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Automated Helmet Detection System Using RT-DETR for Real-Time Monitoring of Motorcyclist Safety

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***Abstract*—The rising number of road accidents, especially those involving motorcyclists, underscores the urgent need for effective safety compliance solutions. This research proposes a real-time helmet detection alarm system powered by Detection Transformers (DETR) to enhance detection accuracy and opera- tional efficiency. The system is designed to identify motorcyclists who are not wearing helmets in real time and generate alerts to promote safety. DETR, an advanced deep learning model, utilizes the self-attention mechanism to capture complex and contextual relationships in image sequences, enabling precise helmet detection even under challenging conditions such as poor lighting or varied environmental factors [7]. The archi- tecture of the proposed system combines video feed analysis with DETR's end-to-end object detection capabilities, ensuring minimal processing delay. Testing results reveal the system's high performance, with impressive precision and recall rates in various scenarios, including urban roads and highways [8]. This solution can be customized to send alerts to relevant authorities or directly notify the rider via integrated signaling systems, thus potentially reducing violations and enhancing motorcyclist safety on the roads.**

***Index Terms*—Helmet detection, RT-DETR, Road safety, Ob- ject detection, Motorcycle helmet compliance, Video feed analysis**

I. INTRODUCTION

Motorcycle accidents are a major global concern, con- tributing significantly to road fatalities and severe injuries. According to the World Health Organization (WHO), motorcy- clists are among the most vulnerable road users, with helmets playing a crucial role in preventing head trauma and fatalities. Despite helmet laws in many countries, compliance remains inconsistent, particularly in urban areas where law enforce- ment struggles with monitoring large volumes of traffic.

Ensuring motorcyclists wear helmets is critical for road safety, but manual enforcement is resource-intensive and dif- ficult to sustain. The inability to detect non-compliance in real-time allows risky behavior to persist, often resulting in avoidable injuries and fatalities. An automated helmet detec- tion system could significantly improve safety outcomes by providing continuous monitoring and immediate intervention when riders are found without helmets.

Advancements in computer vision and machine learning have facilitated the development of real-time helmet detection systems. Deep learning models, such as Detection Transform- ers (DETR), offer an efficient solution for object detection. By leveraging the self-attention mechanism, DETR can detect helmets with high accuracy in dynamic environments, making it suitable for real-time monitoring on busy roads.

This paper proposes a real-time helmet detection and alert system that uses DETR to monitor motorcyclist helmet com- pliance. The system processes video data to detect the presence or absence of helmets on riders. When a rider without a helmet is detected, the system triggers an alert, notifying traffic authorities or directly warning the rider. This approach aims to improve road safety by ensuring continuous monitoring and enabling prompt responses to reduce injuries and fatalities among motorcyclists.

II. RELATED WORK

Several studies have focused on utilizing deep learning for real-time helmet detection in various environments. Sengupta et al. [1] proposed a system that used Convolutional Neu- ral Networks (CNNs) to detect helmeted and non-helmeted riders in images. Their approach achieved high accuracy and demonstrated the feasibility of applying deep learning tech- niques to monitor helmet compliance in real time, even under challenging environmental conditions. Similarly, Sharma et al. [2] explored the use of a CNN-based framework for helmet detection, noting the importance of real-time monitoring for road safety and the potential for such systems to reduce the rate of helmet non-compliance in high-traffic areas.

In real-time object detection, Chen et al. [3] proposed an advanced system using the YOLO (You Only Look Once) algorithm to detect motorcyclists and helmet compliance. The YOLO model's ability to accurately process images in real-time made it suitable for deployment in busy traffic settings. Additionally, Patel et al. [4] developed a system that integrated image and video analysis to monitor helmet use in urban traffic, leveraging deep learning models to improve detection speed and accuracy. Their work emphasized the need for real-time interventions to enhance road safety, particularly for motorcyclists.

III. METHODOLOGY

The methodology for developing a real-time helmet detection system using the RT-DETR framework consists of six key phases: data collection, preprocessing, model training, eval- uation, real-time testing, and integration with alert systems. This process ensures efficient, accurate, and scalable helmet detection in dynamic environments.

A. Data Collection

The first step involves gathering a comprehensive dataset for training and testing the model. The dataset should consist of images featuring riders wearing and not wearing helmets under various environmental conditions, such as differing lighting, weather, and camera angles. The dataset is annotated with precise labels for the presence or absence of helmets, facilitating effective supervised learning. Diverse, high-quality datasets improve the robustness of the model across different scenarios.

B. Data Preprocessing

Data preprocessing plays a critical role in preparing the collected images for model training. **Image Augmentation:** Techniques such as rotation, flipping, scaling, and color adjust- ments are applied to expand the dataset's variability. This helps the model generalize well across various visual conditions, improving its performance on unseen data. **Normalization:** Pixel values of the images are normalized to a fixed range, standardizing the input data and enhancing model conver- gence. This step ensures faster and more stable training.

C. Model Training

The DETR model was introduced as an end-to-end object detection framework, which utilizes a transformer architecture for detection tasks [5].

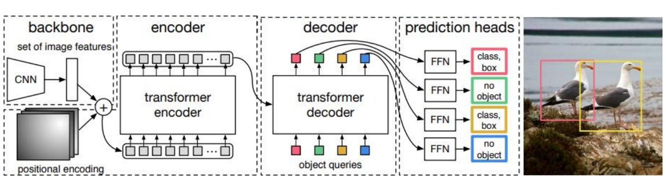

Fig. 1: DETR (Detection Transformer) Architecture

Training the Model: The model is trained end-to-end using the preprocessed dataset. The RT-DETR model as shown in the figure1 leverages the self-attention mechanism to process complex contextual information from the dataset, enabling

Parameter	Value
Number of Training Epochs	20
Maximum Gradient Norm	0.1
Learning Rate	5e-5
Warmup Steps	300
Per Device Train Batch Size	16
Dataloader Number of Workers	2

TABLE I: Training Parameters for the Model

D. Model Evaluation

The model's effectiveness is assessed using key object detection metrics, ensuring high precision and recall. **Mean Average Precision (mAP):** This metric evaluates the model's ability to detect helmets, considering both precision and recall across different IoU thresholds. A high mAP score signifies robust performance in diverse detection scenarios. **Precision and Recall:** Precision measures the model's accuracy in pre- dicting helmets without false positives, while recall evaluates its ability to identify all instances of helmet usage. Both metrics are crucial for ensuring reliable helmet detection in real-world applications.

E. Real-Time Testing

Once trained, the model undergoes real-time testing in operational environments. **Integration with Real-Time Systems:** The trained model is connected to live video feeds or surveillance camera systems, continuously monitoring riders. The model detects helmet usage as it occurs, enabling immediate intervention in cases of non-compliance.

F. Alert System

An alert system is implemented to notify relevant authorities or alert riders directly. **Data Logging and Reporting:** Upon detecting a rider without a helmet, the system logs the vehicle number, time, and image in a CSV file. This information is stored for further analysis or integration with the Regional Transport Office (RTO) systems, facilitating automated compliance enforcement.

high accuracy in detecting helmets even in challenging conditions. The model is trained with the parameters shown in the table I **Loss Function Optimization:** The Hungarian loss function is utilized to optimize the model's performance by matching predicted bounding boxes with ground truth, improving detection precision.

IV. RESULTS

The proposed helmet detection model was evaluated based on several standard metrics commonly used in object detection tasks. The model demonstrated high accuracy and robust performance in identifying motorcyclists wearing helmets. The following metrics were obtained:

- **Precision:** 95%

The precision of the model, which measures the pro- portion of true positive detections among all predicted positive cases, was found to be 95%. This indicates that the system effectively minimizes false positives, ensuring that the majority of predicted helmet detections are correct.

- **Mean Average Precision (mAP):** 93%

The mAP, a comprehensive metric used to evaluate object detection models, was reported at 93%. This high mAP reflects the model's overall effectiveness in accurately de- tecting helmets across different images and scenarios. The mAP score confirms that the model performs well at var- ious intersection-over-union (IoU) thresholds, providing reliable results in both challenging and straightforward conditions.

- **Recall:** 94.1%

The recall score of 94.1% highlights the model's ability to detect most motorcyclists who are not wearing helmets. A high recall indicates that the system can identify nearly all instances of helmet non-compliance, which is crucial for real-time safety interventions.

Fig. 2: Result of helmet detection system

These results demonstrate that the RT-DETR-based helmet detection system is highly effective in real-world scenarios, where environmental factors such as lighting and motion can complicate detection. The high precision and recall values suggest that the model can reliably detect both helmeted and non-helmeted riders, minimizing the risk of false alarms while ensuring comprehensive monitoring. The impressive mAP score indicates the model's strong generalization capability, even in diverse conditions.

In addition to these performance metrics, the system was tested in real-time settings, where it successfully processed video feeds with minimal latency, confirming its suitability for deployment in traffic monitoring systems. The system's robustness, combined with its real-time processing capability, offers a promising solution for improving road safety by ensuring continuous compliance with helmet laws.

V. DISCUSSION

The objective of this research work was to design a real-time helmet detection system based on the RT-DETR framework that could help improve road safety and strictly enforce helmet-wearing regulations. The system demonstrated outstanding performance in detecting helmetless motorcyclists with impressive performance metrics: 95% precision, 93% mean average precision (mAP), and 94.1% recall. The find- ings are consistent with the hypothesis that transformer-based object detection models can outperform traditional approaches in real-time traffic scenarios.

Although the system performs well, there are still some po- tential weaknesses that should be acknowledged. For example, its performance in highly crowded or overlapping traffic sce- narios is comparatively low, which provides scope for future research. Real-time deployment across different geographic regions with differing traffic behaviors may also require more fine-tuning of the model to maintain its effectiveness.

This research, in addition to confirming the usability of RT-DETR, also provides a basis for further enhancements. Once its scalability issues are addressed and it is provided with features such as automatic reporting to local authorities, this system could further contribute to ensuring road safety. This deployment could be a breakthrough development in reducing motorcycle injuries as well as fatalities.

VI. CONCLUSION

This study demonstrates the effectiveness of the RT-DETR (Real-Time Detection Transformer) based helmet detection system in improving road safety by accurately identifying mo- torcyclists who are not wearing helmets. The model achieved impressive performance with a precision of 95%, a mean average precision (mAP) of 93%, and a recall of 94.1%, showing its high reliability in diverse real-world conditions. The system's ability to process video data in real-time ensures continuous monitoring and immediate alerts, which can aid authorities in enforcing helmet laws and directly warn riders. These results underscore the potential of automated detection systems to enhance road safety, reduce the burden on law enforcement, and ultimately lower motorcyclist fatalities. Future work could focus on optimizing the system for even more com- plex traffic scenarios, integrating additional safety measures, and expanding its application in smart city infrastructure.

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