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Bridging AI and Analytics: A Smart Monitoring System for PPE Compliance in Hazardous Workspaces

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Abstract - *This study introduces a YOLOv8-based PPE Compliance Detection System that uses the presence or lack of necessary personal protective equipment (PPE) to guarantee worker safety in industrial settings. We make use of a subset of the SH17 dataset, which comprises 2,350 carefully chosen photos with annotations for 6 PPE-related classifications. LabelImg was used to accomplish the annotation in YOLO format. To maximize training speed and model performance, images were scaled to 640 x 640 pixels. On Google Colab, we used a structured separation of training and validation data to train the YOLOv8n model. The Flask web application, which allows users to upload photos and obtain annotated outputs indicating PPE compliance and associated risk levels, is coupled with the trained model to give real-time inference.*

Key Words: PPE Detection, YOLOv8, SH17 Dataset, Object Detection, Flask Deployment, Industrial Safety, Computer Vision.

1. INTRODUCTION

The foundation of occupational safety and health is ensuring adherence to personal protective equipment (PPE) in dangerous work conditions. PPE is the first line of defense against workplace dangers such as exposure to chemicals, falling objects, extreme heat, and other damaging noises. Non-adherence to PPE requirements is a significant challenge in areas like construction, manufacturing, oil and gas, and healthcare, despite the implementation of strict safety regulations and training programs. According to the International Labour Organization (ILO) [1] inadequate safety compliance and protective measures are mostly to blame for the 2.78 million occupational fatalities that are predicted to occur annually (ILO, 2023). Moreover, non-fatal diseases and injuries caused by poor compliance with PPE account for around 374 million non-fatal occupational injuries annually, causing significant economic losses and decreased productivity (ILO, 2023).

Closed-circuit television (CCTV), supervisory monitoring, and manual checking are all heavily reliant on traditional PPE monitoring methods. However, these procedures are often laborious, prone to human error, small in scope, and lack real-time reaction. According to Smith et al. (2021), manual inspection systems are unreliable and unable to provide real-time feedback [2] , which leads to delayed corrective action and extended risk exposure. Furthermore, human supervisors find it difficult to consistently check on each employee's compliance in large, complex work environments, particularly during high-risk activities or shift changes (Smith et al., 2021). The limitations of the traditional approaches highlight the need for an automated and intelligent solution to increase the accuracy and efficacy of PPE compliance monitoring.

The accelerated development of artificial intelligence (AI) and data analytics holds an unprecedented prospect to revolutionize occupational safety processes. AI-powered smart monitoring systems utilize computer vision, machine learning, and real-time data analysis to automate detection and reporting of PPE infringements in risk-prone workplaces. Jones et al. (2022) showed that AI-powered systems are capable of detecting whether or not workers are wearing the proper protective equipment [3], including helmets, gloves, goggles, and high-visibility vests, with a high degree of accuracy. Such systems employ deep learning models trained on large databases of PPE images and actual working conditions to identify patterns and detect anomalies in real time. With the integration of predictive analytics and AI, such systems can detect non-compliance patterns, predict future safety violations, and offer meaningful recommendations to enhance workplace safety overall [4].

This paper discusses designing and deploying a smart monitoring system based on AI and analytics to augment PPE compliance in high-risk work environments. The envisioned system will offer real-time PPE violation detection, predictive safety insight, and automated reporting to facilitate proactive decision-making. The study aims at filling the gap between conventional safety monitoring practices and AI, proposing a scalable and effective solution towards enhancing occupational safety standards. The study also identifies the possible pitfalls of AI-based monitoring systems such as data privacy issues, biases in algorithms, and system integration issues. By overcoming these issues and tapping the potential of AI and data analytics, this study hopes to make a contribution to a safer and more compliant workplace.

2. PROBLEM STATEMENT

"Safety isn't expensive, it's priceless." As we live in a vast city where the construction industry faces several challenges that impact its efficiency and growth such as Lack of Real-

Time PPE Compliance Monitoring, Inconsistent PPE Usage by Workers, High Rate of Workplace Accidents Due to Non-Compliance, Limited Access to High-Quality PPE Compliance Datasets, Integration Issues with Existing Construction Safety System, Worker Privacy and Ethical Concerns and Limited Predictive Analytics for PPE Compliance Trends. Ensuring PPE compliance in hazardous workplaces is crucial, yet existing monitoring methods suffer from inefficiencies and high human dependency. AI-powered solutions exist but lack robust, labeled datasets for training models effectively. This research proposes a smart monitoring system that builds a comprehensive dataset of workers, labels PPE compliance status, trains AI models, and stores and analyzes data for real-time compliance tracking. By integrating AI and analytics, this system aims to improve workplace safety and standards compliance.

3. RELATED WORK

Ensuring compliance with Personal Protective Equipment (PPE) regulations is crucial for workplace safety, particularly in hazardous environments such as construction sites [5]. Traditional methods such as manual inspections, checklists, and RFID-based tracking systems are labor-intensive and prone to human error. Surveillance cameras are often used, but manual review of footage makes them inefficient for real-time detection. To overcome these limitations, researchers have explored AI-driven solutions that automate PPE compliance monitoring using deep learning techniques, significantly improving detection accuracy and enforcement.

One of the most effective deep learning models for PPE detection is YOLO (You Only Look Once), which provides real-time object detection capabilities. Studies have shown that YOLOv4-based PPE monitoring systems accurately identify workers wearing or not wearing PPE, outperforming models such as Faster R-CNN and SSD (Single Shot MultiBox Detector) in terms of speed and efficiency. However, challenges such as occlusion, lighting variations, and low-resolution images affect model performance, highlighting the need for high-quality annotated datasets [6]. LabelImg, an open-source annotation tool, has been widely used to manually label PPE datasets, ensuring precise object detection and improving AI model training. Additionally, active learning techniques have been explored to reduce manual annotation efforts by refining dataset labels iteratively.

Efficient data management is essential for PPE compliance tracking, as large volumes of compliance data must be stored, retrieved, and analyzed. MySQL, a widely used relational database management system (RDBMS), has been integrated into AI-driven PPE monitoring systems to enable real-time storage and retrieval of compliance records [7]. This allows construction firms to generate compliance reports, track violations, and implement corrective measures. However, challenges such as dataset diversity, real-time deployment on edge devices, integration with IoT and cloud platforms, and privacy concerns remain. By leveraging YOLO for object detection, LabelIng for dataset annotation, and MySQL for compliance data management, this research aims to enhance workplace safety, automate compliance monitoring, and reduce workplace accidents in hazardous environments.

This research aims to bridge these gaps by developing a smart monitoring system that combines AI-based PPE detection with advanced analytics. By creating a labeled dataset of workers, training deep learning models, and analyzing compliance trends, this study seeks to enhance workplace safety through an integrated, data-driven approach [8].

4. METHODOLOGY

4.1 Dataset Collection

This study utilizes a curated subset of the SH17 (Safe Human) dataset [9], consisting of 2,350 images across six object classes related to personal protective equipment (PPE). Rather than using the full dataset, we selected images most relevant to our objectives, introducing modifications and new ideas to enhance PPE detection capabilities in diverse industrial environments. The images were sourced from Pexels, a royalty-free platform ensuring clear usage rights. Relevant keywords like “manufacturing worker” and “industrial worker” were used for image retrieval, and accurate tagging reduced the need for extensive manual filtering. By narrowing the dataset while retaining variation, we ensured a focused yet diverse training set. These refinements aim to boost detection accuracy and support real-world PPE compliance monitoring applications.

4.2 Dataset Details

The images selected from the SH17 dataset were originally sourced from Pexels and resized to 640 × 640 pixels for consistency and computational efficiency. Our subset includes 2,350 images in both landscape and portrait orientations, each containing multiple PPE-related objects. Annotations were formatted in YOLO format for compatibility with object detection models. Smaller objects like ears and earmuffs were labeled to preserve object size diversity. While certain PPE items appear more frequently, resulting in class imbalance, this distribution was analyzed to identify potential bias and support effective model training and performance evaluation.

4.3 Data Annotation Process

This project's annotation procedure was carried out methodically to guarantee precision and coherence. The chosen 2,350 photos from the SH17 collection were labeled by four human annotators. The 6 different PPE-related object types were first marked by three annotators who carried out the main labeling. A supervisor examined and fixed any discrepancies to ensure high-quality annotations.

In order to correct any last mistakes and improve the labels, a comprehensive inspection process was carried out.

For annotation, we utilized LabelImg, an open-source tool for bounding box annotation, ensuring a structured and efficient workflow. The choice of annotation tool was standardized across the team to maintain consistency in labeling quality. This process ensured that our dataset was accurately labeled, enhancing the reliability of our PPE compliance detection model.

Fig -1: Labeling Image

4.4 Class Imbalance and Preprocessing

A noticeable class imbalance exists, with some PPE items (e.g., safety vests, gloves) appearing more frequently than others (e.g., helmets). This imbalance can potentially impact model performance, leading to lower detection accuracy for underrepresented classes. To mitigate this issue, we applied the following preprocessing techniques:

- Data Augmentation: Random transformations such as flipping, brightness adjustments, and cropping were applied to improve model generalization.
- Class-Aware Weighting: Additional weight was assigned to less frequent PPE categories to ensure balanced training.
- Selective Sampling: We carefully balanced the dataset by including more diverse images where underrepresented PPE items appeared.

With these preprocessing strategies, the dataset has been optimized to support a robust PPE compliance detection model that performs effectively across all categories.

4.5 Model Selection and Training

For this study, we employed YOLOv8 (You Only Look Once version 8) as our object detection model for PPE compliance detection. YOLOv8 is a state-of-the-art real-time object detection framework known for its speed, accuracy, and efficiency, making it well-suited for industrial safety applications.

4.5.1 Model Selection

We selected YOLOv8 over other object detection models (e.g., Faster R-CNN, SSD) due to the following reasons:

- High Speed & Efficiency: YOLOv8 provides real-time detection with minimal computational cost.
- Superior Accuracy: It achieves high mean Average Precision (mAP) compared to older YOLO versions.
- Robust Performance on Small Objects: PPE items such as gloves, helmets, and face masks can be small in images, and YOLOv8's anchor-free detection improves detection in such cases.
- Support for Edge Deployment: Due to its lightweight nature, YOLOv8 can be deployed efficiently in real-world industrial environments.

4.5.2 Training Setup

The model was trained using Google Colab, leveraging its GPU (NVIDIA Tesla T4) for faster processing. The dataset was divided into training (80%) and validation (20%) sets to ensure balanced model evaluation.

To further improve model performance, we applied data augmentation techniques, including flipping, rotation, brightness adjustments, and noise addition.

The training process was monitored using mAP (mean Average Precision) as the primary performance metric, along with precision and recall scores. The model was fine-tuned by adjusting hyperparameters and using transfer learning from a pre-trained YOLOv8 model.

4.6 Deployment

After training the PPE compliance detection model, we deployed it using Flask, a lightweight web framework that allows real-time inference through API endpoints. The deployment process enables users to upload images and receive predictions on PPE compliance status.

4.6.1 Model Integration with Flask

- The trained YOLOv8 model is loaded using Ultralytics and serves inference requests through Flask.
- The model takes an input image, processes it, and outputs bounding boxes with PPE classification and risk levels.
- Flask handles incoming HTTP requests, processes images, and returns detection results in JSON format or as an annotated image.

4.6.2 Flask Endpoints

The Flask application provides the following key endpoints:

The Flask application provides the following key endpoints:

1. **/upload (POST)** – Allows users to upload an image for PPE detection.
   - The server processes the image and runs the model.
   - It returns detected objects and compliance classification.

2. **/predict (GET)** – Provides an API to fetch inference results.
   - Users can retrieve previously analyzed images and their results.

3. **/status (GET)** – A health check endpoint to confirm if the server is running.

5. RESULTS AND DISCUSSION

In this study, the YOLOv8 object detection model was trained on a dataset of 2,350 annotated images encompassing six distinct classes of personal protective equipment (PPE). The dataset was carefully curated and split into training and validation sets to ensure proper evaluation. The model was trained for 200 epochs using Google Colab with GPU acceleration, and the training process showed consistent decreases in box loss, classification loss, and distribution focal loss—indicating effective learning.

Model performance was evaluated using standard metrics, including precision, recall, and mean Average Precision (mAP). After training, the model achieved promising detection results, particularly for frequently occurring classes such as helmets and vests. Visual inspections showed accurate bounding boxes around PPE objects, while the mAP score showed improvements across epochs. However, minor misclassifications occurred in visually similar or overlapping PPE items.

These results confirm that YOLOv8 is well-suited for PPE compliance detection, even with moderate dataset sizes. Future work includes extending the dataset and integrating risk-level classification.

6. CONCLUSION

This study presents a Personal Protective Equipment (PPE) compliance detection system based on the YOLOv8 object detection model, trained using a subset of the SH17 dataset comprising 2,350 images across six PPE-related classes. By leveraging a curated dataset, annotating objects with precision, and employing the YOLOv8 architecture, the model demonstrated its ability to identify multiple PPE components in diverse industrial scenarios. Despite training with a limited dataset, the results indicate promising detection accuracy, validating the model’s potential for real-world deployment. Furthermore, integration with a Flask web application enables real-time inference, making it practical for workplace safety monitoring. Future work will focus on expanding the dataset, fine-tuning the model, and addressing class imbalance to further enhance the system’s robustness and performance.

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