

Safety Helmet Detection

Ryza Banu S¹, Naila N N², Harikrishnan S R³

Student, MCA, CHMM College for Advanced Studies, Trivandrum, India¹

Assistant Professor, MCA, CHMM College for Advanced Studies, Trivandrum, India²

Associate Professor, MCA, CHMM College for Advanced Studies, Trivandrum, India³

Abstract: *Construction sites are inherently hazardous environments, with workers exposed to risks such as falling objects, machinery accidents, and head injuries. Ensuring compliance with safety regulations, such as wearing safety helmets, is crucial for mitigating these risks and preventing accidents. However, manual monitoring of construction sites is labor-intensive and prone to errors, leading to gaps in safety enforcement and increased accident rates. There is a critical need for automated systems capable of accurately detecting objects and monitoring workers' compliance with safety protocols in real-time to improve safety outcomes in construction sites. The proposed system aims to develop a custom object detection and safety helmet detection system for construction sites using a custom dataset of construction site images and annotations. The system will be trained on annotated images to learn the characteristics and features of construction site objects, as well as safety helmets worn by workers. Upon deployment, the system will continuously monitor construction sites using computer vision techniques to detect objects and identify whether workers are wearing safety helmets. When safety violations are detected, the system will issue alerts and notifications to site supervisors, enabling timely intervention to address safety concerns. Through this approach, the proposed system aims to enhance safety measures and reduce the incidence of accidents in construction sites.*

Keywords: Machine learning, Deep learning, Neural Network, YOLOv7

I. INTRODUCTION

In industrial and construction sectors, workplace safety remains a critical concern, with safety helmets playing a pivotal role in protecting workers from head injuries. Monitoring compliance with safety regulations regarding safety helmet usage is essential to mitigate risks and ensure occupational safety standards are met. Traditional methods of monitoring, often reliant on manual inspections, are labour-intensive, prone to human error, and may not effectively scale in large industrial environments. Advancements in computer vision and deep learning technologies offer promising solutions to automate safety monitoring processes, particularly through the deployment of robust object detection systems. Safety helmet detection systems powered by deep learning algorithms, such as You Only Look Once (YOLO), have emerged as effective tools in enhancing workplace safety practices. YOLO, known for its real-time processing capabilities and high accuracy in object detection tasks, enables automated identification and classification of safety helmets from video streams or static images. This technology revolutionises safety management by providing instantaneous feedback on safety compliance, thereby facilitating timely corrective actions to mitigate potential hazards.

II. LITERATURE REVIEW

The proposed system for safety helmet detection and object monitoring at construction sites is situated within the broader context of ongoing efforts to enhance workplace safety through advanced technologies. Construction sites are well-documented as hazardous environments where workers are frequently exposed to risks, such as falls, being struck by objects, and accidents involving heavy machinery. These risks are often exacerbated by inconsistent compliance with safety regulations, particularly the mandatory use of personal protective equipment (PPE) like safety helmets. Traditional methods of monitoring compliance, typically involving manual observation by supervisors, are not only labor-intensive but also prone to human error, resulting in potential safety gaps and higher accident rates. In response to these challenges, there has been significant research interest in applying computer vision and machine learning techniques to automate safety monitoring in construction environments. Previous studies have demonstrated the

efficacy of object detection algorithms in identifying and tracking various objects and equipment on construction sites, as well as in recognizing whether workers are wearing PPE. These studies often utilize deep learning models, which are trained on large datasets of annotated images to recognize specific objects and conditions with high accuracy. However, the practical implementation of such systems has been hindered by several challenges, including the need for highly accurate datasets, the variability of construction site environments, and the real-time processing requirements necessary for timely intervention. The development of a custom object detection system tailored specifically for construction sites, as proposed, addresses these challenges by utilizing a dedicated dataset that captures the unique features and risks of these environments. Furthermore, the integration of real-time alert systems enhances the potential for immediate corrective actions, thereby improving overall safety outcomes. The proposed system represents an important advancement in the field of occupational safety, offering a scalable and effective solution to the persistent issue of non-compliance with safety protocols in construction sites. By leveraging the capabilities of modern computer vision technologies, the system promises to significantly reduce the incidence of accidents and injuries, thereby contributing to safer and more efficient construction site operations.

III. PROPOSED METHOD

The proposed system aims to enhance workplace safety by automatically detecting whether individuals are wearing safety helmets in real-time using YOLOv7 (You Only Look Once, Version 7). This system will utilize a camera setup in industrial or construction sites to capture live video feeds. YOLOv7, a state-of-the-art object detection algorithm, will process these video feeds to identify workers and detect the presence or absence of safety helmets. The model will be trained on a comprehensive dataset of images depicting individuals with and without helmets in various working conditions and environments. Upon detection, the system can generate alerts or notifications to ensure compliance with safety regulations.

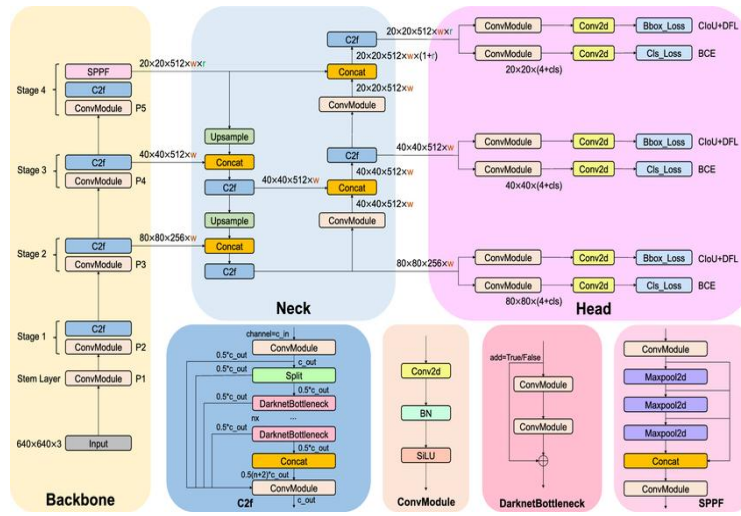
IV. ALGORITHM

Convolutional Neural Network (CNN)

CNNs have been widely adopted due to their ability to automatically learn and identify relevant features directly from the input data, eliminating the need for manual feature extraction. This has led to their dominance in various applications, particularly in areas where analyzing visual data is crucial. The ability of CNNs to generalize across different types of images and their resilience to variations in input data make them a powerful tool in the field of machine learning and artificial intelligence.

YOLOv7

YOLOv7 (You Only Look Once version 7) is a state-of-the-art object detection model that builds on the foundations of previous YOLO versions, known for their real-time object detection capabilities. YOLOv7 introduces several improvements in architecture and performance, making it one of the most efficient and accurate object detectors available. It is designed to balance speed and accuracy, making it particularly suitable for applications requiring real-time processing, such as safety monitoring in construction sites. One of the key innovations in YOLOv7 is its optimized architecture, which enhances both the model's speed and accuracy without significantly increasing its complexity. YOLOv7 employs new strategies such as the Extended Efficient Layer Aggregation Networks (E-ELAN) to improve feature extraction and representation. This allows the model to better detect small objects and distinguish between overlapping objects, which is critical in complex environments like construction sites where workers and machinery may be in close proximity. Another significant feature of YOLOv7 is its ability to perform well on a wide range of hardware, from high-performance GPUs to more constrained devices, making it a versatile choice for deployment in diverse operational settings. Its robustness in handling various object scales and its ability to generalize across different datasets contribute to its effectiveness in real-world applications. In the context of safety helmet detection at construction sites, YOLOv7's high accuracy and real-time processing capabilities make it an ideal choice. The model can quickly and accurately identify whether workers are wearing helmets, even in dynamic and cluttered environments. This ability to detect safety compliance in real-time is crucial for preventing accidents and ensuring that safety protocols are consistently followed.



V. PACKAGES

NumPy

At the core of NumPy is the ndarray object, which represents a n-dimensional array of homogeneous data types, meaning all elements in the array are of the same type. This allows NumPy to execute operations in a highly optimized manner, often using C or Fortran under the hood, making it much faster than standard Python lists for numerical computations. NumPy supports a wide range of mathematical operations, including element-wise addition, subtraction, multiplication, and division, as well as more complex operations like linear algebra, Fourier transforms, and random number generation. These capabilities make it an essential tool for tasks ranging from simple array manipulations to complex numerical simulations.

Pytorch

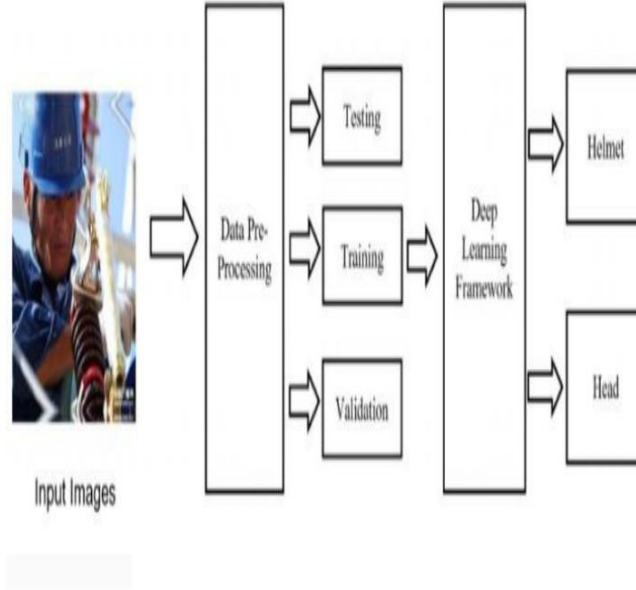
PyTorch provides strong support for tensor operations, which are similar to NumPy arrays but with added capabilities, such as GPU acceleration. This allows for efficient handling of large datasets and complex computations, making it suitable for a wide range of machine learning tasks, from natural language processing to computer vision. Tensors in PyTorch can be moved between CPUs and GPUs seamlessly, enabling the acceleration of computationally intensive tasks. PyTorch's autograd module automatically computes gradients, simplifying the backpropagation process needed to update model parameters. This makes it easier for developers to focus on model design rather than the underlying mathematical details.

VI. EXPERIMENTAL RESULTS & PERFORMANCE EVALUATION

Once the system design phase is over, the next stage is to implement and monitor the operation of the system to ensure that it continues the work effectively and efficiently. The implementation plan is a function of line management at least as far as key decisions or alternative plans are concerned.

Due to the inherent risks in industrial and construction environments, ensuring worker safety is paramount. Safety helmets are crucial protective gear that significantly reduce the risk of head injuries. However, ensuring compliance with safety regulations regarding helmet usage poses challenges, particularly in large-scale operations where manual monitoring is impractical and error-prone. Current methods often rely on periodic visual inspections, which may not promptly identify instances of non-compliance, thereby jeopardising worker safety. The primary issue lies in the inefficiency and limitations of manual safety helmet monitoring systems. Human inspectors face challenges in consistently monitoring all workers across vast industrial sites, especially in environments with complex layouts and varying lighting conditions. This inconsistency in monitoring can lead to instances where workers either do not wear safety helmets or wear them incorrectly.

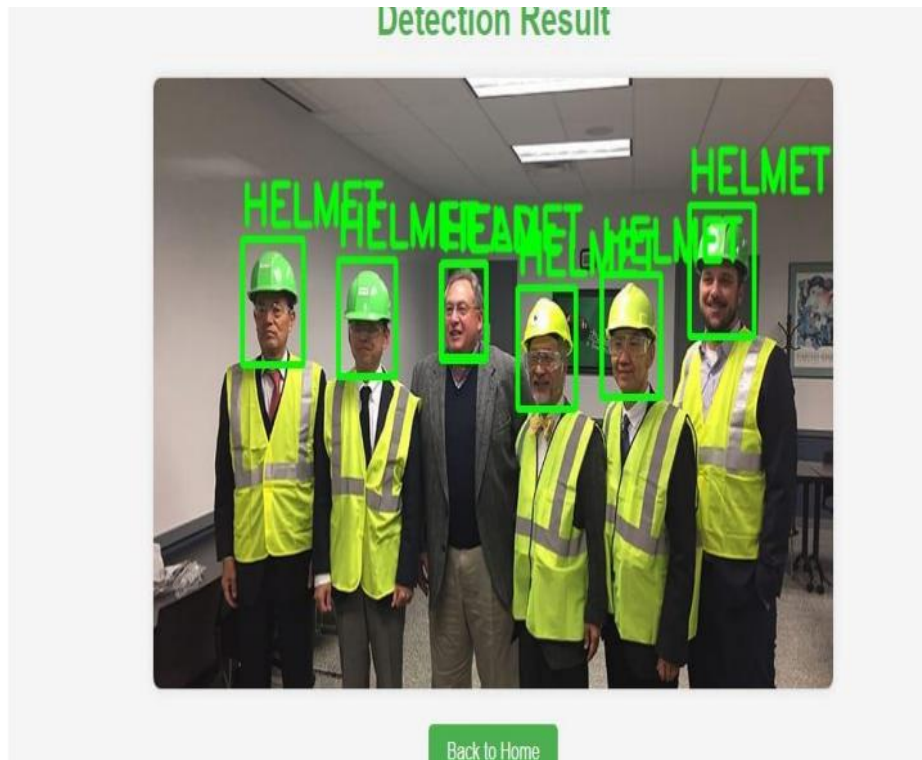
Modular Diagram



All processed images



Object detection

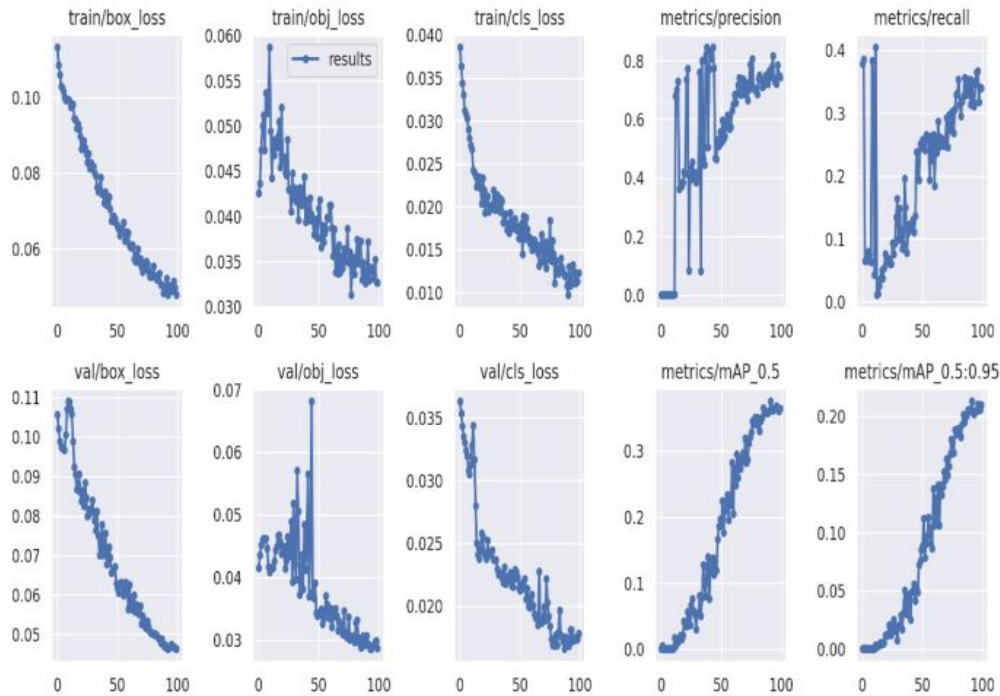


VII. ACCURACY GRAPH

Typically, this graph plots accuracy on the y-axis and the number of epochs (iterations over the entire training dataset) on the x-axis. The graph usually includes two lines: one for the training accuracy and another for the validation accuracy.

The training accuracy line shows how well the model is performing on the training data, while the validation accuracy line indicates how well the model generalizes to unseen data. Initially, as the model begins to learn, both the training and validation accuracies should increase, reflecting the model's improving ability to make correct predictions. An important aspect of interpreting an accuracy graph is observing the relationship between the training and validation accuracies over time. If both accuracies rise steadily and converge, it suggests that the model is learning effectively and generalizing well. However, if the training accuracy continues to increase while the validation accuracy plateaus or begins to decrease, this may indicate overfitting. Overfitting occurs when the model learns to perform exceptionally well on the training data but fails to generalize to new data, as it may be memorizing the training examples rather than learning the underlying patterns.

Conversely, if both training and validation accuracies remain low, the model may be underfitting, meaning it has not learned enough from the data to make accurate predictions. The accuracy graph is thus a critical tool for diagnosing and improving model performance, helping developers to adjust parameters such as learning rate, model complexity, or training duration to achieve better generalization and predictive accuracy.



VIII. LIMITATION

The proposed safety helmet detection system using YOLOv7, while promising in enhancing workplace safety, faces several limitations. One major challenge is the variability in environmental conditions on construction sites, such as changes in lighting, weather, and obstructions, which can negatively impact the accuracy of object detection. Additionally, the system's requirement for real-time video processing demands significant computational resources, often necessitating high-performance GPUs, which may increase costs and limit deployment to sites with adequate infrastructure. If the dataset does not cover all possible variations in helmet types, worker positions, and site environments, the model's accuracy could diminish in unfamiliar scenarios. Furthermore, despite YOLOv7's accuracy, the system may still produce false positives or negatives, leading to unnecessary alerts or missed safety violations. Scaling the system to monitor large or multiple construction sites simultaneously could pose challenges related to data processing, storage, and network bandwidth, requiring substantial technical support. Ethical and privacy concerns also arise from continuous video monitoring of workers, necessitating clear policies and consent mechanisms to balance safety monitoring with privacy rights. The system's focus on helmet detection limits its scope, as comprehensive construction site safety involves monitoring a range of factors beyond just helmet use. Additionally, construction sites are dynamic environments that frequently change, meaning the system may require ongoing updates and retraining to remain effective, which could be resource-intensive. Lastly, if the system depends on cloud-based processing or remote monitoring, stable internet connectivity becomes crucial, and any disruption in connectivity could hinder the system's operation. Addressing these limitations is essential for the successful implementation and long-term viability of the safety helmet detection system.

IX. FUTURE SCOPE

Improved Detection Accuracy: Continuously refine the YOLO model to enhance detection accuracy for safety helmets, even in more challenging conditions such as poor lighting, occlusions, or varying helmet designs.

Expanded Safety Gear Recognition: Extend the system's capabilities to detect additional safety gear such as safety vests, goggles, gloves, and boots, providing a more comprehensive safety monitoring solution.

Predictive Analytics: Integrate AI-driven predictive analytics to identify potential safety hazards before they occur, using historical data and real-time monitoring to forecast and mitigate risks.

Edge Computing: Deploy the system on edge computing devices to reduce latency and ensure real-time processing in environments with limited internet connectivity, enhancing the system's responsiveness and reliability.

Cloud Integration: Enable cloud-based storage and processing to handle large volumes of data, facilitating centralised monitoring, and enabling advanced data analysis and reporting capabilities.

Scalability: Optimise the system for scalability to allow deployment across various types and sizes of workplaces, from small construction sites to large industrial complexes, ensuring it can meet diverse operational requirements.

User Customization: Develop customizable settings for detection sensitivity, alert mechanisms, and user interfaces, allowing organisations to tailor the system to their specific needs and preferences.

Mobile Application: Create a mobile application to provide remote access and management of the detection system, allowing safety officers to monitor and respond to alerts from anywhere.

X. CONCLUSION

In conclusion, the development and deployment of the YOLO-based safety helmet detection system mark a significant advancement in workplace safety and monitoring. This system leverages cutting-edge deep learning and computer vision technologies to ensure real-time detection of safety helmets, thereby enhancing compliance with safety regulations and reducing the risk of head injuries in hazardous environments. Throughout this project, we achieved several key objectives: accurate detection of safety helmets, real-time processing capabilities, a user-friendly interface for easy interaction and management, and robust security and privacy measures to safeguard sensitive data. The YOLO model demonstrated high accuracy across various environments, ensuring reliable identification even under challenging conditions, while the real-time processing allows for immediate detection and response, significantly improving the effectiveness of safety monitoring systems. By implementing intuitive interfaces and strong security protocols, we ensured seamless integration into daily operations and maintained user trust. Looking ahead, future enhancements include refining the YOLO model for improved accuracy, extending its capabilities to recognize additional safety gear, and integrating advanced analytics for predictive safety measures. The system's scalability for deployment across various platforms will further enhance its versatility and accessibility. The YOLO-based safety helmet detection system exemplifies how modern technology can create safer workplaces, and its successful implementation underscores our commitment to leveraging technology for the greater good, ultimately fostering a culture of safety and protecting workers.

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