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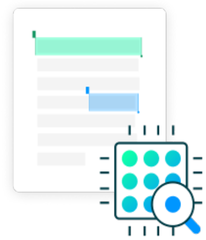

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HelmSecure: AI Helmet Enforcement

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Abstract. Ensuring the use of safety helmets is essential for reducing the risk of head injuries in both workplaces and on the road. However, workers and motorcycle riders often neglect wearing helmets due to discomfort or lack of awareness, leading to increased safety risks. To address this, a dual-purpose detection model has been developed to automatically detect helmet usage in construction sites and monitor motorcycle riders on the road. The system uses the YOLOv8 model to detect helmet usage, automatically capturing images, license plate numbers, and timestamps when helmets are not worn. The system also provides real-time monitoring, enabling authorities to act swiftly on safety violations. The model was tested with a diverse dataset, achieving high accuracy in detecting helmets, even in challenging conditions such as varying lighting and complex backgrounds. The results demonstrate that the system is highly efficient in monitoring helmet compliance, reducing the need for manual checks, and providing accurate, real-time data for enforcement.

Keywords: Helmet Detection ,Workplace Safety, Motorcycle Rider Monitoring, License Plate Recognition, Image Processing, Real-Time Detection, YOLOv8,Object Detection.

1 Introduction

With the fast growth of cities, there has been an increase in the urbanization rate which results in a greater need for infrastructure, resources and efficient management systems and vast amount of infrastructure is needed to be built and construction site safety is gaining even more public attention than before. A lot of incidents can be stopped with the use of personal protective equipment (PPE). Security helmet is major proven PPEs that prevent labour from the blow of drop down construction materials or equipment, and wearing of safety helmets is a legal obligation around the world on building sites. However, safety helmet usage is often neglected due to discomfort and poor safety awareness.

Monitoring workers' compliance with helmet regulations is crucial for safety and improved management at construction sites. Traditional compliance monitoring is widely used, but emerging computer vision technology offers great potential. Algorithms like the Gaussian Mixture Model (GMM)[5], Histogram of Oriented Gradient (HOG)[6], and Support Vector Machine (SVM)[7] have been developed for helmet detection. Video surveillance is the common traditional method for monitoring helmet compliance using camera footage[8].

The continuous advancements in computer vision algorithms and computational power have paved the way for more efficient safety helmet identification methods. Among these, deep learning-based algorithms, particularly the YOLO (You Only Look Once) sequence, have attained a remarkable balance betweenspeed ,precision. Even state-of-the-art YOLObased methods face [9] in accurately detecting helmets, especially in complex environments where small, monochromatic helmets can be easily confused with other objects.

Building upon these challenges, this study introduces a dualpurpose detection system designed to enhance safety in both industrial and vehicular contexts. Our model not only detects Whether a person has a helmet on or not in workplace but also extends its functionality to monitor motorcycle riders, verifying helmet usage and capturing license plate information[10]. This system automatically stores the detected individual's image, the motorcycle's license plate number, and timestamps these details in an Excel sheet, providing a comprehensive data record for safety enforcement.

The license plate is a key identifier for a vehicle, giving it a unique identity. Recognizing license plates is a crucial aspect of developing smart transportation systems, which can help with traffic management, vehicle ¬Currently, license plate recognition technology involves three main steps: detection, segmentation, and recognition. However, this process can be complex, inefficient, and often affected by challenges like uneven lighting and noise, which reduces its reliability.

In latest years, due to fastest advancement of Hardware infrastructure, neural network models based on deep learning they become the most suitable tools for tackling complex problems in computer vision. Convolutional Neural Network (CNN)[14]has shown to be best deep learning techniques for target detection and identification tasks, and most common algorithm for target identification using CNN is YOLO.

As cities grow, construction safety becomes increasingly important. Using personal protective equipment (PPE) can prevent many accidents. such as helmets, which protect workers from falling objects. However, workers often skip wearing helmets due to discomfort and low awareness. Traditional helmet checks rely on manual supervision, but computer vision techniques, like YOLO, offer faster and more accurate detection. This study presents a system that not only checks helmet usage in construction but also monitors motorcyclists, recording license plates and timestamps in an Excel sheet, enhancing safety enforcement in various environments. Subsequent paragraphs, however, are indented.

2 LITERATURE REVIEW

A. Traditional Approaches to Helmet Detection Traditional helmet detection methods relied on manual feature extraction, using techniques like edge detection, color segmentation, and template matching to identify helmets. While simple, these methods often lacked accuracy, especially in complex environments with varied lighting and background clutter, leading to high false positive and negative rates. They struggled to detect small or partially obscured helmets, limiting their real-world effectiveness.

One of the earliest techniques involved By utilizing The combination of Support Vector Machines (SVM) and Histogram of Oriented Gradients (HOG) [12] has been widely utilized for object detection. While HOG effectively captured shape information, it was prone to errors when faced with objects that had similar edge features to helmets, leading to misclassifications. Another method, Circular Hough Transform (CHT) [13], was employed to detect circular shapes resembling helmets. However, its reliance on geometric assumptions made it less effective in dynamic and cluttered environments where helmet shapes could be distorted or obscured.

Traditional helmet detection methods relied on manual feature extraction techniques such as edge detection and color segmentation. These approaches were useful in basic environments but struggled with accuracy in more complex conditions, like when lighting varied or backgrounds were cluttered. They often produced too many errors, with false positives and negatives, especially when helmets were small or partially hidden. As a result, these techniques were not practical for real-world use, where more advanced and reliable methods are needed to ensure proper helmet detection.

B.Advances in Deep Learning-Based Detection With the advent of deep learning, safety helmet detection has seen significant improvements in accuracy and robustness. Convolutional Neural Networks (CNNs) have revolutionized object detection by automatically learning hierarchical features from data, reduces the need for manual feature engineering. This shift has enabled more reliable detection in complex environments and has greatly improved performance in realtime applications.

Deep learning based methods are categorized in two main types: two-stage detectors and one-stage detectors. Two-stage detectors, like the Region-based Convolutional Neural Network (R-CNN) [15] family, first generate region proposals and then classify them. These methods have shown high accuracy but often suffer from slower processing speeds, making them less suitable for real-time helmet detection. Improvements like Fast R-CNN and Faster R-CNN have attempted to address these issues by optimizing the region proposal process and sharing convolutional features, yet they still fall short in scenarios requiring rapid detection.

One-stage detectors like the YOLO series are popular for their ability to perform object detection in a single pass. The latest YOLOv8 offers impressive speed and accuracy, with enhancements like advanced feature fusion and lightweight architecture, making it ideal for real-time helmet detection. However, challenges persist in detecting small objects and handling occlusions in complex backgrounds.

Currently, deep learning methods rely heavily on data, meaning the output of object detection algorithms based on the quality and quantity of the training datasets. However, there aren't many images available for safety helmet detection. To enhance the presentation of YOLO v5 in detecting helmet use, this research used techniques like Utilizing focused data augmentation and transfer learning methods. In the end, a userfriendly interface (GUI) was also designed to build the model simpler to utilize.

The goal is to develop a model that quickly and accurately detects helmet use on construction sites while being easy to use and adaptable to various environments. The model must handle small objects and different helmet sizes effectively. The dataset includes diverse helmet images to ensure real-world performance. Enhancements to YOLO-based models, such as attention mechanisms and multi-scale feature fusion, improve detection of small and partially hidden helmets. Techniques like data augmentation and transfer learning further boost YOLOv8's performance, especially with limited datasets, and a user-friendly interface makes the model accessible to non-experts.

3 METHODOLOGY

Fig. 1. Flow Diagram of Image Preprocessing and Deep Learning-Based Helmet Detection.

Figure 1 shows the helmet detection process using deep learning. It starts with an input image, which undergoes preprocessing (resizing, normalization, augmentation) for analysis. The image is then used in training, validation, and testing to develop and evaluate the model. YOLOv8 classifies images as either "Helmet" or "No Helmet." This process enhances accuracy in detecting and classifying helmet use, crucial for safety monitoring on construction sites.

A. Data Collection A diverse dataset is crucial for developing and testing a helmet detection model. It should include images from various workplaces and conditions, featuring both helmeted and non-helmeted subjects, with different lighting, camera angles, and challenging backgrounds like construction sites. The dataset should also account for varying heights, distances, partial occlusions, and helmet styles to ensure the model's robustness and adaptability in real-world scenarios.

Helmeted and Non-Helmeted Images: The proposed helmet detection required the collection of images-both helmeted and not-helmeted various types of environments, including construction sites, roads, and industrial areas. Data are compiled from various sources such as real footage captured by cameras in live circumstances and frames taken from video recordings. This technique would ensure the coverage of different practical scenarios on how individuals are situated in different contexts under various light conditions and within various environmental sets. Such diverse images will give a strong dataset in enhancing the model in detecting helmet usage from various sets of work or road safety conditions.

Fig. 2. workers and Bike rider images with and without Helemt.

2.Annotations: Each image in the dataset is meticulously annotated to show the presence and location of helmets, involving the creation of bounding boxes and accurate labeling. Annotations are conducted either manually by individuals or with the assistance of semi-automated tools. This detailed labeling is essential for training the detection model, enabling it to recognize helmets accurately across different situations and environments. Properly annotated data plays a vital role in enhancing the model's performance and applicability in real-world.

3. Diversity and Balance: To balance your dataset, aim to have a similar number of helmeted and non-helmeted images. Include a variety of helmet styles, colors, and sizes to reflect real-world diversity. Collect diverse images, label them appropriately, and apply Data augmentation techniques mitigate potential imbalance. Ensure the dataset is evenly splitup into training, validation, and test sets, and observe the prototype performance to confirm it generalizes well across all variations.

B. Data Preprocessing Preprocessing is essential to prepare collected data for training and evaluation. This step involves several key operations to enhance data quality and ensure that the model learns effectively.

1. Image Resizing : To ensure that all images are uniform and can be processed quickly during training, they are resized to a standard size. This helps in maintaining consistency across all images. For many image processing models, common sizes used are 416x416 pixels or 640x640 pixels. These sizes are chosen based on what the model needs to work efficiently. Resizing images to these dimensions helps the model learn better and speeds up the training process.

Fig. 3. Sample images for helmet detection at a construction site.

2.Data Augmentation: To enhance the model's reliability, data augmentation techniques are employed. This includes random rotations, scaling, positional shifts, and color adjustments of the images. These modifications expose the model to diverse scenarios, improving its learning and performance across various conditions.

3. Normalization: Pixel values are adjusted to fit within a range of [0, 1] or [-1, 1] to help the model train more effectively and quickly. This process, known

as normalization, involves scaling the pixel values from their original range to this new range. Normalizing the pixel values ensures that the training is stable and helps the model learn more efficiently.

4.Splitting Dataset: The dataset is split into three parts: training, validation, and testing. Usually, 70used for training the model, 15during training to tune and improve the model, and the remaining 15on new, unseen data. This separation helps in ensuring that the model learns effectively and generalize well to new data.

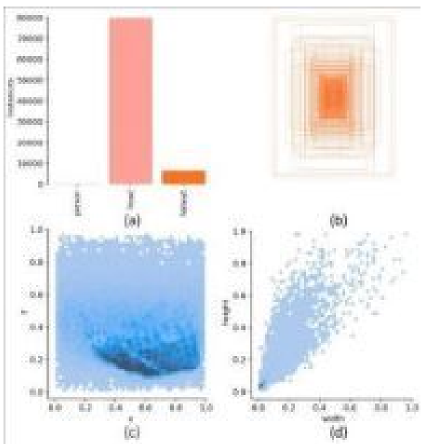

Fig. 4. Visualization results of the training data. (a) A histogram reflecting the frequency of cases within each category; (b) A breakdown of bounding box distribution through the entire dataset; (c) A histogram of the x and y coordinates demonstrating the distribution of the dataset spatially; (d) A histogram describing the width and height variables and the overall distribution of the dataset.

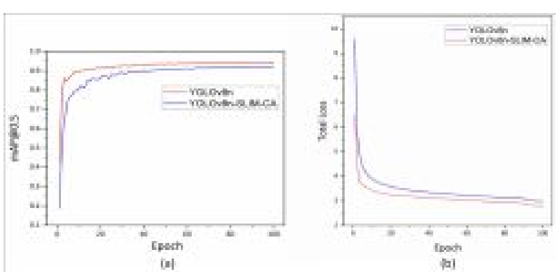

Fig. 5. Comparison of mAP and loss between YOLOv8n and YOLOv8n-SLIM-CA. (a) mAP(%). (b) loss.

C. Model Description The model utilized for helmet detection is based on the YOLOv8 architecture, optimized for improved performance in detecting helmets in various conditions.

1. Base Architecture: YOLOv8 is a modern object detection algorithm known for its high speed and accuracy. It operates using a single-stage detection approach, which simplifies the network and reduces processing time compared to two-stage detectors.

2. Enhanced YOLOv8 Model: Slim-Neck Feature Fusion: The YOLOv8 model is modified to incorporate a Slim-Neck structure. This lightweight [15] fusion network improves the model's efficiency by minimizing‘ the number of features while maintaining detection performance.

Coordinate Attention Mechanism (CA): An attention mechanism is introduced to enhance the model's attention on helmet regions. This mechanism helps the model better localize helmets by incorporating spatial and channel-wise information.

Small Target Detection Layer: An additional recognize head is add-up to improve the prototype ability to remove small and partially obscured helmets. This layer helps in better localization and classification of small targets.

3.Training: The prototype is instructed on the annotated dataset with a resulting presentation performance. combination of loss functions tailored for object detection, such as the focal loss and the Intersection over Union (IoU) loss. Training involves multiple epochs and uses optimization algorithms like Adam or SGD (Stochastic Gradient Descent) to minimize the loss.

Evaluation Metrics: Model performance is estimated while using metrics such as precision, recall, mean Average Precision (mAP), and F1-score. This metrics help in assessing the accuracy and effectiveness of the helmet detection model.

1. Implementation Tools: The model is implemented using popular deep learning frameworks like TensorFlow. These frameworks provide the necessary tools for building, training, and evaluating the model efficiently.

The flow chart shown at the beginning illustrates the detection process of motorcycle riders without helmets based on legal requirements using machine learning models. The video input will be real-time footage collected from the camera, which is stored temporarily. Then, an object detection model such as YOLOv8 is used for detecting motorcycles and obtaining their bounding boxes. In a similar way, a YOLO model detects helmets. When the violation occurs (e.g., when the helmet is not used), it detects the motorcycle and later detects the license plate. The characters found on the license plate and images of these violations detected will be appropriately stored in a folder to review later.

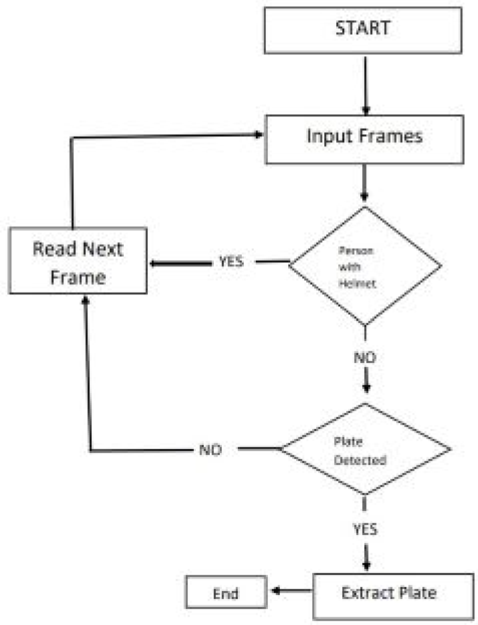

Fig 6:Helmet Detection and License plate Extraction Process.

In Fig6 it shows the step-by-step decision-making process for helmet use monitoring. The system takes video frames as input and checks for the wearing of the helmet by the person in the frame. If a helmet is being worn, it reads the next frame. If there is not a helmet being worn, then the system checks if the license plate of a motorcycle has been detected, checking next steps for detection. After the license plate number has been detected sequentially after having detected are there, they are to be extracted last. If none of the above conditions are met to process the helmet detection or license plate read, then the system again reads the next frame in sequence.

4 Result

In this project, we developed a comprehensive safety monitoring system that not only detects individuals and bike riders but also organizes and stores relevant data systematically. Here are the key results:

1.Detection and Image Storage: The system successfully identifies individuals in the workplace and stores their images in designated folders. This functionality ensures that personnel who are or are not wearing helmets can be monitored effectively.

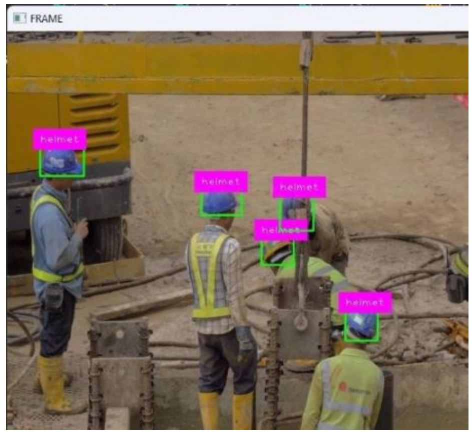

Fig7: Identifying Workers with Safety Helmets in Various Scenarios.

Fig8: Rider Detected Without Helmet.

2.Bike Rider Detection and License Plate Storage: The system is designed to detect whether bike riders are wearing helmets. If a rider is found without a helmet, it automatically captures an image of the bike's license plate. The license plate numbers are stored in folders organized by date and time, making it easy to retrieve this information later. Authorized personnel can access these folders to review the data and take appropriate action. Additionally, the system can generate reports that show how frequently this occurs, helping to improve overall safety.

Fig9: Detected Bike plate number.

3.Data organization and Time Stampping: The system captures and records key details, such as images of bike riders and their license plate numbers. All of this data is stored in an Excel sheet, with each entry automatically labeled with the exact date and time it was captured. This timestamping ensures that every event is accurately documented. By organizing the data in this way, the Excel sheet becomes a powerful tool for monitoring helmet compliance. It allows for easy tracking of when and how often helmet violations occur, making it simple to spot patterns or identify repeat offenders. The well-organized format also supports efficient auditing, enabling authorities to quickly review past records and make informed decisions to improve safety measures.

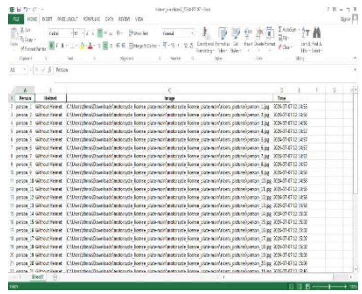

Fig10: Helmet violation log with rider and number plate images recorded.

5 Conclusion:

In this analysis, we developed a Efficient, reliable, and simple-to-use method for detecting whether individuals are wearing safety helmets. To address the challenge of limited data, we applied Applied targeted data augmentation and leveraged a pre-trained model. Additionally, we designed a user-friendly graphical user interface (GUI) to facilitate practical use in real-world applications. The model was tested on a dataset that included various challenges such as scale variations and small objects. Our method is more efficient than traditional manual monitoring, as it alerts personnel only when a labour is not wearing a helmet, reducing the need for constant surveillance and saving time and energy. Looking ahead, we plan to enhance the model by collecting more diverse helmet usage images in different environments, exploring new features to improve its performance, and ensuring stable detection when processing video frames. We also want to make the model smaller and easier to use by applying methods like model pruning, which helps reduce its size. Lastly, we will keep improving the system so it can give quick reminders to workers on construction sites, helping to make the workplace safer.

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