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DEVELOPMENT OF AN OCCUPATIONAL HEALTH AND SAFETY (OHS) VIOLATION EARLY WARNING SYSTEM THROUGH THE INTEGRATION OF CNN–YOLOV8–BASED SMART CAMERAS IN THE COMPANY XYZ

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Abstract

Occupational Health and Safety (OHS) is a crucial aspect of industrial warehouse operations that involve high workplace risk, particularly regarding compliance with the use of Personal Protective Equipment (PPE). This study aims to develop an early warning system for OHS violations through the integration of smart cameras based on Convolutional Neural Networks (CNN) and the You Only Look Once (YOLOv8) algorithm to automatically and real-time detect PPE non- compliance in the Company XYZ. The research employed a Research and Development (R&D) method, consisting of needs analysis, system design, program coding, testing, as well as system implementation and maintenance. The detection objects include compliant and non-compliant PPE classes (hardhat, mask, and safety vest) and neutral objects, namely persons, safety cones, vehicles, and machinery. Experimental results show a significant improvement in model performance, with precision increasing from approximately 0.6 to 0.9, recall from 0.3 to 0.7, mAP@0.5 from 0.3 to 0.8, and mAP@0.5–0.95 from 0.1 to 0.5 at the 100th epoch. These results indicate that the proposed system can reliably detect PPE violations under dynamic working conditions and support the formulation of measurable internal OHS regulations and sanction mechanisms.

Keywords: Early Warning System, Occupational Safety and Health, Personal Protective Equipment, Smart Camera, YOLOv8.

INTRODUCTION

Occupational Health and Safety (OHS) is a vital component of industrial management systems, particularly in the logistics sector, which is characterized by high work dynamics. In warehouse operations, various activities such as material handling, storage, and distribution pose potential occupational accident risks if not supported by adequate safety systems. The use of Personal Protective Equipment (PPE), such as safety helmets and high-visibility vests, represents one of the most fundamental protective measures to ensure worker safety. However, field realities indicate that compliance with PPE usage remains a major challenge, especially in large-scale operations involving numerous workers and extensive work areas. The continued prevalence of occupational accidents resulting from negligence in PPE usage highlights the limited effectiveness of conventional supervision methods that have been applied to date. According to the 2023 Labor Priority Data of the Industrial Data System (SDI) issued by the Ministry of Manpower of the Republic of Indonesia, the number of occupational accidents in Indonesia remains very high. In 2023 alone, a total of 370,747 occupational accident cases were recorded, underscoring the magnitude of national OHS challenges.

Data from BPJS Ketenagakerjaan indicate that throughout 2018 there were approximately 147,000 occupational accident cases in Indonesia, with 3.12%–3.18% resulting in permanent disability and 1.75% causing fatalities. This means that, on average, around 40,273 work-related incidents occurred daily, with approximately 12 workers experiencing disability and 7 fatalities per day (Maulana & Fadillah, 2022). Notably, the majority of these accidents around 80–85% were caused by unsafe actions, including non-compliance with PPE usage, neglect of OHS procedures, and other forms of negligence (Azizah et al., 2025). Furthermore, BPJS Ketenagakerjaan claim records show an increasing trend in occupational accident claims in recent years, rising from 103,349 claims in 2022 to 121,531 claims during the January–November 2023 period, reflecting the growing financial and social burden of workplace incidents (Saputra, 2024).

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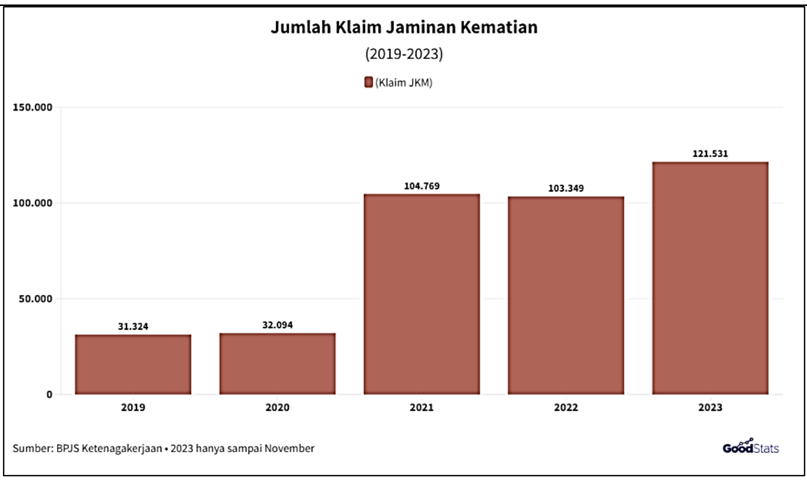

Figure 1. Number of Death Benefit Claims 2019–2023
Source: Yonatan (2024)

Documents from Commission IX of the Indonesian House of Representatives (DPR RI) also record fluctuations and increases in occupational fatality rates: 4,007 fatalities in 2020, a decrease to 3,410 in 2021, followed by a significant rise to 6,552 fatalities in 2022 (Nola, 2023). These data indicate that existing occupational safety policies and programs have not yet been fully effective in sustainably reducing accident rates. In addition to the national increase in fatality figures, various studies demonstrate that human behavior is the primary factor contributing to the high incidence of occupational accidents. A study conducted in Surabaya found that unsafe actions accounted for approximately 57.4% of occupational accidents (Syah & Mirwan, 2022). These findings emphasize the critical importance of procedural compliance, PPE usage, and effective supervision in mitigating accident risks. Similar conditions are also observed in Gresik, a region known for its intensive industrial production and logistics activities. Based on data from BPJS Ketenagakerjaan Gresik Branch, from January to April 2025 a total of 2,028 claims for Work Accident Insurance (JKK) were recorded, with total compensation reaching IDR 7.3 billion. These claims consisted of 1,185 accidents occurring within the workplace, 669 traffic-related accidents, and 174 accidents occurring outside buildings or offices but still within the work environment (Anam, 2025). These figures indicate that occupational accidents remain frequent, particularly in highly active industrial areas such as Gresik and its surroundings.

Based on the discussion above, when examined more specifically within the industrial context, occupational accident risks are particularly dominant in sectors with intensive activities, such as logistics and warehousing. Among various industrial facilities in Gresik, warehouses represent the most relevant setting for analysis due to their intensive and complex work characteristics, involving simultaneous interactions between human labor and machinery. Rapid loading and unloading activities, the use of heavy equipment, and high worker mobility contribute to significant accident risks within warehouse environments. The Concrete Warehouse in the Gresik Industrial Estate (KIG) was selected as the research site because it reflects a dynamic, high-activity, and high-risk work environment. In operational practice, manual supervision systems that rely on field supervisors have inherent limitations, including restricted visual coverage, human fatigue, and the difficulty of monitoring all areas simultaneously. As a result, minor violations such as improper PPE usage often go unnoticed and recur, eventually becoming major contributors to workplace incidents (Rizky & Nugraha, 2022). Based on interviews conducted by the researcher with the OHS Manager of the KIG Concrete Warehouse, it was revealed that incidents related to non-compliance with PPE usage and insufficient direct supervision have occurred in the work area. One example involved a worker not wearing a safety vest while in a loading and unloading area, causing the worker to be temporarily unseen by heavy equipment operators and nearly struck during material movement.

This situation resulted in a near-miss incident and minor abrasions due to contact with surrounding equipment. Such conditions demonstrate that manual supervision systems still have limitations in ensuring PPE compliance and preventing potential incidents in warehouse environments. Because data on Occupational Health and Safety (OHS) violations at PT Petrokopindo Cipta Selaras are internal and not directly accessible, the researcher collected primary data through field observations. This data collection aimed to obtain an empirical overview of worker compliance with PPE usage and the actual implementation of OHS practices in the work area. Observations were conducted over five consecutive days within one week, with six observation slots per day. In total, 30 observation sessions were carried out, covering various working conditions, worker activities, and environmental situations in the concrete warehouse area. Each observation slot lasted approximately one hour and was conducted at different times to capture representative variations in field conditions. The selection of 30 observations was based on the Central Limit Theorem principle, which states that a minimum sample size of 30 is sufficient to produce stable data that can be statistically analyzed and considered representative (Acra, 2020).

Table 1. Distribution of PPE Usage Violations Based on 30 Observation Sessions

No.	Type of Violation	Frequency	Percentage
1	Not Wearing a Safety Helmet	76	34%
2	Not Wearing a Mask	68	31%
3	Not Wearing a Safety Vest	72	33%
4	Unauthorized Presence in Work Area	5	2%
	Total	221	100%

Source: Primary Data (2025)

Based on observations conducted over five consecutive days with a total of 30 observation sessions, data were obtained regarding the level of worker compliance with the implementation of Occupational Health and Safety (OHS), particularly in the use of Personal Protective Equipment (PPE). During this period, a total of 221 actual violations of OHS provisions were directly observed in the work area. These findings provide an initial indication that worker compliance with safety procedures still requires serious attention. When viewed in terms of time frequency, an average of approximately 44 violations were identified per day, or about 7 violations within each one-hour observation slot. This figure indicates that in every work period there are still workers who do not comply with established safety standards. Such conditions suggest that the implementation of an OHS discipline culture in the workplace has not yet been fully optimized. More specifically, the most frequent violation was the failure to wear safety helmets, with 76 cases or approximately 34% of the total violations. This type of violation ranked first and was categorized as the most risky, considering that helmets function as the primary protection against potential head injuries caused by impacts or falling objects. The second most frequent violation was the failure to wear safety vests, with 72 cases (33%), followed by not wearing masks, with 68 cases (31%). The least frequent violation was being present in the work area without authorization, which was found in only 5 cases (2%) during the observation period.

Based on the results of the 30 observation sessions, a total of 221 actual violations of PPE usage and OHS–Environment (OHS-E) regulations were identified in the work area. The violation with the highest frequency was not wearing a helmet (76 cases, 34%), followed by not wearing a safety vest (72 cases, 33%), and not wearing a mask (68 cases, 31%). The violation with the lowest percentage was unauthorized presence in the work area, with 5 cases (2%). These results indicate that the level of worker compliance with PPE usage remains relatively low, highlighting the need for continuous efforts to enhance supervision and socialization in order to reduce the number of violations in the field. Although the basic principle of risk control in OHS places hazard elimination as the most effective measure, this approach cannot be fully applied in industrial warehouse environments. Loading and unloading activities and the operation of heavy equipment are essential components of work processes that cannot be eliminated (NIOSH, 2021). Therefore, optimizing supervision systems represents the most realistic and strategic step to mitigate risks and ensure that workers consistently use PPE. Moreover, warehouse environments often present extreme conditions, including dusty areas, human activities around heavy equipment and machinery that cause visual disturbances, objects obstructing camera views, and rapid worker movements, all of which pose significant challenges for conventional monitoring systems. Under such dynamic conditions, a monitoring system is required that is not only reactive but also capable of adapting to variations in visual conditions in the field.

As a solution to these challenges, this study proposes the development of an early warning system for OHS violations based on smart cameras capable of automatically and real-time detecting non-compliance with PPE usage. The system leverages Artificial Intelligence (AI) technology using a Convolutional Neural Network (CNN) approach combined with the YOLOv8 (You Only Look Once version 8) object detection algorithm to rapidly and accurately recognize objects such as helmets and safety vests. Integration with cameras that enable on-device processing (edge computing) allows the system to operate continuously, autonomously, and with minimal dependence on a central server (Nguyen et al., 2024). Thus, the integration of Artificial Intelligence, visual surveillance, and early warning mechanisms can serve as a modern, efficient, and adaptive preventive solution, expected to create an OHS monitoring system that is adaptive, efficient, and scalable. With the implementation of this system, OHS supervision can transition from manual methods to an automated system that operates continuously and objectively. A smart camera- and AI-based approach not only assists in detecting PPE violations but also encourages the development of a stronger safety culture within industrial environments. This study is expected to make a tangible contribution to the development of more effective OHS monitoring systems, particularly in the Concrete Warehouse of the Gresik Industrial Estate (KIG). Consequently, the results of this research may serve as a foundation for the implementation of intelligent visual-based monitoring systems that are preventive, adaptive, and aligned with the operational needs of modern logistics and warehousing sectors.

METHOD

This study employs a Research and Development (R&D) method with a quantitative approach to develop and evaluate an early warning system for Occupational Health and Safety (OHS) violations based on the integration of smart cameras and the CNN–YOLOv8 algorithm. The research stages follow a waterfall model, encompassing needs analysis through observation and interviews, system architecture design, program code implementation, functional and model performance testing, as well as system deployment and maintenance in a real working environment. Data collection was conducted through direct observation of workers' behavior related to PPE usage, photographic documentation, and the utilization of both internal and external image-based datasets. The collected data were subsequently processed through a pre-processing stage that included data selection, labeling, transformation, and augmentation, before being developed within machine learning stages consisting of training, validation, and testing to produce a reliable detection model, which was then deployed using a Python-based open-source framework with GPU support.

RESULTS AND DISCUSSION

Integration into the Company HSE System

To ensure that the model operates optimally, it is necessary to identify the required operational stages. This identification is carried out by referring to the company's Standard Operating Procedures (SOPs), so that the integration of the model into the workflow can be implemented appropriately and aligned with established operational practices.

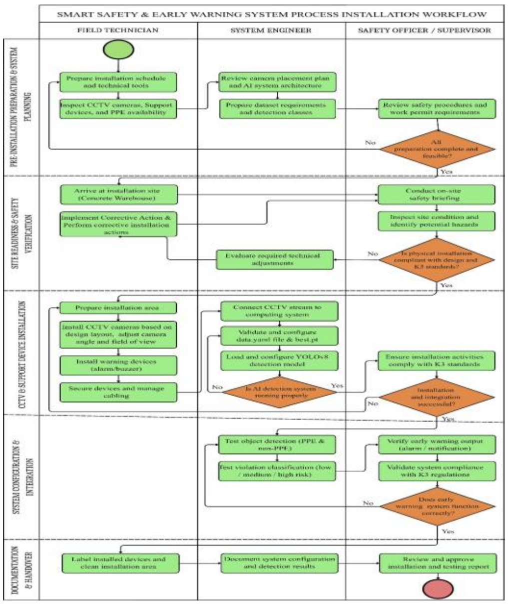

Figure 2. Early Warning System Process Installation Workflow at Company X
Source: Processed Data (2025)

The installation workflow of the Smart Safety & Early Warning System begins with the pre-installation preparation and system planning stage, which involves three main roles: the Field Technician, the System Engineer, and the Safety Officer/Supervisor. The Field Technician is responsible for preparing the installation schedule, technical equipment, and checking the availability of CCTV cameras, supporting devices, and PPE. Meanwhile, the System Engineer reviews the camera placement plan, system architecture, and prepares the dataset and detection classes. The Safety Officer ensures that safety procedures and work permits are complete. All of these preparations are then verified for completeness before proceeding to the next stage. Once the preparation stage is deemed adequate, the process moves to site readiness and verification. The Field Technician arrives at the site (Concrete Warehouse) and implements corrective actions if required. The System Engineer evaluates any necessary technical adjustments, while the Safety Officer conducts safety briefings, inspects potential hazards, and ensures that physical installations comply with OHS standards. If any non-conformities are identified, corrective measures are applied until all requirements are fully met before continuing to the next stage. The next stage is CCTV and support device installation. At this stage, the Field Technician prepares the installation area, installs CCTV cameras according to the design layout, adjusts camera viewing angles, installs alarms or buzzers, and secures and organizes cabling. The System Engineer connects the CCTV stream to the computing system, validates configuration files, and loads the YOLOv8 model for object detection. Throughout this process, the Safety Officer continuously supervises to ensure that all installation activities comply with safety standards. The success of both the physical installation and AI detection functionality is rigorously verified before the stage is declared complete.

After the devices are installed, the process continues with system configuration and integration. The System Engineer tests object detection (PPE and non-PPE), classifies violation levels (low, medium, and high), and verifies early warning outputs such as alarms and notifications. The Safety Officer validates that the system complies with applicable OHS regulations. The early warning functions are thoroughly tested, and if the results are not yet optimal, testing is repeated until satisfactory performance is achieved. The final stage is documentation and handover. The Field Technician labels the installed devices and cleans the installation area. The System Engineer documents the system configuration and detection results, while the Safety Officer reviews and approves the overall installation and testing reports. Once all stages are completed and approved, the Early Warning System is officially handed over and ready for operation, with a strong emphasis on safety aspects, AI detection accuracy, and compliance with OHS standards throughout the entire process. Regarding the workflow of the camera-based system in the early warning system for OHS violations using computer vision, the process begins with real-time image acquisition, followed by violation detection and classification, and concludes with evidence storage and violation data recapitulation.

Camera Image Acquisition

The process begins by establishing a connection to the camera as the main image source of the system. To ensure smooth processing and minimize latency, image acquisition is performed in parallel using a capture thread. Through this mechanism, the camera continuously captures the latest frames and places them into a frame queue. When the queue is full, older frames are discarded, ensuring that the system always processes the most recent images. This approach is intended to prevent data accumulation and maintain system responsiveness to field conditions.

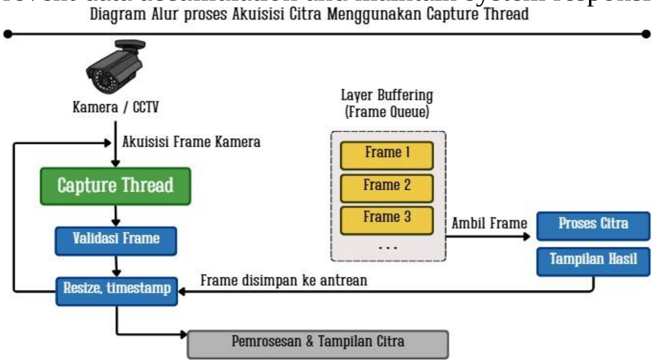

Figure 3. Flow Diagram of the Image Acquisition Process
Source: Processed Data (2025)

YOLOv8 Preprocessing and Inference

Frames retrieved from the frame queue are then processed through a preprocessing stage involving image resizing. This step aims to increase inference speed without compromising the main visual context. Subsequently, the preprocessed images are processed by the YOLOv8 model to detect objects related to PPE compliance and work activities. The inference results include object classes, confidence scores, and bounding box coordinates. The detected coordinates are then rescaled to match the original image dimensions.

Figure 4. Example of YOLOv8 inference results showing bounding boxes and PPE object labels
Source: Processed Data (2025)

Classification of OHS Violation Levels

Based on the detected object classes, the system performs classification of OHS violation levels. This process uses predefined rules to categorize working conditions into several categories, namely Safe, Minor, Moderate, and Severe. The determination of these categories is formulated with reference to the company's risk assessment results, so that each violation level represents the actual risk level in the working environment. The classification results reflect the detected risk level at a given time and serve as the basis for subsequent decision-making processes, such as alarm activation and evidence storage.

Figure 5. Overlay display of violation levels on images resulting from camera detection
Source: Processed Data (2025)

Visualization and Information Overlay

To support real-time monitoring, the system applies a visual overlay to the detected images. This overlay includes bounding boxes, object labels, confidence scores, violation levels, and event timestamps. Such visualization not only assists operators in continuously monitoring working conditions but also serves as visual evidence in the event of occupational health and safety (OHS) violations.

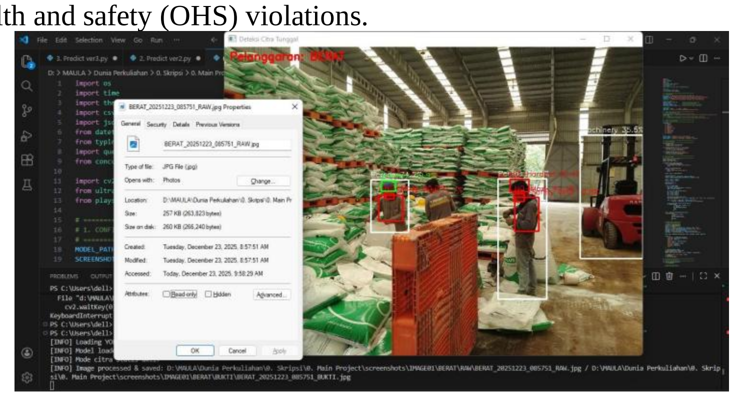

Figure 6. Live camera monitoring display with bounding boxes, object labels, and violation information.
Source: Processed Data (2025)

Alarm and Early Warning System

When the system detects a violation exceeding the "Safe" level, it automatically activates an early warning alarm. This alarm is intended to increase the awareness of workers and supervisors regarding unsafe conditions. To prevent continuous or repetitive alarm activation, the system implements a specific time interval (throttling) before the alarm can be triggered again.

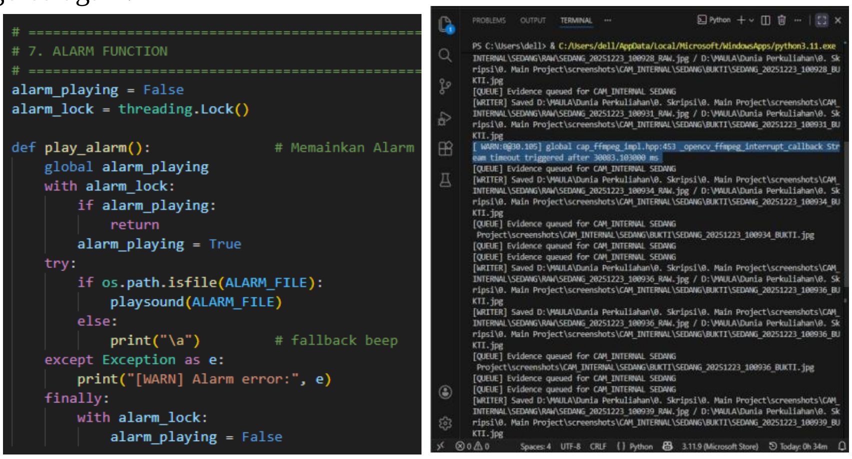

Figure 7. Alarm activation as a response to OHS violations: program interface (left) and terminal log display (right).
Source: Processed Data (2025)

Storage of Violation Evidence

When a violation occurs, the system stores visual evidence in the form of two types of images: RAW images without annotations and EVIDENCE images that are equipped with overlays and event time information. The storage process is carried out asynchronously using a writer thread, so it does not interfere with the main detection process. Evidence files are stored in an organized folder structure based on camera ID and violation severity level.

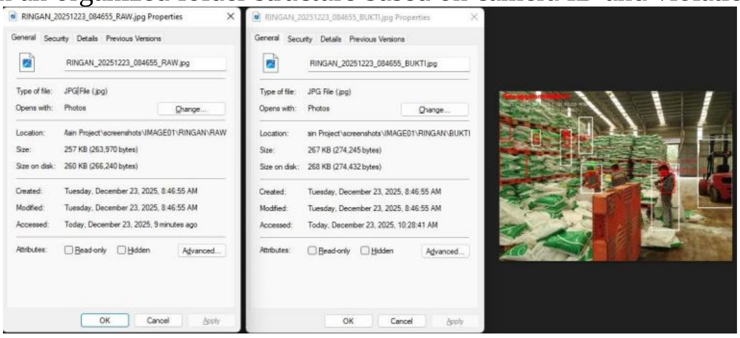

Figure 8. Example of a comparison between stored RAW images and EVIDENCE images resulting from violation detection.
Source: Processed Data (2025)

Recapitulation and Logging of Violation Data

In addition to image storage, the system also records each violation event into a CSV file as a form of data recapitulation. The recorded data include the time of occurrence, camera ID, detected object class, violation severity level, and the location of the evidence file. This recapitulation serves as a basis for evaluating OHS compliance and can be utilized for further analysis by management or OHS officers.

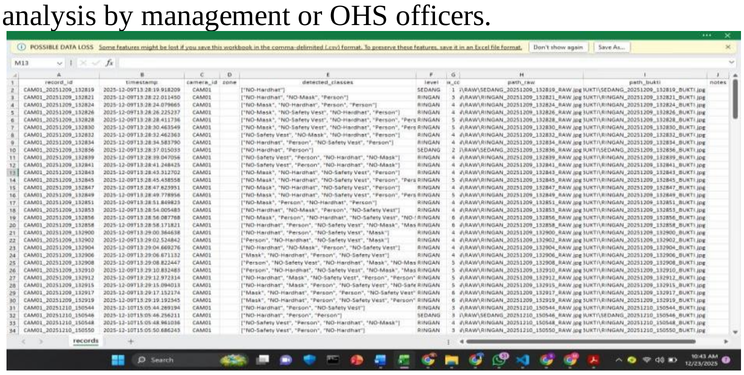

Figure 9. Example of CSV file contents displaying the recapitulation of OHS violation data.
Source: Processed Data (2025)

Figure 9 illustrates an example of the CSV file used to recap OHS violation data recorded by the system. The CSV file contains structured, tabular data that include essential information such as record identity, time of occurrence, camera ID, monitoring zone, type of detected violation, severity level, number of detected objects, and storage locations of both raw images and evidence images. Presenting data in CSV format facilitates recording, management, and further analysis of OHS violation incidents.

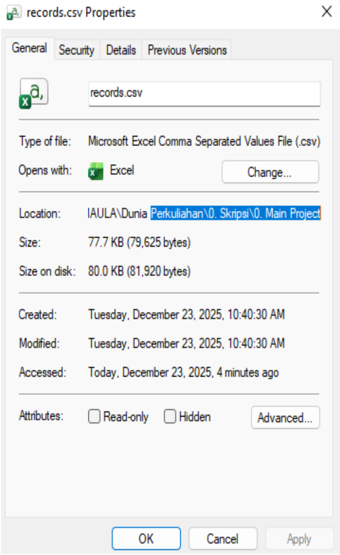

Figure 10. Detailed view of the CSV file showing the recapitulation of OHS violation data.
Source: Processed Data (2025)

Figure 10 presents a more detailed view of the CSV file contents, showing each data row as a single OHS violation event detected by the system. This view demonstrates consistency in data entry across columns, ensuring that each event is clearly and chronologically documented. The information stored in the CSV file can be used as material for evaluating worker compliance with OHS procedures, as well as a basis for report preparation and decision-making related to improving workplace safety.

CONCLUSION

Based on the overall research progress and system implementation that have been carried out, several conclusions can be drawn as follows:

1. A smart camera–based OHS monitoring system integrated with the CNN–YOLOv8 method was successfully designed and developed. The system is capable of automatically and real-time detecting non-compliance in the use of Personal Protective Equipment (PPE), including safety helmets, masks, and safety vests. The implementation of capture threads, writer threads, and parallel processing mechanisms ensures continuous image processing, real-time display of violation evidence overlays, and prevention of data bottlenecks that could degrade detection performance.
2. Evaluation results indicate that the detection model achieved strong performance, with precision approaching 0.9, recall of approximately 0.7, and an mAP@0.5 value of 0.8. The system is able to operate responsively under various dynamic workplace conditions, including changes in lighting and worker density, thereby maintaining both detection speed and accuracy.
3. Analysis of detection results shows that the system can classify OHS violations into minor, moderate, and severe levels based on combinations of detected PPE violations. These data can serve as a basis for developing more measurable internal regulations and objective sanction mechanisms, thereby significantly improving PPE compliance within the warehouse work area.

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