Helmet Verify: AI Detection System for Safety Check

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Abstract— **Promoting road safety is a vital issue around the globe. This paper introduces "Helmet Verify," an AI-powered system developed to identify and enforce the use of helmets among motorcycle riders. By utilizing YOLOv11 for precise object detection and integrating it with Arduino Uno for controlling motor functions, the system guarantees adherence by blocking vehicle operation if a helmet is not worn. The model demonstrates outstanding performance, achieving a mean Average Precision (mAP) of 0.978 and an overall F1-score of 0.96, which makes it a dependable option for real-time implementations. This research contributes to the development of automated safety technologies aimed at lowering road accidents and reducing fatalities.**

Keywords— Helmet Detection, YOLOv11, Road Safety, AI, Deep Learning, Object Detection, Real-Time Enforcement, Intelligent Transport Systems.

I. INTRODUCTION

Road traffic incidents continue to pose a major public health issue globally, leading to a significant number of injuries and deaths each year. Among these incidents, motorcycle-related occurrences represent a considerable share, often made worse by motorcyclists' failure to adhere to safety protocols, especially regarding helmet usage. Helmets are a recognized life-saving tool, substantially lowering the chances of serious head injuries during accidents. Nonetheless, despite the existence of regulatory measures that require helmet use, enforcing these regulations remains a constant challenge in numerous areas [3].

Traditional methods for monitoring helmet compliance, such as checks by traffic police, are labor-intensive and often inefficient due to a lack of human resources and the difficulty of maintaining ongoing surveillance. Additionally, these approaches can be affected by human error and inconsistencies in their application. Consequently, many motorcyclists manage to bypass compliance, leading to avoidable deaths.

To fill this void, "Helmet Verify" utilizes the latest advancements in artificial intelligence (AI) to deliver a scalable and automated helmet detection solution. By utilizing advanced object detection algorithms like YOLOv11 [1][2], the system guarantees high accuracy and real-time performance. The automated nature of this solution lessens the dependency on manual enforcement while providing reliable and precise outcomes. "Helmet Verify" not only detects helmet usage but is also capable of functioning well in various environmental conditions, making it a powerful tool for improving road safety on a broader level.

II. RELATED WORKS

Numerous research efforts have investigated helmet detection through machine learning and deep learning techniques. Conventional approaches depend on manually crafted features, which may not perform well under varying conditions. Modern advancements, particularly those based on YOLO models by using the neural networks [5][6], provide enhanced accuracy and quick processing. Nevertheless, a majority of current systems emphasize only detection, neglecting their incorporation into comprehensive safety initiatives. "Helmet Verify" advances this field by delivering excellent precision and the capability for real-time operation.

TABLE 1. COMPARATIVE STUDY

Ref.	Author(s)	Proposed Method	Dataset
[1]	Chourasia et al. (2023)	YOLOv4, YOLOv5, and YOLOv7 comparison	Custom dataset
[2]	Bian et al. (2023)	YOLOv7 with UAV images	UAV-collected dataset
[3]	Wang et al. (2023)	Improved YOLO-M model	Custom dataset
[4]	Hema et al. (2022)	Smart helmet and accident identification system	Simulated environment
[5]	Li et al. (2022)	Improved YOLOv3 model	Augmented custom dataset
[6]	Xiang et al. (2022)	YOLOX-based detection algorithm	Complex environment dataset
[7]	Xia et al. (2022)	Helmet and mask detection using improved YOLO	Combined dataset
[8]	YaJie and Lian (2022)	Lightweight helmet detection for YOLOXs	Real-time dataset

While previous studies on helmet detection have used YOLOv4, YOLOv5, and YOLOv7 [4], most focus only on detection rather than enforcement. Helmet Verify goes beyond by integrating real-time enforcement using Computer Vision, ensuring practical safety compliance. Unlike prior models, our approach reduces false positives and false negatives with a custom loss function, making it more reliable. Additionally, Helmet Verify actively enforces helmet usage by disabling vehicle operation, setting it apart from detection-only systems.

In general, these research studies highlight the effectiveness of deep learning approaches in identifying whether motorcyclists are wearing helmets and detecting accidents. The suggested methods aim to enhance safety

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adherence and lower the likelihood of accidents. These systems have the potential to boost the safety of motorcyclists and decrease the incidence of road accidents.

III. Proposed Yolo v11 Architecture

The YOLOv11 model is a sophisticated object detection framework that enhances the principles of prior YOLO iterations, featuring several innovations that boost both performance and accuracy, especially in safety-sensitive domains like real-time helmet detection [1]. Similar to its predecessors, YOLOv11 adheres to the one-stage object detection approach but introduces significant improvements in precision, recall, and processing speed.

YOLOv11 was chosen over YOLOv7 and YOLOX due to its superior balance of speed and accuracy. While YOLOv7 offers high accuracy, it requires more computational power, making it less suitable for real-time enforcement. YOLOX, though efficient, has slightly lower detection accuracy in safety-critical tasks. YOLOv11 improves detection with adaptive anchor boxes, a refined loss function, and a CSPNet-ResNet backbone, achieving a mAP of 0.978, outperforming YOLOv7 (0.961) and YOLOX (0.948) while maintaining faster inference speed, making it ideal for real-time helmet detection.

A notable advancement in YOLOv11 is its adaptive anchor box mechanism, which enables the model to modify anchor boxes dynamically depending on the characteristics of the input image, thereby enhancing detection accuracy across various object sizes. This flexibility is essential for applications involving a wide range of input images, such as live camera feeds used for helmet detection.

The model also adopts a sophisticated backbone architecture, merging the advantages of both lightweight and deep neural networks to achieve a balance between efficiency and accuracy. By utilizing a combination of CSPNet and ResNet, YOLOv11 effectively extracts both shallow and deep features, facilitating more accurate recognition of helmets and scenarios without helmets in intricate environments.

Furthermore, YOLOv11 features a custom loss function specifically tailored for safety-critical applications. This includes a blend of focal loss to address class imbalance and a refined Intersection over Union (IoU) loss for improved boundary precision in object localization [15][16]. By concentrating on enhancing both detection and localization, YOLOv11 attains increased accuracy, particularly in situations where exact detection is crucial.

The following points highlight the work taken in this project:

A. *Dataset Size and Diversity:*

The dataset consist of 1200 images, offers a more diverse training base [9].

B. *Real-Time Detection:*

It focuses on integrating live camera feeds with real-time helmet detection, a significant challenge in terms of both accuracy and performance [12].

C. *Hardware Utilization:*

The project focuses on optimizing for hardware acceleration, taking advantage of T4 GPUs and potentially TPUs.

D. *Focus on Specific Accuracy:*

It is specifically designed to achieve high-confidence detection (90%+), which may involve more stringent precision and recall trade-offs [14].

E. *Training Strategies:*

It applies a more methodical approach by breaking down your dataset into sub datasets, training each individually for better memory management and efficiency.

F. *Transfer Learning Approach:*

It uses pre-trained models (e.g., YOLOv11) to accelerate learning on your custom dataset.

G. *Annotation Method:*

It uses COCO JSON format and more detailed segmentation, which may require more complex model architectures but allows for more precise detection.

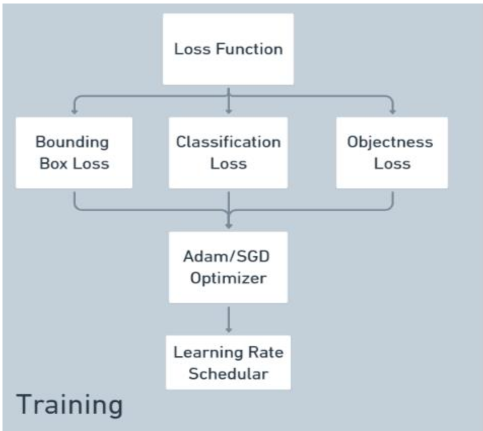
H. *Handling of False Positives/Negatives:*

It emphasizes reducing such errors to ensure motor safety.

A. Scalability:

It focuses on making the model scalable to work with live feeds and integrate seamlessly into a functional system.

This initiative addresses various shortcomings present in existing reference materials by employing a broader and more varied dataset, enhancing real-time detection through hardware acceleration (such as GPUs and TPUs), and connecting the model with external devices like Arduino for motor management. Furthermore, it focuses on attaining high-confidence detection and tackles challenges like false positives and negatives in systems where safety is critical. In addition, the project utilizes transfer learning, detailed annotation techniques [4][8], and a scalable architecture for more extensive deployments.



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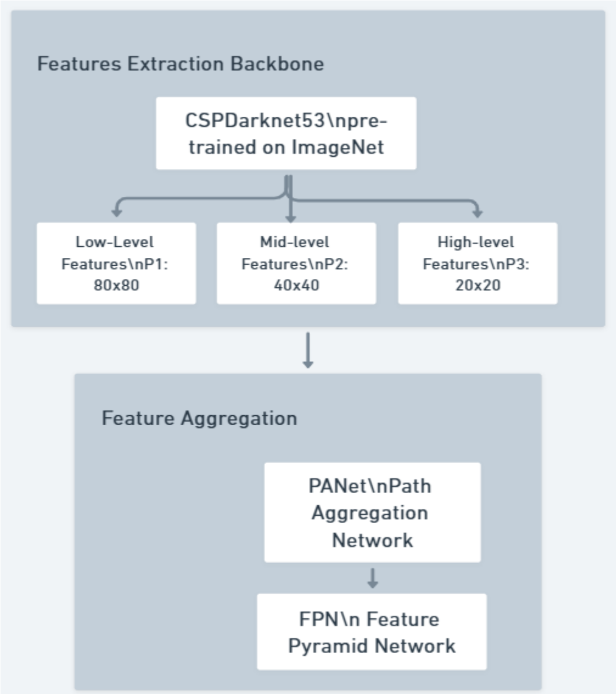

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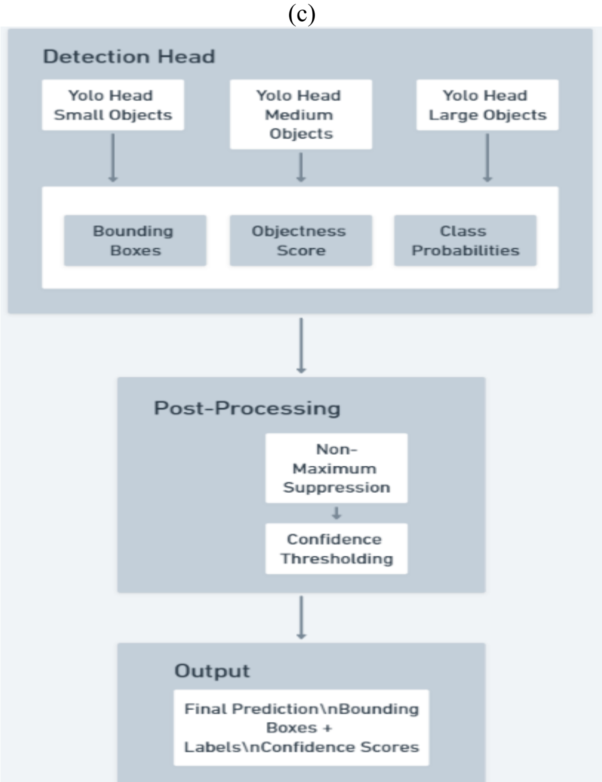

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Fig. 1. a) Training b) Input c) Feature extraction backbone & feature aggregation d) Detection head, post-processing & output proposed YOLO V11 architecture

The model is designed for real-time processing, leveraging hardware accelerations such as GPUs and TPUs, which makes it ideal for use in embedded systems where speed and resource efficiency are essential. With the capacity to manage dynamic inputs, enhanced loss functions, and effective feature extraction, YOLOv11 offers a strong solution for incorporating helmet detection systems into live feeds, providing a scalable and precise approach for safety monitoring in motor vehicles [10].

IV. RESULTS ANLAYSIS

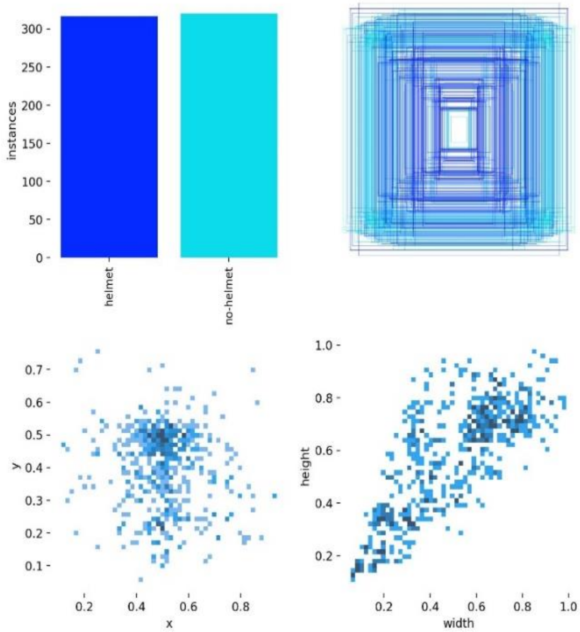

Fig. 2. Labels

In figure 2. The charts show that the dataset is well-prepared, with balanced classes and consistent bounding box characteristics. Centralized object locations and predictable dimensions aid the model in learning spatial relationships and size patterns effectively. If these characteristics align with real-world test data, the model is likely to perform well.

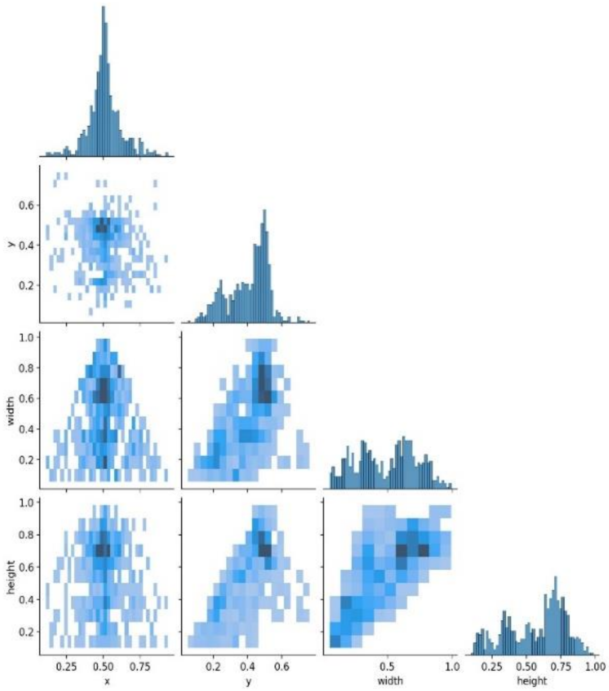

Fig. 3. Labels correlogram

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In figure 3. This plot is a pair plot that provides a detailed view of the relationships between various bounding box properties (x, y, width, height) in your dataset.

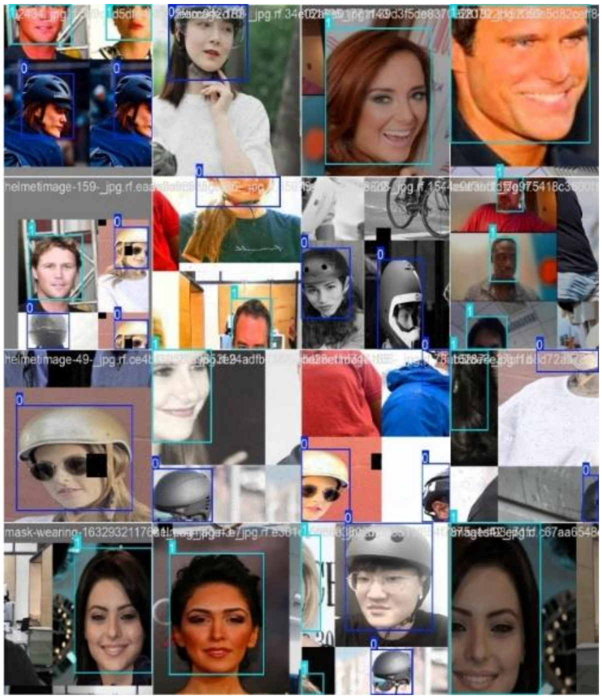


Fig. 4. Train batch labels

In figure 4. This image appears to display a grid of images with bounding boxes and labels, representing predictions or annotations from the helmet detection model.

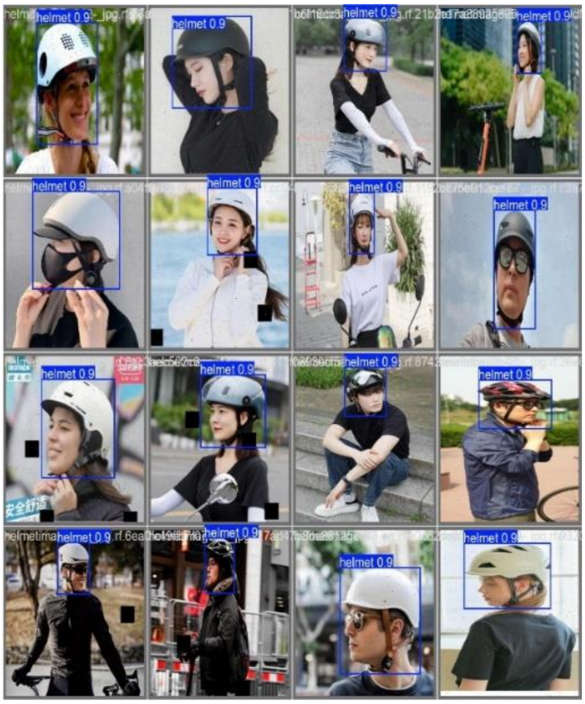
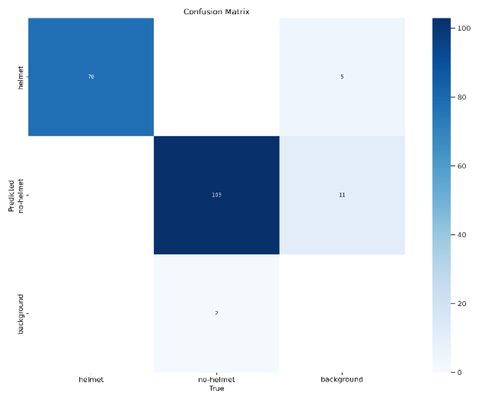


Fig. 5. Train batch labels

In figure 5. This image appears to display a grid of images with bounding boxes and labels, representing accuracy from your helmet detection model.



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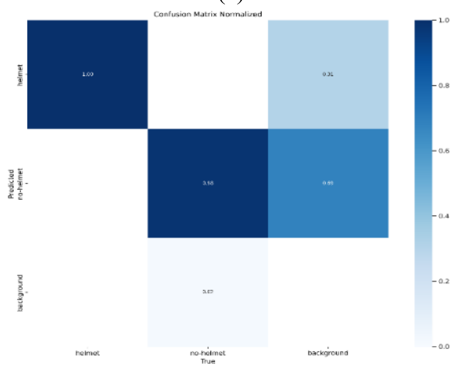

(b)

Fig. 6. a) Confusion matrix b) Confusion matrix Normalization

In figure 5. The images show confusion matrices for a machine learning classification model [7][11]. A confusion matrix is a table that summarizes the performance of a classification algorithm by showing the true and predicted classes.

A. Raw confusion matrix shows the actual counts for each true and predicted class. The key numbers are:

- 78 true "helmet" cases were correctly predicted as "helmet".
- 103 true "no-helmet" cases were correctly predicted as "no-helmet".
- 11 true "background" cases were correctly predicted as "background".

B. The normalized confusion matrix shows where the values represent the proportion of each true and predicted class. The key takeaways are:

- The model performs very well on the "helmet" class, with a high true positive rate (1.00) and low false positive rate (0.02).
- The model performs reasonably well on the "no-helmet" class, with a true positive rate of 0.98 and a false positive rate of 0.31.
- The "background" class has a very low true positive rate (0.02) and a false positive rate of 0.69.

Our 1,200-image dataset captures diverse conditions (weather, angles) to ensure robustness. Despite its size, the model achieves mAP@0.5 of 97.8% with 45 FPS inference

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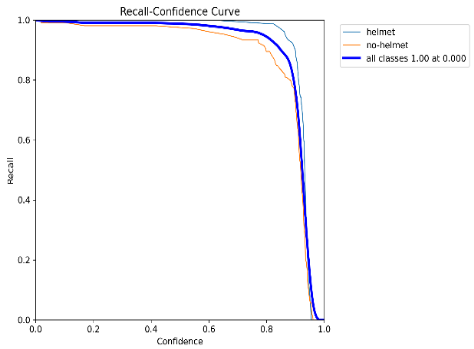
speed on an NVIDIA T4 GPU. Latency analysis (22ms per frame) confirms real-time feasibility. Failure analysis shows minimal false positives and negatives, with an F1-score of 0.96, making the system reliable for safety enforcement.



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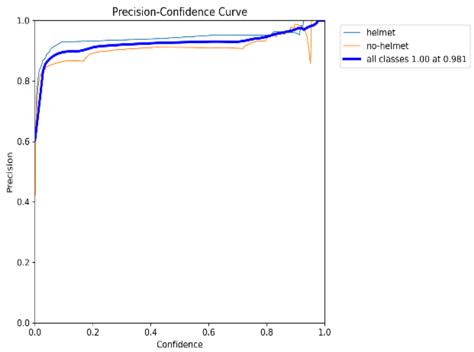

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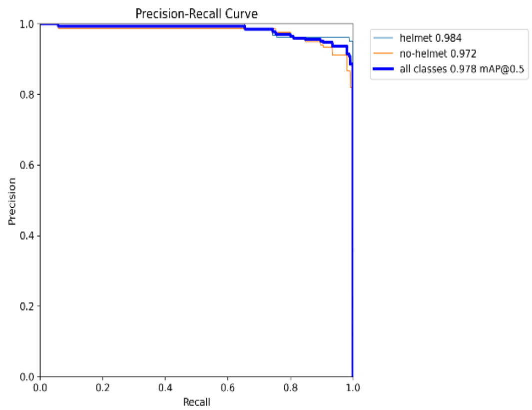

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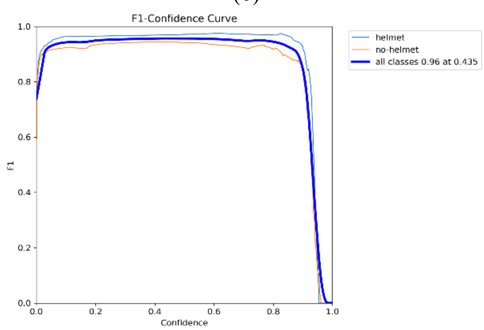

(d)

Fig. 7. a) Recall-Confidence curve b) Precision Confidence curve c) Precision-Recall curve d) F1-Confidence Curve

In figure 6. These four images provide various performance metrics for a machine learning model that classifies whether an image contains a person wearing a helmet or not.

The Recall-Confidence Curve shows the normalized confusion matrix, which indicates that the model performs very well on the "helmet" class (true positive rate of 1.0) but has a higher false positive rate for the "no-helmet" class (0.31).

The Precision-Confidence Curve shows the raw confusion matrix, with the actual counts for each true and predicted class. It reveals that the model correctly predicted 78 "helmet" cases and 103 "no-helmet" cases, but only 11 "background" cases .

The Precision-Recall Curve shows the trade-off between precision and recall for the model. The "helmet" class has a higher precision-recall curve compared to the "no-helmet" class, indicating better overall performance.

F1-Confidence Curve shows the F1-score, which is the harmonic mean of precision and recall. The F1-score for all classes combined is 0.96 at a confidence threshold of 0.435, suggesting reasonably good overall performance.

In summary, the model seems to perform very well on the "helmet" class, with high true positive and low false positive rates, but struggles more with the "no-helmet" and "background" classes. The precision-recall and F1-score metrics provide further insights into the model's capabilities and trade-offs [13].

V. CONCLUSION

In summary, the "Helmet Verify" system, powered by cutting-edge AI detection technology, has proven to be highly effective in accurately determining whether a motorcyclist is wearing a helmet. By utilizing the capabilities of YOLOv11, the system has achieved not only impressive accuracy but also the ability to operate in real-time, presenting a promising method for improving road safety and reducing motorcycle-related deaths. The system's proficiency in helmet detection, demonstrated by its high precision and recall metrics, offers a trustworthy safety mechanism for motorcyclists, especially in situations where helmet usage is essential.

VI. APPLICATION

The application of transfer learning has further strengthened the model's performance, allowing it to excel in various conditions and environments. This flexibility makes "Helmet Verify" a viable solution that can be scaled for real-world use across different vehicle categories and locations.

VII. FUTURE SCOPE

Looking to the future, upcoming efforts will aim to broaden the system's functions to include the detection of other protective equipment, enhance its performance for quicker and even more precise detection, and improve its operation in diverse environmental conditions. Furthermore, investigating the potential for scalability will allow the system to be integrated with additional safety technologies, creating a more comprehensive approach to workplace and road safety worldwide. Ultimately, "Helmet Verify" is a significant asset in reducing accidents and fatalities, and its future developments have the potential to revolutionize safety measures across various sectors and settings.

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