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***Abstract*—K3 Helmet Usage Warning System Using Deep Method Learning Algorithm YOLOv8 is a technological innovation that combines the advanced object detection method YOLOv8 (You Only Look Once version 8) with the needs of safety in the work environment, especially the use of K3 (Occupational Health and Safety) helmets. This research aims to improve compliance with the use of K3 helmets through an automation approach using Deep Learning technology.The YOLOv8 algorithm is used to detect whether individuals in the work area are wearing K3 helmets or not. The detection results will be processed by the system to provide automatic warnings if individuals do not wearing an OHS helmet according to safety regulations. The use of Deep Learning technology in this method enables fast and accurate detection, contributing to increased awareness and compliance with workplace safety policies.With proper implementation, the system is expected to help create a safer work environment and improve the safety of workers, making the workplace more compliant with established OHS standards.**

Keywords—Safety Helmet; Deep Learning; YOLOv8; Object Detection; Real Time

I. Introduction (*Font 14*)

Ensuring worker safety in construction is a complex undertaking. Factors besides human error and technical shortcomings often contribute to a rise in work-related injuries and illnesses, impacting projects significantly[1]. A critical but overlooked aspect in improving overall well-being and worker productivity is the current state of knowledge, awareness, and responsible behavior among the workforce[SM1] regarding Occupational Helath and Safety (OHS) practices[2].

Disturbing statistics reveal a high number of construction accidents every year, causing fatalities, property damage, and production halts. Data from Jamsostek in 2021 suggests a concerning number of cases 7,298 resulting in a staggering 9,224 worker casualties[3]. This alarming trend underscores the urgent need for a robust, integrated occupational health and safety (OHS) management system in construction projects.

Strict adherence to regulations encompassing engineering practices, safety protocols, worker health, environmental protection, and energy usage is crucial for ensuring orderly construction activities. Personal Protective Equipment (PPE) plays a vital role in mitigating work-related risks[4].

The growing emphasis on personal protective equipment detection underlines its critical importance for construction worker safety and productivity. Advancements in personal protective equipment detection technology offer a promising solution to this persistent problem[5].

Advancements in AI have led researchers to explore **deep learning algorithms** for **detecting people without helmets** on construction site[2] [6]. These automated systems use **computer vision and machine learning** to create a reliable framework for identifying helmet usage[7].

A 2021 study by Widodo et al. investigated this concept. They developed a **helmet detection system** using deep learning techniques on a dataset of construction site images. Their system, employing **Convolutional Neural Networks (CNNs) and transfer learning**, achieved an impressive **93.33% accuracy** in real-time helmet detection, processing 45 frames per second.This research showcases the potential of deep learning for **revolutionizing**

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construction safety. By automating helmet compliance checks, these systems can significantly **improve safety** by identifying and addressing violations[8].

This Final Year Project focuses on developing a helmet detection tool for construction workers using the YOLOv8 framework. Deep learning models serve as the backbone of the machine learning process, enabling the tool to recognize human head conditions and effectively detect workers wearing and not wearing helmets within the project area.

II. Research Methodology

A. Occupational Health and Safety

Ensuring Occupational Health and Safety (OHS) in Indonesia necessitates a collaborative effort from all parties involved, including government agencies, businesses, and the workforce itself[9].Indonesia's construction industry is grappling with a severe occupational safety problem. Data from Satudata Kemnaker reveals a staggering 370,747 work accidents in 2023, surpassing the previous year's figures. The informal sector is particularly concerning, with a high number of accidents. Even more alarming, 18 workers tragically lose their lives daily due to work-related mishaps[3].

This crisis sytems from a confluence of factors: a lack of awareness and ingrained culture of occupational health and safety (OHS), inadequate supervision, unsafe work environments with faulty equipment, and limited OSH training programs.

Helmet usage enforcement in construction zones is crucial for ensuring adherence to safety regulations and preventing accidents[10].Thankfully, advancements in technology offer solutions. Various technologies, including sensors, machine learning, and deep learning, have been developed specifically for helmet detection[11].

The latest deep learning-based object detection methods are gaining traction in the field of helmet detection research. Wang et al[5]. employed different YOLO architectures to successfully detect not only helmets, but also people and vests, in various colors. Their research showed that YOLOv5x offered the highest accuracy, while YOLOv5s provided the fastest processing speed. Similarly, Geng et al[12]. Utilized YOLO-based architectures for helmet detection. Geng et al.'s approach involved using the YOLOv3 architecture to tackle the challenge of imbalanced datasets in helmet detection. They employed a Gaussian blurring method to improve the accuracy of YOLOv3 for this specific task. Wu et al[13]. Proposed a single-shot CNN model for automatic object detection, including helmets.

Future research efforts can focus on enhancing helmet detection accuracy under challenging conditions, such as extremely low light or situations where objects are obscured[14] Additionally, researchers can explore developing systems that not only detect helmets but also identify different helmet types and provide additional worker information, such as their identity and location on the construction site.

B. Deep Learning

Deep learning constitutes a subfield within artificial intelligence (AI) and machine learning (ML). It leverages the development of multi-layered neural networks to attain superior accuracy in a variety of tasks, including object detection, speech recognition, and language translation[15].

Inspired by the structure and function of the human brain, deep learning, often abbreviated as DNNs (deep neural networks), represents a distinct area of study within artificial intelligence and machine learning. In contrast to traditional machine learning models that employ only one or two neural network layers, deep learning utilizes intricate, multi-layered architectures. This enables deep learning to progressively extract patterns and representations from data in a hierarchical fashion.

Convolutional Neural Networks (CNNs) and YOLO (You Only Look Once) represent advancements in technology driven by the evolution of deep learning from multi-layered neural networks[16].

Convolutional Neural Networks (CNNs) represent a potent form of deep learning architecture, meticulously tailored for image analysis. They replicate the hierarchical information processing of the human brain through intricately interconnected layers of neurons.

Convolusional Neural Networks (CNNs) represent an advanced form of deep learning architecture specifically tailored for processing and analyzing visual data[17]. By utilizing complex layers of interconnected neurons, CNNs are engineered to identify patterns and features in images, mirroring the hierarchical information processing of the human brain. This hierarchical approach empowers CNNs to recognize intricate visual information, making them exceptionally adept at tasks like image recognition, object detection, and image classification.

Convolutional neural networks (CNNs) have been trained on large sets of labeled image data, enabling them to continually learn and improve. Their adeptness at extracting meaningful information from images has driven advancements in fields such as computer vision, autonomous vehicles, medical imaging, and beyond. As research progresses, CNNs are poised to play an increasingly influential role in shaping the future of technology[18].

YOLO is a pioneering approach to object detection, differentiating itself from traditional methods with its single-shot approach that enables real-time processing. It boasts a unified architecture integrating object detection and class prediction for enhanced efficiency[19].

To maximize speed, YOLO divides the image into a grid, with each cell responsible for detecting objects within its designated area[20]. It utilizes convolutional neural networks (CNNs) to extract features, predict bounding boxes, and assign class probabilities to detected objects. Trained on a vast dataset of labeled images, YOLO excels in real-time applications such as robotics and autonomous vehicles. Its speed, accuracy, unified framework, and adaptability make it an invaluable tool for various object detection tasks[21].As deep learning advances, YOLO is poised to play an even more significant role in shaping the future of computer vision[22].

In summary, this research compares the two methods to evaluate the better neural network method for use in the K3 Helmet detection system

C. System Design Model

Sometimes, research methodology is demonstrated in form of diagrams or tables. Author(s) should ensure that those diagrams and tables are clearly readable if placed in one column, however, if the diagrams or tables require more spaces, the diagrams or tables can be placed in two columns, but it should still confirmed in balanced format.

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Sometimes, research methodology is demonstrated in form of diagrams or tables. Author(s) should ensure that those diagrams and tables are clearly readable if placed in one column, however, if the diagrams or tables require more spaces, the diagrams or tables can be placed in two columns, but it should still confirmed in balanced format.

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III. Results and Discussion

In this section, author(s) must express and show the obtained results of his/her/their research whether it obtained from laboratory based research or simulation results. The results can be in figure, diagram, or table which is in turn must be followed by comprehensive explanation. Figure or Table must be numbered in sequence. Example of Figure and Table can be seen as follow:

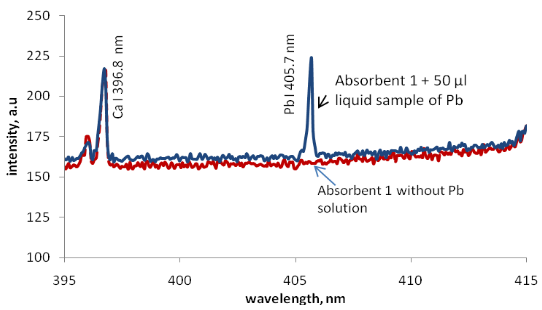

Figure 1. Simulation result (*Font 10*)

Table 1. Collected Data (*Font 9)*

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Row Name Goes Here	X	x
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All equations must also be numbered in sequence where the number is placed in parentheses.

$$a + b = \gamma \quad (1)$$

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IV. Conclusion

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3. In this part suggestions can also be included
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Acknowledgement can be applied for bodies which have given very positive contributions in conducting the research such as sponsorship, etc.

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References style would be in IEEE standard as shown below. It is strongly recommended that author(s) use Endnote or Mendeley software in managing the IEEE referencing format.

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