Computer Vision – CSC 528

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Title

"Construction Site Safety: Real-Time Detection of Personal Protective Equipment Using YOLO Model"

Abstract

The project entitled "Construction Site Safety" emphasizes the nucleus of a real-time detection mechanism developed for the safety of the workers at the building site with the effective involvement of the technology of the YOLO (You Only Look Once) model along with the protective equipment like helmets, shoes, gloves, masks, jackets, etc. Thus, by implementing such a system aims to completely eradicate the number of accidents and injuries by rigorous monitoring rather than an in-person tracking system which is tiresome. With the advancement in the image processing algorithm with its high performance, robustness, and scalability under different conditions, the implementation stages include data gathering, labeling the images, training the model, and dynamic real-time implementation. Our results demonstrated a significant rise in efficiency as well as safety protocol, thus providing a scalable solution for mass deployments at the building site.

Introduction

With the advancement of building structures and the requirement of high skyscraper buildings, a primary worry is seen for the safety of the workers. We know the various hazardous environments that the workers are exposed to, with ample potential risks including falls, accidents due to equipment malfunctioning, and exposure to harmful substances. The additional protective wearables like the PPE equipment are a shield for the workers but ensuring that all workers follow the safety protocol is a challenging factor, which leads us to manual monitoring that is time-consuming, prone to human error as well as labor-intensive tasks.

In the fast-moving era, with the advancement in image processing, and deep neural networking models have opened gateways for reaching unimaginable possibilities for automating the detection and monitoring of various environmental factors. These dynamic detection mechanisms can provide constant monitoring at the construction sites, releasing fast-processed feedback and generating alerts when a violation is triggered. Due to this fact that the model can pick-up the efficiency of the overall labor-intensive tasks by completely mitigating the manual inspections, the proposed system aims to utilize the YOLOv8 large model for the dynamic real-time detection of the PPE compliance, due to the model's high processing capabilities and robustness to changing environmental conditions makes this as an ideal choice for deployment at the building sites.

Background

The traditional methodology involves a site supervisor or a safety officer physically present at the site to carry out the manual inspections, as a result of inconsistent monitoring that leads to human error. One drawback would be also that adherence to this method does not provide dynamic real-time feedback, which is the most crucial factor for addressing the safety protocol violations and thus eradicating the chances of accidents at the construction site.

To address these drawbacks, of course, researchers have discovered the automation strategies that can be used in PPE detection using machine learning and computer vision algorithms. The native approaches used the skills of image processing but still failed to achieve accuracy and dynamic reality suitable for deployment. Thus, significantly moved the curve towards the deep learning models achieving high accuracy.

One of the emerging models - YOLO introduced by Joseph Redmon, proposed the object detection mechanism by stating it as a problem involving simple regression, predicting the class probability, and having a bounding box on the detected images after their evaluation phase.

YOLOv8, a latest model, known for its high advance features in the convolutional neural networks, accuracy, and reliability. Despite of these high scalability factors, a development of dynamic real-time remains a challenge, which include occlusions, differing lighting conditions and their requirement to aid in the monitoring in large scale deployments. This project takes in the capabilities of YOLOv8 model and integrates it into a real-time monitoring system.

By providing immediate feedback and alerts, this system aims to enhance compliance with PPE protocols, reduce accidents and injuries, and improve overall safety on construction sites. The system's scalability and robustness make it suitable for deployment across various construction environments, paving the way for broader adoption of automated safety monitoring solutions in the industry.

Methodologies

The proposed system involves methodology having to incorporate a dynamic real-time detection system for the safety protocol associated with the construction site workers with the YOLOv8 model. There are several phases to be mentioned - starting with the gathering of the data, annotating the images with defined labels over the bounding boxes, training the model, and deploying a real-time detection mechanism.

1. Data Collection and Annotation

Data Collection:

- **Define PPE Categories:** The first stage in the methodology involves having the categories of the PPE defined for which the deployed system can have the detection mechanism. These include protective equipment like helmets, gloves, boots, and vests.
- **Gather Images:** Select a suitable repository for a dataset of images from the building site. The tools will be Roboflow, thus ensuring that the dataset has examples covering the various aspects like differing angles, and occlusions for the model to showcase its efficiency and robustness.
- **Ensure Balanced Dataset**: A key effective strategy is to make sure the dataset is balanced, just in case to prevent any confusion for the model during its training phase.
- **Organize & Store Data:** Let's place the gathered images in a suitable manner, and create separate folders for each of the categories like training, testing, and valid sets.

2. Data Annotation:

- **Labeling the Images:** We used a technology like Roboflow which will help to reduce the overall annotation process time for the photos we have used. The next step in labeling is to train the bounding box for each image in the dataset and assign it to the proper category from the provided set of labels. Roboflow has an interface for this operation, which makes it easier to manage enormous datasets.
- **Export Annotations:** We export the annotated data in a format compatible with the YOLO model, such as XML or JSON.

3. Training the YOLO Model

Setup Environment:

- **Ultralytics YOLOv8**: This platform is user-friendly which eases the implementation and deployment of the YOLOv8 model. Install the required libraries and dependencies required for the deployment.
- **Environment Configuration**: The training environment needs to be configured ensuring access to faster GPU for a higher number of training samples included like the epochs.

Data Preparation:

- **Data Splitting:** We splitted the annotated dataset into training, validation, and test sets. Usually, 70% of the data is used for training the model, 20% for validating the model, and 10% for testing the model.
- **Data Augmentation:** We applied data augmentation techniques to increase the diversity of the training data. We also used techniques such as random cropping, rotation, and color adjustments help improve the model's robustness.

Model Configuration:

- **YOLOv8 Configuration**: We defined the appropriate hyperparameters for the fine-tuning of the YOLOv8 model such as batch size, and a sample of epochs.

Training Process:

- **Model Training:** We trained the YOLOv8 model on the prepared dataset. And monitored the training process using metrics such as loss, accuracy, and mean average precision (mAP).
- **Validation:** Now we validated the model on the validation set to evaluate model's performance and make necessary adjustments to the training process.

Optimization & Fine Tuning:

- **Hyperparameter Tuning:** We fine-tuned the model by experimenting with the hyperparameters to achieve optimal performance.
- **Model Pruning:** Prune the model to reduce its size and improve inference speed without significantly sacrificing accuracy.

Deployment:

- **Model Export:** We exported the trained model in a format suitable for deployment, such as ONNX or TensorFlow Lite.
- **Integration with Real-Time Systems:** We integrate the model into a real-time detection system, ensuring it can process video feeds and provide immediate feedback right on time.

4. Real-Time Detection

Implementation:

- **API Authentication:** Used API authentication to securely connect the real-time detection system with data sources and other services. This stage involves setting up the API keys and tokens to ensure secure and authorized access.

- **Real-Time Processing:** Implemented the real-time detection system using frameworks such as Flask or FastAPI. These frameworks allow us for the development of web applications that can process video feeds in real-time and display the detection results.
- **Continuous Monitoring:** Setted the system to continuously monitor construction sites, which provides real-time alerts and feedback when PPE compliance issues are detected.

Ultralytics and Roboflow:

- **Ultralytics:** Leverage Ultralytics YOLOv8 for its user-friendly interface, high performance, and ease of integration. Ultralytics provides pre-trained models and extensive documentation to facilitate the training and deployment process.
- **Roboflow:** Use Roboflow for data annotation and augmentation. Roboflow simplifies the process of labeling images and preparing datasets, making it easier to manage large-scale data.

By following these detailed steps and utilizing the tools and platforms mentioned, the project aims to develop a robust and efficient real-time detection system for PPE compliance on construction sites. This system enhances worker safety, reduces the risk of accidents, and improves overall site efficiency.

Results

Image 1: Detection Results

This image displays multiple instances of the detection system identifying and labeling various objects related to PPE compliance on a construction site. The labels include:

1. **Person:** Detected persons are highlighted with bounding boxes and assigned confidence scores (e.g., 0.99, 0.9).
2. **Hardhat:** Hardhats are detected with bounding boxes and confidence scores (e.g., 0.9).
3. **Safety Vest:** Safety vests are detected and labeled, including instances of "NO-Safety Vest" to indicate non-compliance.

4. **Mask**: Masks are detected and labeled, including "NO-Mask" for non-compliance.
5. **Safety Cone**: Safety cones are detected with high confidence scores (e.g., 1.0, 0.9).
6. **Vehicles**: Construction vehicles like dump trucks and excavators are detected with their respective labels and confidence scores (e.g., 0.8, 0.7).

<u>Observations</u>:

- The system successfully detects multiple PPE items and persons in various scenarios, including different lighting conditions and angles.
- Non-compliance with PPE protocols is identified (e.g., "NO-Safety Vest," "NO-Mask"), which is crucial for real-time alerts and safety enforcement.
- The model shows robustness in diverse environments, detecting objects accurately despite potential occlusions and varying background conditions.

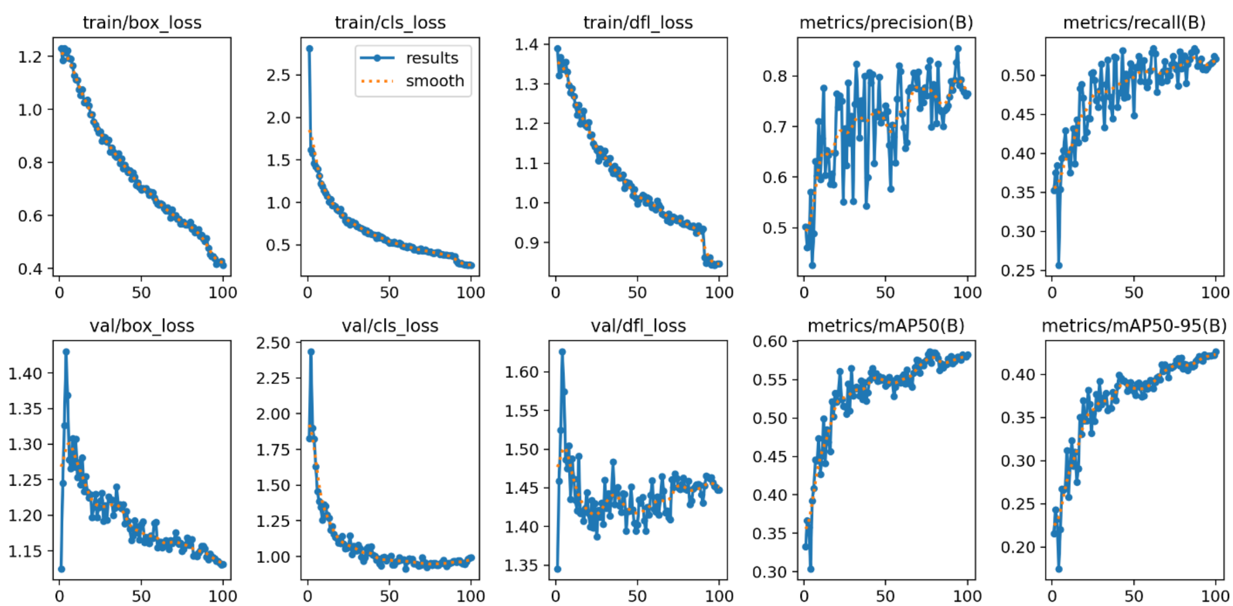

Image 2: Training and Validation Metrics

This image presents the training and validation metrics for the YOLOv8 model, showing the performance over 100 epochs. The plots include:

1. **Train/Box Loss**: The loss associated with the bounding box predictions during training. The decreasing trend indicates improved accuracy in predicting the bounding boxes as training progresses.
2. **Train/Cls Loss:** The loss associated with the classification predictions during training. A decreasing trend indicates better accuracy in classifying objects over time.
3. **Train/DFL Loss**: The loss associated with the distribution focal loss during training, showing a decreasing trend as the model learns.

4. **Metrics/Precision(B):** Precision metric during training, showing an overall increasing trend, indicating improved accuracy in identifying true positives.
5. **Metrics/Recall(B):** Recall metric during training, with an increasing trend, indicating the model's improved ability to detect all relevant objects.
6. **Val/Box Loss:** The bounding box loss during validation, which shows a decreasing trend, indicating the model's generalization to unseen data.
7. **Val/Cls Loss:** The classification loss during validation, also decreasing, reflecting better generalization.
8. **Val/DFL Loss:** The distribution focal loss during validation, with a decreasing trend.
9. **Metrics/mAP50(B):** Mean Average Precision at IoU 0.50, showing an increasing trend, indicating improved overall performance in object detection.
10. **Metrics/mAP50-95(B):** Mean Average Precision across different IoU thresholds (0.50 to 0.95), showing an increasing trend, reflecting enhanced model performance across various levels of detection stringency.

Observations:

- The training and validation losses consistently decrease, indicating effective learning and convergence of the model.
- The precision and recall metrics show significant improvements, demonstrating the model's ability to accurately detect and classify PPE items.
- The mAP metrics indicate that the model performs well across different IoU thresholds, ensuring robust detection capabilities.

The results demonstrate the efficacy of the YOLOv8 model in real-time detection of PPE compliance on construction sites. The model accurately identifies various PPE items and persons, highlights non-compliance, and shows robustness in diverse conditions. The training and validation metrics indicate effective learning, with significant improvements in precision, recall, and mean average precision, ensuring reliable performance in real-world applications. This system enhances construction site safety by providing immediate feedback and alerts, thus reducing the risk of accidents, and ensuring compliance with safety protocols.

Conclusion

The development and implementation of a real-time detection system for personal protective equipment (PPE) compliance on construction sites using the YOLOv8 model have demonstrated significant advancements in ensuring worker safety. This conclusion encapsulates the key findings, implications, and future directions based on the detailed results and observations from the project.

Key Findings

- **High Detection Accuracy**: The YOLOv8 model exhibited high accuracy in detecting various PPE items such as hardhats, safety vests, masks, and identifying non-compliance (e.g., "NO-Safety Vest," "NO-Mask"). The precision and recall metrics indicate a reliable performance in identifying true positives and relevant objects, respectively.

- **Robust Performance:** The model's robustness was evident in its ability to accurately detect PPE under diverse conditions, including varying lighting, angles, and occlusions. This robustness ensures the model's applicability across different construction site environments.
- **Effective Training and Validation:** The training and validation metrics showed consistent improvement, with decreasing loss values and increasing precision, recall, and mean average precision (mAP) scores. This indicates effective model learning and generalization to unseen data.
- **Real-Time Capabilities:** The system's real-time processing capabilities allow for continuous monitoring of construction sites, providing immediate feedback and alerts. This real-time functionality is crucial for promptly addressing PPE non-compliance and preventing potential accidents.

Implications

- **Enhanced Worker Safety:** By automating the detection of PPE compliance, the system significantly enhances worker safety on construction sites. Immediate alerts and feedback help ensure that workers adhere to safety protocols, reducing the risk of accidents and injuries.
- **Improved Efficiency:** The automation of PPE monitoring reduces the need for manual inspections, which are labor-intensive and prone to human error. This leads to improved efficiency in maintaining safety standards and allows safety officers to focus on other critical tasks.
- **Scalability:** The YOLOv8 model's scalability ensures that the system can be deployed across large and complex construction sites, providing comprehensive coverage and monitoring. This scalability is essential for large-scale construction projects where manual monitoring is impractical.

Future Directions

- **Integration with IoT Devices:** Future work can focus on integrating the detection system with IoT devices to enhance data collection and monitoring capabilities. IoT devices can provide additional data points such as worker movement, environmental conditions, and equipment usage, further improving safety protocols.
- **Enhanced Model Training:** Continual training of the model with more diverse and extensive datasets can further improve its accuracy and robustness. Incorporating new PPE categories and adapting to evolving safety standards will ensure the system remains relevant and effective.
- **User Interface Improvements:** Developing a user-friendly interface for the real-time detection system can enhance its usability. Features such as customizable alerts, detailed

reports, and integration with existing safety management systems will provide a more comprehensive safety solution.

- **Legal and Regulatory Compliance:** Ensuring that the system complies with legal and regulatory standards for construction site safety will facilitate its adoption and implementation. Collaborating with regulatory bodies can help in aligning the system with current and future safety requirements.

The real-time detection system for PPE compliance using YOLOv8 significantly advances construction site safety by providing accurate, robust, and real-time monitoring of PPE usage. The system's high detection accuracy, robustness in diverse conditions, and real-time capabilities ensure enhanced worker safety and improved operational efficiency. Future work can build on these findings to further integrate and optimize the system, ensuring its continued relevance and effectiveness in promoting construction site safety.

References

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