. The approach explains that better cross environment generalization requires more advanced detection systems. Taking this concept further, the authors introduce a deep learning framework that is based on the YOLO algorithm for enhancing the effectiveness of detection accuracy and reliability in real-time applications [13]. The current monitoring methods of helmet usage are traditional and have uncertainties due to human errors, hence the need for automation. Various approaches to object detection have been used previously, ranging from YOLO and Faster R-CNN. However, such approaches often experience accuracy and real time processing in a complex analysis. Consequently, the newly suggested DWCA-YOLOv5 model attempts to improve detection by highlighting feature attention capabilities and optimal anchor box optimization. Such considerations will contribute to more secure construction practices [14]. Motorcycle detection and helmet detection present different approaches towards improving safety on the roads. Earlier researches have focused on vehicle detection through background subtraction techniques and features extraction techniques where classification was done by using neural networks. Helmet detection has also been addressed using geometrical methods such as the Hough transform, which detects shapes containing a circle which resembles helmets in the real world [15].

For instance, in object detection, Local Binary Patterns and Histogram of Oriented Gradients have been found to be pretty effective while Hough Transform has been of immense use in isolating some shapes that are found in images. This paper presents some of the foundational techniques to base a combined novel method that improves the accuracies and reduces false positives in real-time helmet monitoring systems [16]. Methods to use include: Adaptive Gaussian mixture background subtraction, feature-based vehicle classification through the aspect ratio and hue, and circular Hough transform helmets with edge detection. However, most approaches rely upon single characteristics that in several cases will become computationally costly, or even fail to provide robust solutions. The proposed work counters these limitations by integrating

multi-features along with popular classifiers like logistic regression, as well as support vector machines [17]. Traditional approaches tend to utilize motion segmentation and hand designed feature descriptors, which poses real-time detection issues and decreases the accuracy, especially in crowds. Recent deep learning techniques, including different versions of the YOLO algorithm, have promised an improved detection ability. However, many of these studies still rely on background subtraction for motorcycle detection, which tends to have trouble when complex traffic occurs; hence, there is a need for more powerful datasets and state-of-the-art detection frameworks [18]. A means to use edge detection, Gaussian models, and CNNs in detecting whether the helmets are worn or not. However, many of them were affected by occlusion and time-varying environment. The proposed system is able to utilize machine learning and image processing resources such as OpenCV and Optical Character Recognition in order to improve the accuracy of the detector and reduce the time spent on sending out the notices directly from the interface. This research builds on existing methodologies while addressing the limitations of those methodologies, hence paving the way for a more effective solution in traffic rule enforcement [19]. Circular object detection, presented later, proved to be insufficient because the system generated many false positives and could not differentiate between helmets and human heads. The authors present a more robust technique using support vector machines with histograms trained from head region images which do indeed capture well helmet's reflective property. It incorporates background subtraction for object segmentation and a tracking mechanism to enhance classification accuracy, and it has performed well on both still images and video sequences [20].

### III. METHODOLOGY

This section provides detailed elaboration on the methodological choices and their implementation in the SafeRide project to establish a real-time helmet detection system. The project, using YOLOv8 as an object detection model, provides a response to rider safety by attaining both accuracy and efficiency in helmet detection. The methodology combines strong data collection preprocessing and training techniques in the construction of a system scalable in real-world conditions.

#### A. Training Process

The training process for YOLOv8 involves optimizing a multitask loss function that combines several components tailored for object detection tasks. For the SafeRide helmet detection project, the loss function can be expressed as:

$$\alpha_t = \gamma_C \times \lambda_C + \gamma_b \times \lambda_b + \gamma_0 \times \lambda_0$$

$\alpha_t$ : It combines all individual loss components to guide the model's optimization.

$\gamma_C$ : It is a Weighting factor for classification loss and controls its importance relative to the other losses.

$\lambda_C$ : A Classification loss measures the accuracy of class predictions (e.g., helmet or no helmet).

$\gamma_b$ : The weighting factor for bounding box loss adjusts the focus on improving box accuracy.

$\lambda_b$ : Bounding box regression loss evaluates how well the predicted bounding boxes match the ground truth.

$\gamma_0$ : The weighting factor for confidence loss balances how much confidence impacts the optimization.

$\lambda_0$ : Confidence loss assesses the model's certainty in detecting an object.

#### a. Algorithm:

**Algorithm 1:** Adam Optimization  
Algorithm for  
YOLOv8

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**Input:** Gradient  $g_t$  at time step  $t$ , learning rate  $\alpha$ , first moment decay rate  $\beta_1$ , second moment decay rate  $\beta_2$ , small constant  $\epsilon$ .

**Output:** Predicted nonverbal vocalization category  $\theta$ .

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**Steps :**

- 1 : **start**
- 2 : **Initialize** first moment vector  $m_0$  and second moment vector  $v_0$  to zero
- 3 : **Initialize** time step  $t = 0$
- 4 : Set learning rate  $\alpha, \beta_1, \beta_2$ , and  $\epsilon$
- 5 : **for** each iteration **do**
- 6 :   Increment time step  $t$
- 7 :   Compute gradients  $g_t$  of the model parameters
- 8 :   Update biased first moment estimate using  $\beta_1$
- 9 :   Update biased second moment estimate using  $\beta_2$
- 10 :   Compute bias-corrected first moment estimate
- 11 :   Compute bias-corrected second moment estimate
- 12 :   Update parameters  $\theta$  using the corrected moment estimates
- 13 : **end for**
- 14 : Return the updated model parameters  $\theta$
- 15 : **end**

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**Variables used in Algorithm 1:**

- $g_t$ : Gradient of the loss at time  $t$
- $t$ : Current iteration step
- $\alpha$ : Learning rate for updates
- $Q_1$ : Decay rate for first moment (gradients)
- $Q_2$ : Decay rate for second moment (squared gradients)
- $\epsilon$ : Small value to avoid division by zero
- $\theta$ : Model parameters (weights)

**B. Dataset and Data Preprocessing:**

The dataset utilized in this project was taken from the Roboflow website with different classes namely Helmet and Non-Helmet to evaluate the performance of the YOLOv8 model in classifying whether the user wears the helmet or not. The dataset consisted of a total of 1200 images, two classes, namely Helmet and Non-Helmet with 600 images each, thus ensuring an imbalance-less dataset to offset the chances of biased prediction. These images were in 640\*640 pixels which satisfy optimal input conditions for the YOLOv8 model. JPEG format is applied to ensure the minimum storage space with the most compatibility. The DPI of the original images is 96 for both horizontal and vertical axes, while the resized images are of reasonably high quality. The dataset consists of RGB images which ensured sufficient color information in making the detection much more accurate. Data augmentation techniques including shearing, zooming, and horizontal flipping were applied to augment the training dataset and aid in generalization in predicting cases. Such augmentations simulated various conditions like variations in orientation and intensity, thus keeping the model robust. This dataset is oriented towards the training of the YOLOv8 model in the task of helmet detection, where the model learns to classify between images with and those without helmets and achieve high precision rates when put to the test in applications like monitoring safety and workplace inspection. The balanced dataset and augmentations ensured that YOLOv8 got adequate features for duly carrying out detection tasks.

### C. Model Architecture:

This Project continues the lineage of real-time object detection models with the state-of-the-art YOLOv8. The improvements made to the criteria of accuracy, speed, and programmatic efficiency over the previous versions are quite enormous. The architecture of YOLOv8 is made up of various, mostly, core components that serve the purpose of extracting, processing, and predicting object particulars like the backbone, neck, and head. They are highly significant because they support the working of the model around object detection in a particular manner.

**Backbone** The YOLOv8 backbone extracts hierarchical features from the provided input images. Deep convolutional layers have been utilized for the task of learning and executing spatial patterns and structures at several levels of abstraction. The YOLOv8 generally uses CSPDarknet53, an optimized organism of the Darknet53 backbone previously seen in earlier YOLO versions. The balance between model complexity and computation efficiency has been used, along with multiple convolutional layers, batch normalization, and activation functions, which is how so much eccentricity can be captured into the backbone length scales essential for accurate detection. The hierarchical features obtained by the backbone should then form the basis for object detection in an image.

**Neck** The neck generates feature pyramids which helps the model detect objects of various scales. PANet is a method for feature aggregation via a backward layer-bound electronic point aggregation network helping pan-structured pathways. The PANet aids in better feature fusion between various model levels, adding robustness to the enabled output after mixed level sequences have been adjusted. This makes it easy for YOLOv8 to detect small objects or larger ones. The neck helps the YOLOv8 detect objects at a variety of scales and circumstances. The neck component of the model aids in perceiving objects at various resolutions under varied circumstances.

**Head** The head of YOLOv8 is where the actual object predictions are made. This component is responsible for outputting the bounding box coordinates, the objectness score (which indicates whether an object is present in a given bounding box), and the class labels for each detected object. One of the key innovations in YOLOv8 is its ability to produce predictions in an anchor-free manner; as a result, anchor boxes need not be predefined for the model. Instead, the model directly predicts the bounding boxes from objects in order to enhance flexibility and declutter the model. The head consists of several convolutional layers followed by fully connected layers, which output the final detection results, including bounding box coordinates, class scores, and confidence levels. Based on the output feature map, each grid cell will correspond to a possibility of detection, and for each grid cell, predictions will be made on the bounding box, object class, and confidence.

**Inference** During inference, YOLOv8 first follows a series of steps to pass the input image through the backbone, neck, and head to make predictions regarding the existence and location of the objects. Filter predicted bounding boxes based on their confidence levels and class labels to eliminate low-confidence predictions. Non-maximum suppression (NMS) removes overlapping bounding boxes while keeping only the best predictions. This enables YOLOv8 to come up with predictions fast and with reliability, which can be a good fit for real-time object detection tasks. The architecture, consisting of the backbone, the neck, and the head, guarantees that YOLOv8 achieves high accuracy and speed in object detection, which is crucial for applications in helmet detection, wherein not only is speed required but also accuracy is vital.

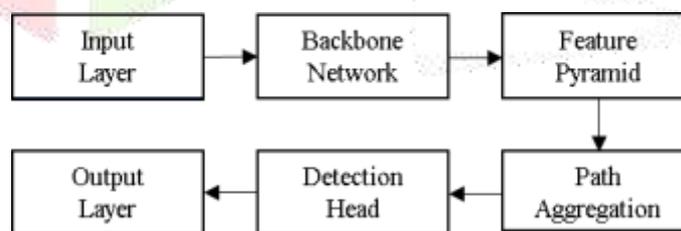


Fig 1. Architecture of YOLOv8

The YOLOv8 framework begins with the Input Layer, resizing and normalizing the raw input images so that they are prepared for further feature extraction. These input images then pass over the Backbone Network—that coincidentally is a CSP, designed to serve general feature representations well across different layers in a way that balances accuracy with computational efficiency. This backbone captures low-level details with high level semantic information in an impressively resilient hierarchical feature map. Then the feature maps are passed through the Feature Pyramid in the Neck module. The Feature Pyramid enables a strong multi-scale representation that is only possible when a model scans the feature maps at different scales to ascertain objects of various sizes. Subsequently, Path Aggregation is applied so that it aggregates and enhances multi-scale features. It offers spatial and semantic ties between various tiers within the network; thus, it leads to high-quality feature integration. After feature extraction, the features are passed to the Detection Head, which is engineered specifically for three tasks: an object classification task, objectness score prediction (which is the

probability of an object existing within a region), and regression of bounding boxes (prediction of coordinates of the object). The YOLOv8 approach is anchor-free detection, unlike most other anchor-based methods. This simplifies the whole prediction process and enhances the model ability to identify objects, particularly in cases with high object density. The Output Layer interprets the predictions that the Detection Head generates and displays the final results. The results would contain the coordinates for bounding boxes associated with each detected object, class labels assigned to them correctly, and confidence scores that represent the confidence of the prediction. This modularity ensures efficient yet accurate detection in an extremely wide variety of applications that range from object detection and segmentation to classification.

#### IV. RESULT AND DISCUSSION

The actual helmet detection system designed in this study employed YOLOv8 to detect helmets, riders without helmets, and different background parts within the images. The analysis was based on a custom dataset, and the analysis indicated the strengths as well as the limitations of the model. The confusion matrix (Figure 2) gives insight into the performance of the system for the three types:

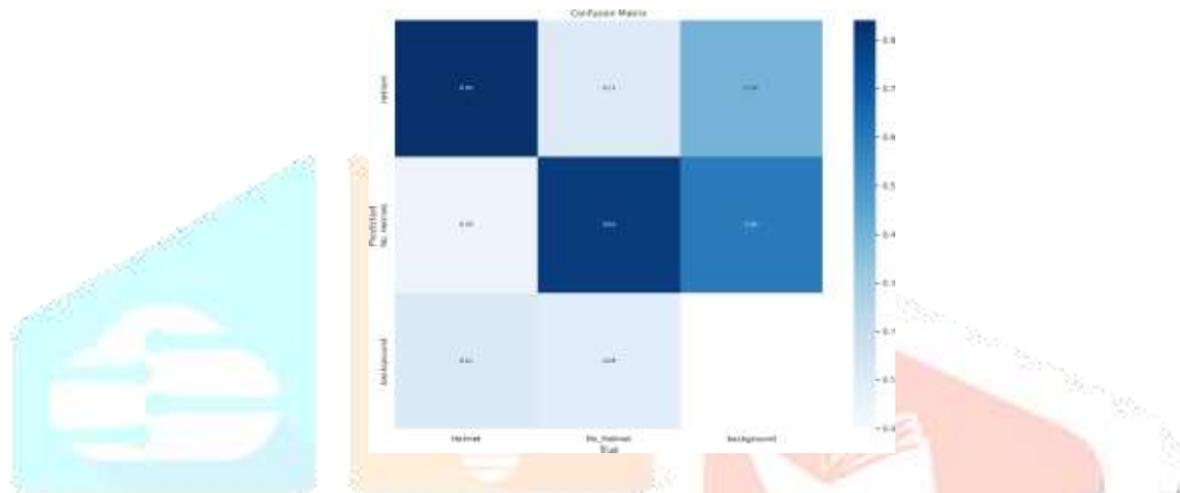


Fig 2. Confusion Matrix of Custom YOLOv8 model

The model was correctly only able to classify 84% of helmeted riders with an 11% false positive rate in which helmets were misclassified as background. Precision rate for the "No-Helmet" class was 80% but showed a degree of confusion with the background class. Though the background class excelled, some overlap with the helmet class was seen, indicating areas where improvement could be gained.



Fig 3. Result of Custom YOLOv8 model

Figure 3 demonstrates a few samples of the system performance on helmeted vs. non-helmeted rider detection. In most test cases, the model's accuracy and confidence were high as it indicated correctly helmets on riders' heads, sometimes with confidence larger than 0.9. In general, riders without helmets also underwent correct detection at different viewing angles and illumination conditions. But some false negatives and misclassifications came out, mainly for images for which the helmet or the rider was partially occluded or where the background was cluttered or low resolution. Apart from this, the demonstration of the hardware confirmed that the system was operationally feasible. The hardware setup responded promptly to the model's predictions-where a motor and LED would turn on in case a helmet is detected and, conversely, a buzzer would go off once a helmet is not present. Smoother interaction between the detection system and the hardware components points to the potential use of this system in enforcement campaigns for safety. Despite its success, there were certain issues with the network. It struggled with detection in dimly lit environments or when helmets had colors similar to that of the background. At times, helmet-like objects also resulted in false positives. This prototype, if developed further, could overcome these limitations through a larger dataset, sophisticated data augmentation approaches, and higher robustness in models. Testing with live feeds would also go on to test the effectiveness of this network in real-life scenarios. Generally, the result shows that YOLOv8 is appropriate for helmet detection and can improve the safety protocol if adaptive hardware configuration is embedded.

## V. CONCLUSION

The project was indeed a real-time helmet detection system using YOLOv8, capable of operating with very high accuracy and reliability under a variety of real-world conditions. It integrates the feature extractor CSPDarknet53, multi-scale feature aggregator PANet, and an anchor-free detection mechanism for robust performance. Immediate feedback mechanisms, such as activating a servo motor and buzzer upon non-compliance, enhance its practical application for rider safety. The study elaborates on YOLOv8's efficacy as applied to safety issues and its potential applicability in more widespread real-time object detection scenarios. Further work may include more safety features and IoT integration to further increase functionality and scalability.

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