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# Drowsiness Detection of Construction Workers: Accident Prevention Leveraging Yolov8 Deep Learning and Computer Vision Techniques

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**Abstract:** Construction projects' unsatisfactory performance has been linked to factors influencing individuals' well-being and mental alertness on projects. Drowsiness is a significant indicator of sleep deprivation and fatigue, so being able to identify the cognitive and physical preparedness of workers on site to engage in construction tasks is important. As a consequence of the strenuous nature of the work involved in construction, long work hours, and environmental conditions, drowsiness is commonplace and has received less attention despite being a leading cause of accidents occurring on-site. Detecting drowsiness is essential for determining the safety and well-being of site workers. This study presents a vision-based approach using an improved version of the You Only Look Once (YOLOv8) algorithm for real-time drowsiness exposure among construction workers. The proposed method leverages computer vision techniques to analyze facial and eye features, enabling the early detection of signs of drowsiness, effectively preventing accidents, and enhancing on-site safety. The model showed significant precision and efficiency in detecting drowsiness from the given dataset, accomplishing a drowsiness class with a mean average precision (mAP) of 92%. However, it also exhibited difficulties handling imbalanced classes, particularly the underrepresented 'Awake with PPE' class, which was detected with high precision but comparatively lower recall and mAP. This highlighted the necessity of balanced datasets for optimal deep learning performance. The YOLOv8 model's average mAP of 78% in drowsiness detection compared favorably with other studies employing different methodologies. The system improves productivity and reduces costs by preventing accidents and enhancing worker safety. However, limitations, such as sensitivity to lighting conditions and occlusions, must be addressed in future iterations.

**Keywords:** construction; deep learning; drowsiness; construction safety; computer vision; accident; Yolo

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## 1. Introduction

As ensuring safety is paramount in all infrastructure projects, there is a pressing requirement for implementing on-site safety regulations and protocols. This is essential to enhancing the well-being and security of construction workers, as highlighted in the works of [1,2]. This can be ascribed to the fact that the construction site is one of the most hazardous environments, with several safety concerns stemming from the intricate and fluid interaction that exists between employees, materials, equipment, and the actual execution of construction tasks [3,4]. Fatigue stands out as a prominent contributor that jeopardizes the health, safety, and overall welfare of individuals working within the construction industry. Fatigue, which results from lack of sleep, negatively impacts a person's well-being, ability to function at work, and safety [5,6]. As indicated by prior research conducted by the National Safety Council, every single surveyed construction worker exhibited at least one case of susceptibility to workplace fatigue, a condition that can result in hazardous work environments and heightened injury hazards [5]. In total, 71% of construction industry employers who responded to the survey claimed that their employees' lack of sleep had an effect on productivity, and 45% of respondents said that weariness was to blame for safety-related incidents [5,6]. The vision-based drowsiness detection system has broad applications in the construction industry. It can be integrated into existing safety protocols, enabling real-time alerts to supervisors or workers when drowsiness is detected [3,4].

Drowsiness is an indication of fatigue, which can have a substantial negative impact on a person's well-being, productivity, and ability to stay safe. Fatigue is a difficult ergonomic/safety "issue" in several sectors such as manufacturing [7], construction [8,9], and others [9], since it reduces productivity and raises the likelihood of accidents. These consequences could result in decreased performance, decreased production, deficiencies in the quality of the work, and human errors.

Construction tasks often entail heavy workloads, uncomfortable working postures, and long working hours, making construction employees susceptible to weariness and drowsiness [8,9]. We emphasize the significance of drowsiness research by highlighting the long-term consequence of unchecked fatigue as leading to chronic fatigue symptoms and reduced immune abilities. It has also been pointed out that these outcomes have been highlighted with reduced quality of life, socioeconomic disruption to way of life, increased absenteeism, etc. However, while drowsiness holds significant implications for the well-being of workers and project performance, its detection among construction workers is low [10]. Traditional methods, including using an on-site sleepiness assessment to combat fatigue, typically rely on a visual examination carried out by a trained observer. This is despite the fact that drowsiness is becoming an increasingly significant topic in the fields of health, safety, and well-being research [11]. These approaches do not effectively grasp the interconnectedness of numerous risk elements and the diversity in the tasks undertaken [5,6].

Despite its severity, numerous serious workplace mishaps continued to have been linked to insufficient sleep. Still, a common challenge is that people often do not comprehend their level of fatigue, its effects, or both. Previous studies such as those [3] have discovered that adults need 8 h of sleep daily to be fully restorative. Yet, most only receive 7 h, leaving them with a sleep deficit. Therefore, it is imperative to develop innovative methods to identify drowsiness on site [12]. This is critical to reducing the likelihood of accidents on site as drowsiness impairs attention, reaction time and judgement. The employment of innovative methods to identify the fatigue state through drowsiness has further been postulated to be vital to avert falling from heights [13], slow reflexes leading to collisions with equipment [14], workers inability to operate machinery [15], poor decision making [16], inefficient work performance [9], and elevated stress levels, amongst others [17].

Therefore, observation of risky situations and action is necessary for construction safety and health to eliminate possible risks quickly [18]. However, such observations become ineffective and laborious when using subjective and manual assessment methods. Such manual assessments of the worker's safety conditions are laborious and error prone since they depend so much on the inspector's physical condition and level of knowledge [19]. This has required the development of inventive digital methods that make use of computer vision and deep learning.

In recent times, computer vision methods have emerged as a reliable and automated means of conducting field observations, extracting safety-related insights from images and videos recorded on the site. These approaches are seen as useful replacements for manual observational methods, which take a lot of time and are not very trustworthy [16,19]. The current surge in interest and uptake of computer vision can be attributed to its capability for automated and continuous monitoring of construction sites. By taking pictures or videos of a construction scene, computer vision may reveal a wealth of information about it, such as the locations and behaviors of project entities and the circumstances of the site [20]. This has the potential to enable a quicker, more precise, and all-encompassing comprehension of complex construction activities [13]. As a consequence of this, computer vision has been integrated into a number of distinct parts of the construction industry, such as the tracking of progress, the evaluation of productivity, the identification of defects, and the automation of documentation [19,21–23].

With the aim of overcoming the constraints associated with traditional manual methods for detecting drowsiness as a fatigue indicator, this research employed computer vision and deep learning techniques. This enabled the early identification of signs of drowsiness, offering a potent approach to accident prevention and the enhancement of on-site safety. This study contributes to improved health, safety, and well-being on construction sites by developing a vision-based approach using an improved version of the You Only Look Once (YOLOv8) algorithm for real-time drowsiness detection in construction workers. The approach was based on the preparation of datasets, the training of deep learning models, and the evaluation of the models using testing images. Specifically, the awakeness pose estimate dataset is acquired from photographs and videos recorded on actual and non-actual construction building sites. Subsequently, critical key points encompassing complete equipment body postures are delineated and labelled within the collected images. The results of the experiments demonstrated that the suggested methodology framework can rapidly and accurately anticipate the whole drowsiness postures of construction workers. The model displayed significant precision and efficiency in detecting drowsiness from the provided dataset. It achieved a mean average precision (mAP) of 92% and an inference speed as low as 0.4 ms for preprocessing and 7.5 ms for inference. Both of these figures are quite low. However, it also exhibited difficulties in handling imbalanced classes, particularly the underrepresented 'Awake with PPE' class, which was detected with high precision but comparatively lower recall and mAP. This highlighted the necessity of balanced datasets and appropriate hyperparameters for optimal deep-learning performance. The YOLOv8 model's mAP of 78% in drowsiness detection compared favorably with other studies employing different methodologies.

The subsequent sections of the document are organized as follows: Section 2 delves into a thorough review and discussion of previous research; Section 3 offers an extensive depiction of the proposed methodology; Section 4 showcases the outcomes achieved using deep learning techniques. The fifth and concluding section of the paper presents a summary of the research's core content, underscores its implications, addresses limitations, and outlines potential avenues for future exploration.

## 2. Construction Workers Well-Being

The construction industry exerts a profoundly influential effect on the economic prosperity of every country, as demonstrated by its impressive USD 10 trillion addition to the global gross domestic product (GDP), as reported by [19]. Nevertheless, because of the large number of accidents and fatalities that occur within the industry, its influence is negatively impacted as a direct result. This highlights an urgent need to improve its workforce's health, safety, and well-being operations. A worker's performance suffers due to fatigue in the workplace, which is a multifaceted construct [23]. It is the product of continued action and is influenced by psychological, socioeconomic, and environmental factors [6]. Recent evidence suggests that improved operational practices that have enhanced workers' wellness and safety are influenced by studies on improving the well-being of workers [15,23,24].

Despite the fact that working on a construction site while feeling overly fatigued could be risky, just 75% of construction employees believed that it was, but 98% of construction employers concurred [5]. In addition, there was a disparity between the percentage of employees (78%), who believed that driving when fatigued is risky and the percentage of employers (96%), who agreed with this sentiment. Most construction employees (76%), who identified job demands as a risk factor for weariness, indicated they were affected by them. The number two spot was taken by lengthy commutes, with 46% of workers considering this a contributing factor. Working during nighttime or in the early morning hours ranked third at 46%, following factors such as receiving less than 7 to 9 h of sleep per night (41%), working 50 or more hours per week (28%), and working shifts lasting 10 h or more (27%). This was followed by obtaining less than seven to nine hours of sleep per night. According to the findings of a report compiled by the National Safety Council on "Fatigue in Safety-Critical Industries—Impacts, Risks & Recommendations" [5]. The challenge this demonstrates is the disparity between workers' responses in subjective assessment of their state of fatigue and actual readiness to engage in construction tasks. Recent evidence by Financial Times [25], revealed that between 400 and 500 workers died due to the 2022 world cup projects. This indicates how dangerous infrastructure delivery can turn out when the fatigue assessment is only left to subjective measures.

### *2.1. Unsafe Behavior in the Construction Sector*

As per the findings of Yu et al. [8], about eighty percent of construction accidents are the result of risky practices carried out by workers. This can include unsafe behavior on the part of individuals, unsafe behavior on the part of teams, and unsafe practices in relation to machines, equipment, and robots [1,2]. Unsafe behavior, often driven by fatigue or the pressure to meet deadlines, can lead to a higher incidence of workplace accidents and fatalities in the construction industry. When workers are fatigued, their decision-making, attention to detail, and ability to follow safety protocols deteriorate. This increases the likelihood of errors, injuries, and accidents. The long-term impact of such behavior is a potentially higher number of workers' compensation claims, lawsuits, and damage to the industry's reputation. The future of the construction industry depends on ensuring that worker safety is prioritized and that steps are taken to reduce accidents, which ultimately requires addressing fatigue and unsafe behavior [13,19]. Fatigued workers are less productive due to reduced focus, slower reaction times, and an increased likelihood of making mistakes. In the construction industry, which often operates under tight deadlines, this can lead to delays, poor-quality work, and increased rework. Over time, continued unsafe behavior and fatigue will result in more project delays and cost overruns, affecting the bottom line of construction firms and the industry as a whole. If this issue is not addressed, it could hinder the industry's growth and development, impacting the global competitiveness of construction companies [15,23]. On the other hand, the introduction of robots and automation can create new job opportunities, especially in fields such as robotics maintenance, programming, and data analysis. These roles tend to require more specialized skills, which can lead to higher-paying jobs. However, workers may need to undergo training or education to transition into these new roles, and not all workers may have access to the resources to upskill. Due to the restrictions associated with traditional methodologies, it has been difficult for project and construction managers to monitor workers' unsafe behaviors; as a result, innovative applications are being launched to increase the efficiency and efficacy of unsafe behavior monitoring. This involves the development of technologies such as motion capture technologies [8], computer vision and deep learning [26], and wearable robots [13]. As stated by Yu et al. [8], some examples of unsafe behavior on construction sites are sleeping on sills and pulling trolleys on stairs. Others include drowsiness, working at heights without proper fall protection, improper use of tools and equipment, disregarding safety guidelines and procedures, etc. However, most incidents can be reduced with increased alignment and obedience to required safety principles and guidelines [27]. Unsafe behavior on construction sites can often be attributed to factors such as fatigue, lack of training, and insufficient safety measures. While safety programs are integral, they must be backed by legislation to ensure effective implementation. Governments play a critical role in enforcing safety standards, particularly through regulations such as OSHA (Occupational Safety and Health Administration) guidelines, which mandate the use of safety equipment and proper training for all workers. Moreover, laws regarding minimum age requirements for workers are essential to ensure that individuals engaged in hazardous tasks are physically and mentally capable of handling the demands of the job. In addition, labor laws that regulate wages, working hours, and safety standards contribute to reducing risks associated with unsafe working conditions. These legal frameworks, in conjunction with technological innovations, such as real-time drowsiness detection systems, are pivotal in enhancing safety and minimizing risks on construction sites [11]. Although governing laws and safety regulations, such as OSHA-1926.28(a) [28], typically place the responsibility on employers to enforce, monitor, and uphold proper safety protocols, as highlighted by Nath et al. [27], employees often neglect to adhere to these regulations on the job site. This disregard can stem from a lack of awareness regarding safety measures, discomfort associated with wearing personal protective equipment (PPE), and the belief that PPE hampers their job performance. Vision-based and sensor-based automated PPE compliance monitoring technologies are the two primary types of this type of monitoring technology now available. In approaches that are based on sensors, a sensor will be installed, and the signals it produces will be analyzed. As an example, one approach could involve affixing RFID tags to individual pieces of personal protective equipment (PPE) and positioning a scanner at the workplace's entrance to read these tags. This would help to ascertain whether employees are complying with the mandatory PPE requirements.

The ever-changing and intricate characteristics of construction projects almost certainly increase workers' dangers on the job. Without systematic and comprehensive safety and health management procedures in place on construction worksites, it is unfeasible to completely eradicate occupational risks, as emphasized by Seo et al. [18]. These measures encompass safety planning, worksite analysis, prevention and control of hazards, as well as safety and health training. Consequently, it becomes necessary to implement actions like monitoring unsafe practices. Monitoring risky situations and behaviors during construction is crucial to identifying them and acting quickly to avert further safety and health problems by removing them from the causal chain [9]. In the practice of construction, site observations and inspections are frequently utilized in order to determine the level of risk that is linked with ongoing projects and the present state of the site. Observational methods are costly and time consuming due to the fact that they require supervisors or safety employees to manually make and record observations. According to Seo et al. [18], one of the limitations of manual observation is that it cannot provide timely access to information that is either incomplete or incorrect. While fatigue affects workers universally, the extent to which it is recognized and addressed can vary geographically due to cultural, regulatory, and environmental factors. In this study, the focus is on the construction industry in developing countries, where the prevalence of fatigue-related accidents remains a significant safety concern. This geographic focus reflects the particular challenges faced by workers in high-risk sectors in this region, where factors such as long working hours, environmental conditions, and inadequate safety systems contribute to fatigue-related incidents.

### *2.2. Fatigue Amongst Construction Workers*

The majority of the jobs that site employees perform in the construction industry are repetitious and physically taxing. According to Ray and Teizer [9], people who perform this kind of job in abnormal postures put unnecessary strain on their body parts, which can lead to weariness and drowsiness, both of which can result in injuries or, in the most extreme situations, permanent disability. In accordance with ref. [22], fatigue is characterized as a shift in task performance resulting from the initial mental and/or physical exertion that is so demanding on the worker's comfort that it hinders their ability to meet the demands placed on their cognitive functioning. As previously mentioned, occupational fatigue has a variety of components, including both physical and mental fatigue.

Physical fatigue is a decrease in one's capacity to perform a physical task due to earlier physical activity [6,24,25]. Fatigue may be especially problematic in the built environment since it reveals discomfort, impaired motor function, and decreased strength capability. After completing physical duties for an extended amount of time, a person becomes physically exhausted, which eventually affects their capacity to conduct physical tasks successfully [23]. Also, performing mental tasks for a prolonged time causes mental tiredness, which reduces a person's cognitive capacity. Conversely, Ibrahim et al. [23] argue that there are limitations to different means of measuring fatigue. Anwer, Li et al. [21] present an account of fatigue measurement using subjective and physiological metrics. However, it is difficult to assess fatigue on the job site due to the building site's dynamic nature and the wearable sensors' intrusive nature. Contemporary approaches to detect and track physical fatigue typically hinge on invasive monitoring of brain activity, such as employing electroencephalography (EEG), or recording sleep habit diaries to evaluate whether the worker possesses the requisite capacity prior to commencing their tasks. When workers are fatigued, their ability to accurately comprehend job-related information that could potentially endanger them becomes more challenging. This heightened difficulty in comprehension elevates the risk of accidents occurring in that specific work environment. According to ref. [22], there have been very few occupational applications directly related to the detection of physical exhaustion in the most physically demanding occupations. Some examples of these occupations are construction, manufacturing, and agriculture. Sleep deprivation is a key factor contributing to fatigue, especially in industries where workers are subject to long hours and intense working conditions. Research has shown that workers operating under such conditions, often for minimum wages, are more likely to experience fatigue due to insufficient rest [9,13]. The financial strain of low wages may further discourage workers from taking necessary breaks or seeking medical attention for fatigue-related issues, creating a vicious cycle [4,7]. Studies have consistently demonstrated that sleep deprivation impacts cognitive function, reaction times, and overall health, making it a critical factor in workplace safety. In the construction sector, where workers are exposed to physical exertion, long shifts, and high-risk environments, the impact of sleep deprivation can be especially severe, contributing to increased accident rates [15].

### 2.3. Drowsiness of Workers in the Construction Industry

Sleep deprivation can be brought on by a wide variety of circumstances, such as the choices one makes in their lifestyle, the effects of stress, bad sleeping habits, and sleep disorders like sleep apnea and restless legs syndrome. Whatever the cause may be, sleep deprivation and a lack of sleep can have a negative impact on performance, which in turn raises the risk of accidents for both the worker and others in the workplace [3]. The major consequence of drowsiness on construction sites is its likelihood of leading to accidents or wrong decision-making, affecting project performance and the risk of chronic health challenges [9].

According to Seo et al. [18], carrying out job safety observations and inspections is one of the most popular methods that is utilized in the construction industry to evaluate ongoing operations. These actions are included in a more comprehensive safety and health monitoring category. During the observation, the human observer serves to detect and eliminate the potential causes of accidents (i.e., unsafe conditions and acts) by watching workers perform a specific task (i.e., safety observation) or visually inspecting the work area and work equipment (i.e., safety inspection) with a checklist [12]. This is accomplished by observing workers as they carry out a particular task (also known as "safety observation") or by visually inspecting the workspace and the equipment that is used for the job (also known as safety inspection) [8].

Questions have been raised about the quality of sleep needed to remove drowsiness; previous studies have postulated that adults need 8 h daily to be fully restorative. Yet, most only receive 7 h, leaving them with a sleep deficit [22]. Sleep deprivation occurs when an individual gets less sleep than is necessary for complete recovery. Serious or ongoing sleep deprivation can harm the person experiencing it and anyone else affected by their behavior. While increased attention is paid to task-specific and known risks, it has been identified as a significant reason why the number of fatalities that occur in the construction industry keeps rising. One example of this is the failure to take into account unknown or conspicuous dangers, such as drowsiness [23]. Effective elimination of safety and well-being risks on sites depends on preventive strategies for easily identified and known risks and not easily perceived or recognized risks such as drowsiness [27,29,30].

Studies performed in the past have also investigated the connection between a lack of situational awareness and tiredness while on the job. Drowsiness in workers can have a significant impact on their situational awareness, which can cause difficulties for workers in recognizing, perceiving, and analyzing hazards, as well as in making projections and establishing control [31]. Therefore, effective identification of indicators of fatigue, such as drowsiness, is imperative. Ibrahim et al. [23] identified the recognition of hazards as the awareness that a situation might be dangerous, with two forms of hazard recognition being predictive and retrospective. This study takes a predictive approach to fatigue recognition, utilizing drowsiness as an indicator. It aims to build a vision-based strategy by employing an upgraded version of the You Only Look Once (YOLOv8) algorithm for real-time drowsiness detection in construction workers. The retrospective technique analyzes data from past safety incidents to prevent future recurrences, whereas the predictive approach forecasts future working scenarios and predicts safety threats.

Previous development in this area has revealed that by leveraging deep learning algorithms, mental alertness due to drowsiness can be effectively measured compared to other less-effective methods, such as physiological metrics. This has been demonstrated by [32], who utilized pressure sensors to measure subject fatigue, and a combination of deep learning algorithms and biomechanical analysis was employed to provide a non-intrusive method of monitoring the physical exhaustion of the complete body while the construction process was taking place. Other methods of determining mental exhaustion entail constructing a model that can objectively identify the level of mental weariness in construction workers based on data from the wearable electroencephalogram sensors that were administered to 15 participants [33]. It is becoming increasingly common to apply computer vision techniques in safety monitoring in addition to sensor-based methods [12,34].

A multi-sensor data monitoring system is required because of the complex nature of the factors contributing to fatigue development. In order for technological approaches to the measurement of physical fatigue to be effective, the system must be able to predict physical fatigue (before it has a negative impact on productivity or safety), measure and monitor physical fatigue in the operational environment, and enable intervention when deficits are discovered or foreseen with the use of appropriate interventions [35]. According to Mariam et al. [11], one of the obvious measures for detecting physical weariness in the workplace is to ask the worker to rate their perceived level of physical fatigue. However, the practice has shown that the majority of workers report incorrectly in order to avoid being replaced on duties. Hence, self-reported fatigue is largely limiting in predicting construction workers' mental alertness and cognition.

Drowsiness is imperative to be measured amongst construction workers for a couple of reasons; due to hazardous weather, use of mobile equipment, several work sites needing travel, and unpredictable and demanding schedules mandating extra work hours, risks on construction sites may be increased [9]. All of these might heighten fatigue and exhaustion. These factors strain human physiology and can cause weariness that impairs performance and increases worker risk [11]. When performance and decision-making are impaired, this not only puts the worker at safety risk but places the tasks being conducted at risk, which can have a monumental effect on the structure's integrity. While previous studies have given valuable contributions to the impact of fatigue on workers' operations, little is still known about identifying drowsiness as an early indicator of mental and physical fatigue.

### 2.4. Computer Vision Techniques and Deep Learning in Construction

The field of computer vision is one that draws from several disciplines; it investigates the ways in which computers can gain significant knowledge from viewing digital images or videos. Deep learning approaches have recently attracted a lot of interest in the field of computer vision due to their capacity to acquire valuable features on their own from enormous volumes of annotated training data [27]. This ability has contributed to the increased popularity of deep learning techniques. The reason for this is that approaches of deep learning have the capability of improving themselves by studying their past errors. It intends to automate tasks that, from an engineering point of view, the human visual system is unable to execute [36,37]. According to Seo et al. [18], computer vision-based safety and health monitoring require the capture of photos or videos of the construction sites where the activity to be monitored is taking place. This is a prerequisite for the monitoring process. For the purpose of obtaining the 2D imaging data (sometimes referred to as 2D videos or sequential images), which is important for computer vision-based monitoring, the photos or videos may serve as low-cost alternatives.

Considered to be one of the most essential components of computer vision is the criteria for recognizing object tracking on building sites [18,22]. Several parameters that need to be considered include frame rate, outdoor application capabilities, reliable reading range, object localization capability, and 3D modelling capacity. Second, in order to verify the identities of the workers and determine whether or not they are licensed to carry out the work, we utilize facial detection and recognition methods. These procedures help us determine whether or not the workers are authorized to carry out the task. CNN enables the automatic recognition of a large variety of objects contained inside an image, which is a vital step for ongoing study. These stages essentially consist of face detection and recognition, object detection and tracking, as well as object detection and tracking [23,38]. Face detection is required before moving on to the next step of face recognition. According to Cha et al. [32], the classification of facial recognition performed by computers requires images that are up close and solely show the face. Computer vision approaches are more versatile and adaptable than sensors because they do not require workers to wear additional equipment [38,39].

This was made much simpler by the development of new algorithms such as Faster R-CNN, which are able to recognize and keep track of resources such as people, plants, and equipment, as well as identify personnel who are behaving in a risky manner [38,40,41]. According to Fang et al. [12], action recognition is the most important aspect of computer vision-based systems. These systems make use of manually constructed features (such as shapes) in images or videos. Image representation systems that are used to recognize human behaviors are able to extract information from images, such as shapes and temporal motions, which are used to do so. In order to correctly identify and evaluate a wide range of actions, the action identification features must contain extensive information. Classifier tools (such as Support Vector Machines [SVM]), temporal state–space models (such as Hidden Markov models [HMM] and conditional random fields [CRF]), and detection-based techniques (such as bag-of-words coding) can all be used to assess such properties [12]. Due to the advantageous trade-off between model correctness and inference speed, the You Only Look Once (YOLO) series algorithm models 30–32 are recommended for use in real-time applications [13,40].

Edge detection on images was one of the key methods that was utilized for excavator pose estimates in the early days [15]. Also, ref. [19] employed silhouette-based tracking algorithms to extract binary images from videos captured by stationary security cameras to estimate trolley movement along the crane jib. These algorithms relied on the films captured by the cameras. Refs. [20,41] employed a non-rigid equipment posture estimation based on construction pictures and videos to establish a model for detecting equipment parts using support vector machines (SVMs) and histogram-oriented gradient (HOG). This model was developed for detecting equipment parts using support vector machines (SVMs) and histogram-oriented gradient (HOG). By incorporating the k-means methodology, background subtraction algorithm, and the part-based posture estimation method, Soltani et al. [31] improved it and produced more accurate findings. In another study conducted by Soltani et al. [31,41], the time and coordinate systems of multiple cameras and the real-time location system (RTLS) were synchronized. This allowed the RTLS to combine the data from those sources, which allowed the researchers to extract two-dimensional equipment poses and estimate the three-dimensional poses of excavators.

Deep learning strategies have been increasingly popular for use in a variety of occupations within the construction sector. These jobs include the monitoring of construction sites and the health inspection of civil infrastructures. These jobs were created to address challenges that were previously resolved using normal computer vision methods. Convolutional neural networks, also known as CNNs, are a type of neural network that is frequently utilized in deep learning approaches [34,42]. According to Fang et al. [12], approaches to deep learning that are based on CNN are effective for computer vision and pattern recognition. Concrete crack detection using CNN-based approaches has been used for civil infrastructure health inspection; the results showed that CNN is superior to other computer vision methods [19,30].

An algorithm for deep learning was developed with the help of a faster Region-Based Convolutional Neural Network (Faster-RCNN), which was used to identify four distinct types of sewer pipe failures. This highlights the benefits of using deep learning algorithms for analyzing images and videos in even more detail. LeNet-5 is a CNN model that was constructed by LeCun and his colleagues that deciphers handwritten digits. The dataset that was used to build the model was produced by the mixed National Institute of Standards and Technology. CNN models are able to efficiently and automatically identify attributes from static images [12,22]. This capability is achieved by stacking several convolutional and pooling layers.

Fang et al. (2018) [12] created two algorithms based on Faster-R-CNN and CNN models that are used to (1) recognize the presence of employees and (2) decide the harness that is fastened to them in an effort to solve the problem of workers working at heights forgetting to wear their harnesses. This was conducted in order to address the problem of workers working at heights and forgetting to wear their harnesses. Similar to this, Fang et al. [12] developed a deep learning method to automate the process of inspecting the use of personal protective equipment (PPE) by steeplejacks in aerial works. Nath et al. [27] constructed three deep learning (DL) models built on You Only Look Once (YOLO) architecture to verify the PPE compliance of employees and [30] completed an automated examination of large-scale bridge constructions just using photos. The selection of YOLOv8 for drowsiness detection was driven by several key advantages over alternative object detection models. First, YOLOv8's single-stage detection architecture enables real-time processing with an inference speed of 7.5ms, crucial for timely drowsiness alerts in construction environments. Second, YOLOv8's anchor-free detection approach improves accuracy for detecting subtle facial features and head movements indicative of drowsiness, while reducing computational overhead compared to two-stage detectors like R-CNN. Additionally, YOLOv8's enhanced backbone with CSPDarknet offers superior feature extraction capabilities particularly beneficial for distinguishing between alert and drowsy states under varying lighting conditions common on construction sites. The model's efficient architecture also allows deployment on standard hardware, making it practically viable for on-site implementation. These characteristics make YOLOv8 particularly suited for our application compared to alternatives such as R-CNN or earlier YOLO versions (which lack YOLOv8's architectural improvements for fine-grained feature detection).

Other applications of deep learning include the application of two CNN models with an extremely high level of accuracy to recognize safety harnesses worn by workers to prevent falling from heights [12]), the recognition of unsafe behaviors [42], the estimation of the poses and activities of construction employees [19,43], and the recognition and tracking of equipment [26]. On the other hand, CNN has served as the foundation for virtually all of the effective algorithms that have been created for the purpose of image categorization, object detection, and visual tracking. Because of this, their use in the construction industry for use cases involving visual detection has been further promoted. The findings of these studies offer valuable insights into improving building processes through the application of deep learning and computer vision techniques. Even though the relevant research is still in its early stages, the current state of the art implies that deep learning and computer vision techniques offer substantial potential for monitoring, even for fatigue-associated instances such as drowsiness. This is despite the fact that the relevant research is still in its early stages.

## 3. Methodology

In this study, we elaborate on developing and implementing a vision-based model that is adeptly trained on a substantial corpus of visual data, encompassing both videos and still images. This methodology has been widely used in similar studies that were conducted in the construction industry [30,35]. The dataset for this study was collected using a convenience sampling method due to logistical and resource constraints. Thirteen operatives were selected from construction sites actively involved in tasks relevant to the study's objectives. The selection process prioritized accessibility and willingness to participate, ensuring that participants were available and capable of providing the required data within the study's timeframe. To engineer a rich and varied dataset, video footage acquired from the above sources was systematically processed to generate additional image data, thus enhancing the density of our dataset. These activities were primarily aimed at simulating indicators of drowsiness, thereby promoting a model attuned to early recognition of potential safety hazards.

The drowsiness detection model was trained to identify specific visual indicators that were simulated and recorded in our dataset. These indicators included yawning patterns, slower blinking rates, lethargic head movements, and visible signs of fatigue in the eyes. The selected operatives included a mix of roles commonly found on construction sites, such as supervisors, skilled laborers, and machine operators. While the sample was not randomly selected, efforts were made to include individuals with varying levels of experience to reflect the diversity of skill levels in the workforce. During the data collection phase, construction operatives were specifically instructed to simulate these drowsiness behaviors, ensuring the model was trained on these key visual cues that are commonly associated with fatigue in construction workers. These indicators were chosen based on their observable nature and their established relationship with drowsiness states, enabling the model to effectively distinguish between alert and drowsy conditions in real-time monitoring scenarios with each of these activities is a well-documented precursor of drowsiness, a state of potential risk in the challenging working conditions of the construction industry [34]. Data collection used dual-purpose cameras to simultaneously capture still images and video recordings. To ensure the accuracy and relevance of our drowsiness simulations, we conducted preliminary interviews with construction safety experts and site supervisors to identify the typical signs of drowsiness observed among workers on-site. This consultation process was instrumental in refining our selection of behaviors, allowing us to align our simulations more closely with real-world indicators of fatigue prevalent in construction environments. Data were collected over a three-week period, with each participant observed and monitored during their regular work shifts. All participants provided informed consent before data collection commenced. Confidentiality was maintained by anonymizing the data, ensuring that individual identities and specific worksite details could not be traced. This process involved removing any personal identifiers such as names, job titles, and site-specific details from the dataset. Each participant was assigned a unique code to facilitate data analysis while maintaining anonymity. For example, instead of using a participant's real name, identifiers like "Participant 1" were applied. Data were securely stored in encrypted digital formats and accessible only to the research team. Digital data were stored on password-protected devices, with backup copies maintained on a secure, encrypted cloud storage platform.

Following the simulation of drowsiness behaviors, we implemented a validation step wherein we compared video recordings of these simulated actions with real-life video footage and other documented instances of drowsiness in workplace settings. A panel of safety experts was enlisted to review these recordings, confirming that the simulated behaviors accurately represented actual fatigue-induced actions commonly observed on construction sites. We acknowledge that individual responses to fatigue can vary significantly based on factors such as age, physical health, and specific work conditions. To address this variability, we ensured that our data collection included a diverse sample of operatives, varying in age, experience, and background. This diversity was crucial in capturing a broader range of fatigue responses, thus enhancing the robustness of our findings. Furthermore, we incorporated advanced machine learning techniques to manage individual variations in fatigue expression. Specifically, the YOLOv8 model was trained using a weighted approach, which prioritized the detection of common drowsiness markers while maintaining flexibility to identify subtler differences in fatigue levels among individuals. This approach allowed for a more nuanced understanding of drowsiness detection within the context of construction worker safety. The data comprised 1.5 h of video footage recorded at 1080 × 1920 resolution with 28 frames per second. Figure 1 presents the flowchart of model training, validation, and testing procedures. This is conducted in order to accomplish the goals of the study.

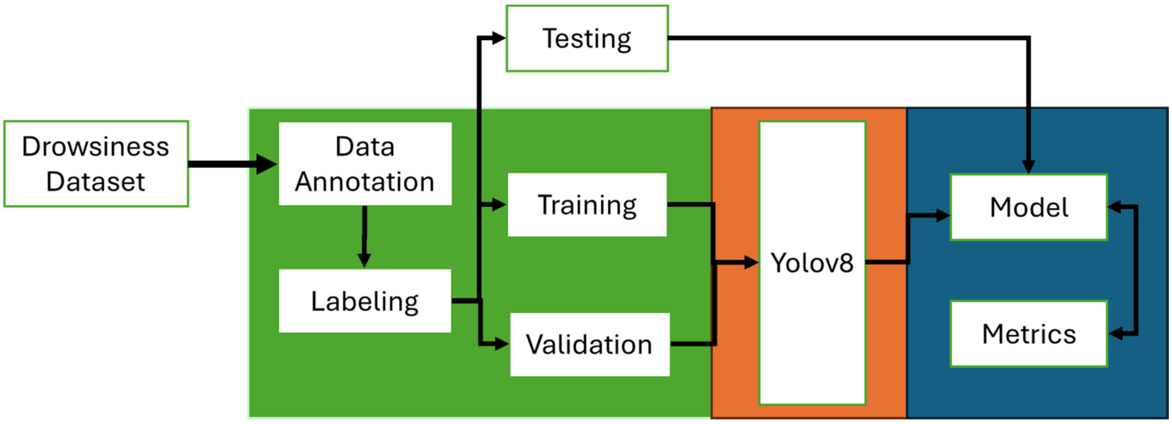



**Figure 1.** Flowchart of the model training, validation and testing on the dataset.

### *3.1. Dataset Extraction*

The process of dataset extraction involved the meticulous extraction of still images from the recorded videos. These images were subsequently employed as inputs to the Yolov8 model. We set the interval between the extracted frames at 36 s to maintain consistency and ensure an evenly spaced data distribution. This interval was chosen after a series of experimental observations, aiming to maximize the quality and representativeness of the data whilst minimizing redundancy, as shown in refs. [35,36]. Utilizing the robust OpenCV algorithm, these frames were converted into still images, yielding approximately 149 images. In addition to this, we also incorporated self-captured images, thereby increasing the depth and variety of our dataset, resulting in a total of 605 distinct images.

Given the variance in image resolutions within our drowsiness image dataset, we undertook a rescaling operation to standardize the resolution of all images to 416 × 416 pixels. The 416 × 416 image resolution was chosen for its optimal balance between computational efficiency and feature extraction, ensuring high accuracy in detecting drowsiness-related visual cues while maintaining real-time processing capability.

In the scheme, 605 images were classified into four distinct categories: 'Awake with PPE', 'Awake without PPE', 'Drowsy with PPE', and 'Drowsy without PPE'. Table 1 shows the distribution of the images. To ensure data validity, the image acquisition process followed a structured protocol where each operative was recorded under consistent lighting conditions and at similar distances from the camera, using a 16MP camera with 1080 × 1920 resolution.

Inter-rater reliability was established through independent verification of the drowsiness classifications by three qualified safety professionals with over five years of construction site experience. The study's methodology, dataset preparation, annotation process, and model configuration have been detailed to ensure transparency and reproducibility.

The use of well-documented libraries like OpenCV, along with deterministic settings, minimizes variability and enhances reliability. However, reproducibility may be influenced by differences in environmental factors such as lighting and worker attire. Adapting the dataset to new contexts would require additional fine tuning and validation to maintain reliability and validity.

**Table 1.** Distribution of the dataset.

| Class | Numbers Included |
|---|---|
| Awake with PPE | 98 |
| Awake without PPE | 121 |
| Drowsy with PPE | 159 |
| Drowsy without PPE | 227 |

In the course of our experiment, we utilized a random data partitioning approach, in which we allocated seventy percent of the dataset to training, fifteen percent to validation, and fifteen percent to testing. The purpose of this split is to evaluate the model's performance in a way that is both reliable and preventative of overfitting.

### *3.2. Computation Specifications*

The construction operatives' drowsiness detection framework was built, leveraging hardware and software resources. We utilized Keras, and OpenCV libraries, owing to their capabilities in implementing and optimizing deep learning architectures [44]. Python 3.9, a dynamic and high-level programming language that is well-known for its readability and convenience of use in scientific computing, was used in conjunction with these libraries. Our model architectures, namely the YOLOv8 by Ultralytics, were trained without using high-performance Graphics Processing Units (GPUs) [45]. Rather, we relied on an 11th Gen Intel® Core™ i7-11800H @ 2.30 GHz 2.30 GHz computer, equipped with 16 GB of RAM. The Jupyter Notebook was the development environment of choice during model training and evaluation. All the data for our study were collected using a 16MP camera, further attesting to our commitment to maintaining high-quality data.

### *3.3. Evaluation Metrics*

In assessing the performance of our machine learning model, we have elected to employ a set of computational metrics designed to offer nuanced insights into the efficacy of the model. These metrics are particularly relevant in object detection and classification and are grounded in the calculation formulas derived from the datasets at our disposal. The maximum number of batches, denoted as 'Max batches', is calculated as the product of the number of classes and a factor of 2000. Moreover, the steps are determined by a range between 80% and 90% of the maximum batches. The filter parameter is determined by multiplying the value obtained from adding the number of classes to 5 by a factor of 3.

$$\text{Max batches} = \text{number of classes} \times 2000 \tag{1}$$

$$\text{Steps} = (\text{Max batches} \times 0.8, \text{Max batches} \times 0.9) \tag{2}$$

$$\text{Filters} = (\text{number of classes} + 5) \times 3$$

These calculations inform the analysis of the model's performance in classifying objects. The model's effectiveness in correctly predicting a positive class is denoted as a True Positive (TP). In contrast, its ability to correctly predict a negative class is signified as a True Negative (TN). Conversely, an incorrect prediction of a positive class is termed a False Positive (FP), and an incorrect prediction of a negative class is regarded as a False Negative

(FN). These are fundamental metrics retrieved from the output of the object detection algorithm [37].

Precision, the ratio of True Positives to the sum of True Positives and False Positives, measures the model's capacity to correctly predict positive instances Aich et al. [38]. Conversely, recall is computed as the ratio of True Positives to the sum of True Positives and False Negatives, offering a measure of the model's aptitude in accurately identifying all positive instances. Mathematically, these are represented according to Equations (1) and (2) [39].

$$P = \frac{TP}{TP + FP} \tag{3}$$

$$R = \frac{TP}{TP + FN} \tag{4}$$

A further measure of model performance, the average precision (AP), is a function of the relationship between precision and recall rates within a given data sample. This measure incorporates the intersection over union and assesses the model's ability to identify an object correctly. The average precision (AP) is calculated as the mean of recall rates with precision ranging from 0 to 1, as shown in Equation (3).

$$AP = \mathrm{N}\sum \mathrm{k} = 1P(k)\Delta r(k) \tag{5}$$

In this context, "N" denotes the total number of images included in the dataset that was utilized for the calculation. $P(k)$ signifies the precision rate for image k, and $\Delta r(k)$ denotes the difference in recall rate from image (k − 1) to image k. The AP is then calculated for each class and averaged to yield the mean average precision (mAP) for all classes combined.

Accuracy, which describes the frequency with which the model correctly classifies a data point, is computed as the ratio of the sum of True Positives and True Negatives to the total count of True Positives, True Negatives, False Positives, and False Negatives [38]. Symbolically, this is expressed as follows in Equation (4):

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

However, it is important to note that accuracy has limited utility as a performance metric in object detection due to the negligible relevance of True Negatives. Instead, we focus our evaluation on recall and precision measures and construct a precision–recall curve to visualize the trade-off between these two metrics [40]. A model exhibiting high recall and low precision suggests a high volume of detections, most of which are incorrectly labelled. Conversely, a model characterized by high precision and low recall indicates a lower volume of detections, most of which are correctly labelled.

### *3.4. YOLOV8 Model*

The YOLOv8 model, a renowned member of the YOLO model lineage, has earned its reputation through its profound capabilities for joint detection and segmentation [27,41]. It shares its architectural construct with its predecessor, the YOLOv7 model, encompassing distinct components such as a backbone, head, and neck [42]. However, the YOLOv8 model distinguishes itself with its novel architecture, fortified convolutional layers that comprise its backbone, and a significantly enhanced detection head as shown in Figure 2. These advancements render it an optimal choice for real-time object detection tasks. Complementing this, the YOLOv8 model also extends support for state-of-the-art computer vision algorithms, particularly instance segmentation. This attribute enables the model to detect multiple objects within a single image or video proficiently. The model operationalizes the Darknet-53 backbone network, a notable improvement over the network used in YOLOv7 in terms of speed and precision [43]. A distinct feature of YOLOv8 is its adoption of an anchor-free detection head for predicting bounding boxes, further enriching its detection capabilities [42,46].

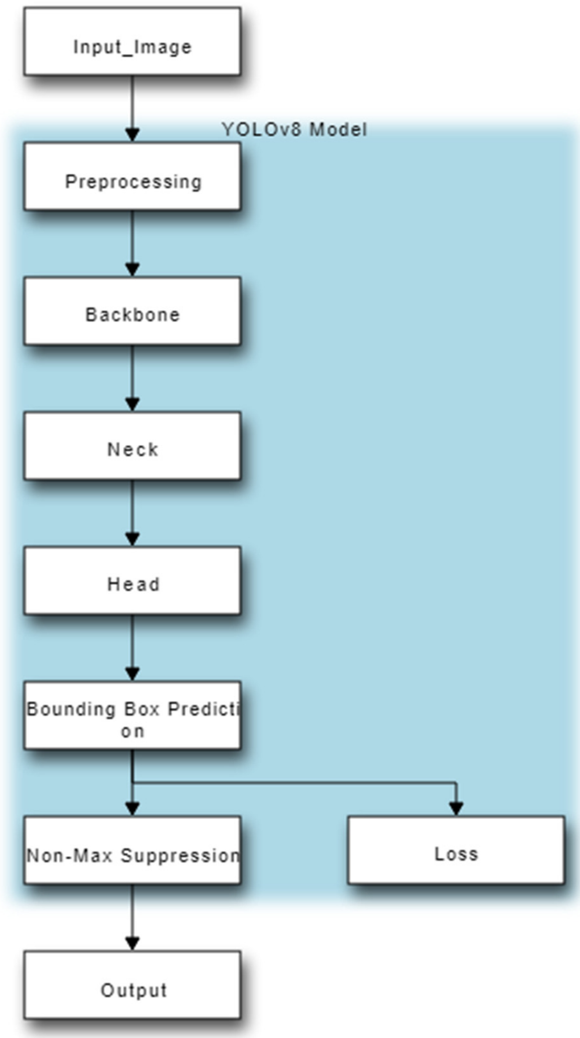



**Figure 2.** Typical architecture of YOLOv8 algorithm model.

### *3.5. Dataset Labeling*

Two file extensions—.jpeg for images and.txt for text—are used by the YOLO family to identify objects. A text file is utilized to keep track of the labels, object types, and coordinates of their bounding boxes; in contrast, the picture file merely contains images. The image object count is proportional to the row count in the text file. Manually annotating drowsiness on the collected images is labour intensive and time consuming. As such, we harnessed the capabilities of LabelImg, an interactive graphical image annotation tool [40]. The labelling tool was instrumental in easing the dataset creation process, allowing for the seamless importation of a series of images. This was followed by the manual delineation of bounding boxes around objects of interest within each image. The identified objects were then classified according to a predefined list of classes specifically curated for this research: 'Drowsiness with PPE', 'Drowsiness without PPE', 'Awake with PPE', and 'Awake without PPE'. The repetitive process of drawing bounding boxes and assigning class labels was undertaken for all objects within each dataset image. Upon completion, the LabelImg tool facilitated the exportation of annotations as text files in the YOLO format. These files contained critical information, including the coordinates of each bounding box and the corresponding label attributed to the enclosed object. Such annotated data serve as an invaluable ground truth for training the detection algorithms, empowering them to identify and classify details within novel, unseen images accurately.

## 4. Results

The principal aim of the experiment conducted herein was the detection of construction operatives' drowsiness with high precision and, in real-time, leveraging the YOLO-v8 model to train our datasets. This section elucidates the training process, the variety of hyperparameters employed, the optimization methods adopted, and the results of the model's performance. The implementation utilized the YOLOv8s architecture (sourced from the base model 'yolov8s.pt') with modifications to accommodate our four-class detection problem. The model architecture maintained its original backbone structure while adapting the classification head to our specific use case. The selection of optimal hyperparameters was conducted through a systematic grid search approach, evaluating multiple parameter combinations using 5-fold cross-validation on the training dataset.

The hyperparameter optimization process explored learning rates between 0.001 and 0.05, batch sizes ranging from 8 to 32, and image sizes from 416 to 640 pixels. Momentum values were tested between 0.937 and 0.97, while weight decay was evaluated from 0.0005 to 0.005. This comprehensive search across 108 different combinations revealed that a learning rate of 0.01, batch size of 16, and image size of 416 $\times$ 416 pixels yielded the highest mean average precision (mAP@50) while maintaining computational efficiency. The momentum coefficient of 0.937 and weight decay of 0.0005 were selected based on their superior performance in preventing overfitting while ensuring stable convergence.

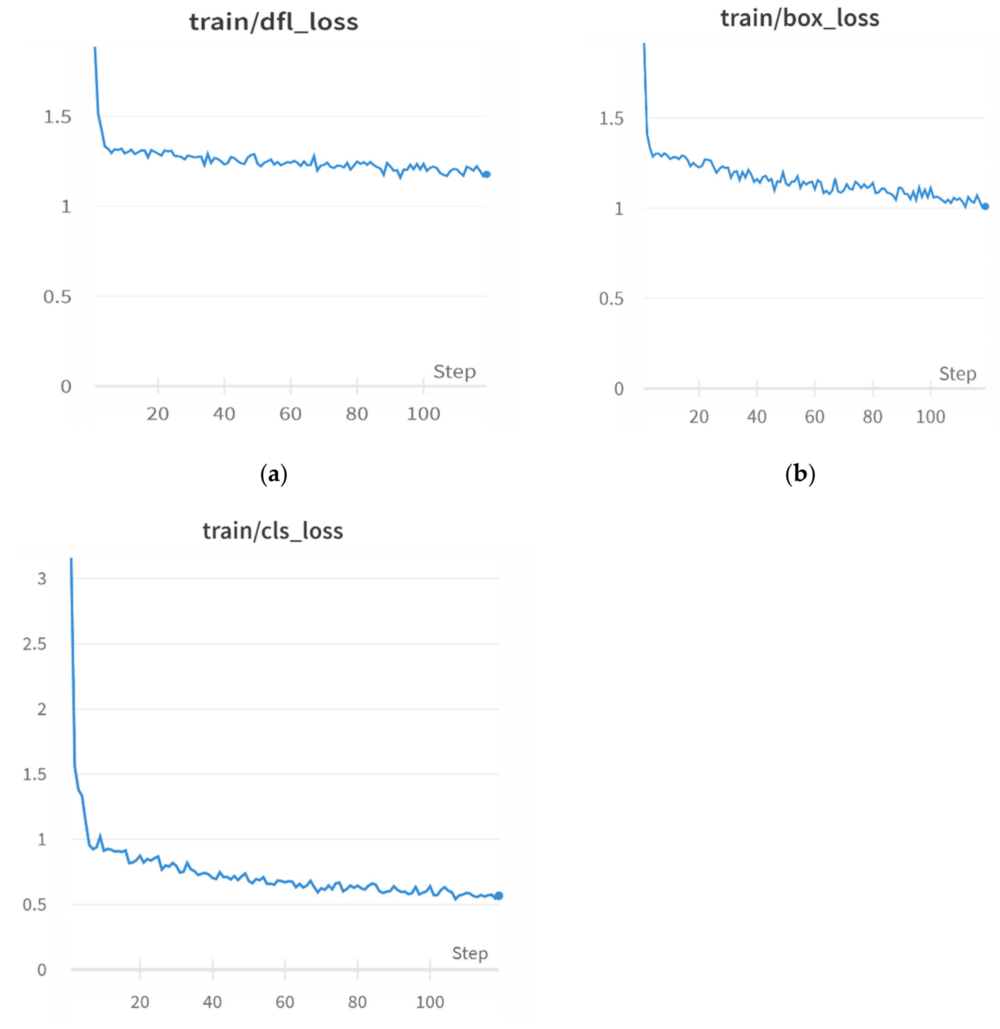
The final training protocol implemented these optimized parameters over 600 epochs with an early stopping patience of 50 epochs to prevent overfitting while ensuring adequate model convergence. To enhance model robustness and generalization, mosaic augmentation was employed with overlap mask enabled and a mask ratio of 4:1. The optimization strategy centered on Stochastic Gradient Descent (SGD), with the learning rate maintained at 0.01 throughout training. A warm-up period of 3.0 epochs was implemented with a momentum of 0.8 and a bias learning rate of 0.1 to ensure stable initialization as detailed in Table 2.

**Table 2.** Optimized model configuration and training parameters.

| Parameter Category | Parameter | Value | Search Range/Justification |
|---|---|---|---|
| Optimization | Learning Rate (lr0) | 0.01 | Tested: [0.001, 0.01, 0.05]; best convergence rate |
| | Final Learning Rate (lrf) | 0.01 | Matched to initial learning rate |
| | Momentum | 0.937 | Tested: [0.937, 0.95, 0.97]; YOLOv8 recommended |
| | Weight Decay | 0.0005 | Tested: [0.0005, 0.001, 0.005]; best regularization |
| Warm-up Configuration | Warm-up Bias LR | 0.1 | Default value; reliable start |
| | Warm-up Epochs | 3.0 | Default value; stable initialization |
| | Warm-up Momentum | 0.8 | Default value; consistent performance |

Computational efficiency was enhanced through the implementation of automatic mixed precision (AMP), while resource utilization was carefully managed through controlled worker thread allocation to prevent memory saturation. The 'deterministic' parameter was set to true, ensuring reproducible behavior from PyTorch, cuDNN, and CUDA, with a fixed random seed of 0. While the selected configuration demonstrated strong performance, it is important to acknowledge that these parameters may not represent the global optimum. Future work could explore broader parameter ranges, finer granularity in parameter values, or alternative optimization strategies such as Bayesian optimization.

One of the integral performance metrics deployed was the box loss metric. This metric assesses the proximity of the model's predicted bounding boxes to the actual objects within the dataset. A value close to 1 for this metric indicates a consistent improvement in the model's ability to generalize and accurately delineate the identified objects in the dataset as shown in Figure 3.




(**a**) (**b**) (**c**)

**Figure 3.** Outcomes of the training loss: (**a**) dfl loss, (**b**) box loss and (**c**) class loss. The X axis describes the steps and Y axis describes the loss for each training metric.

The YOLO-v8 model underwent training with the drowsiness dataset for 600 epochs, with a batch size 16. The early stopping mechanism activated after 119 epochs due to a lack of observed improvement in the previous 50 epochs in adherence with the specified patient setting. The overall training phase spanned roughly 0.3 h on a Jupyter Notebook, with the best results manifesting at epoch 69.

## 4.1. *Performance of the Yolov8*

When subjected to cropped images of operatives, the accuracy of the YOLOv8 model in categorizing the images into classes—Awake with PPE, awake without PPE, Drowsy with PPE, and Drowsy without PPE—was recorded as 64%, 43%, 83%, and 95%, respectively. Interestingly, the model displayed greater proficiency in detecting classes characterized by drowsiness with or without PPE than classes depicting Awake with or without PPE. Notably, the class 'Awake without PPE' was misclassified as 'Drowsy without PPE' 56%

of the time, indicating a propensity for false positive detection in the model as detailed in Figure 4. This observation may be attributable to the imbalance in the dataset composition.

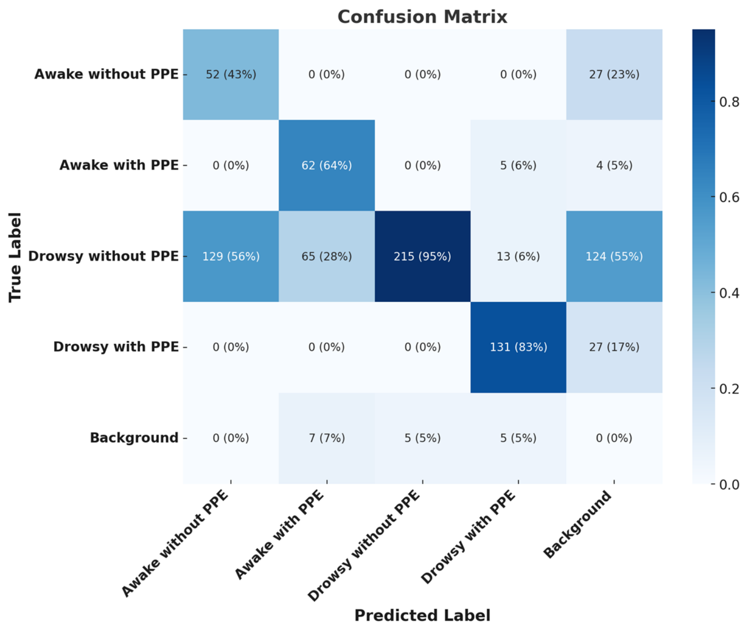
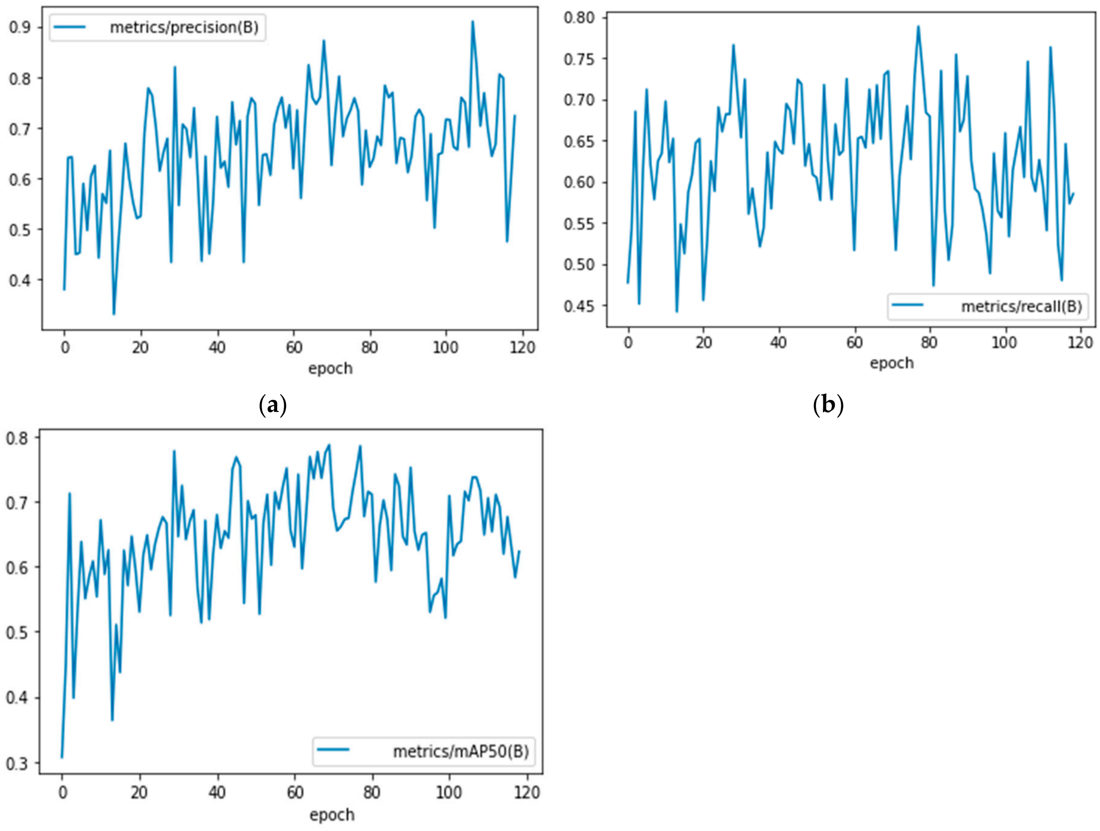



**Figure 4.** Confusion matrix for Yolov8 accuracy for the dataset.

The model's performance, evaluated based on precision, recall, and mAP at the 50 IoU threshold, with the drowsiness dataset, is illustrated in Figure 5.




(**a**) (**b**) (**c**)

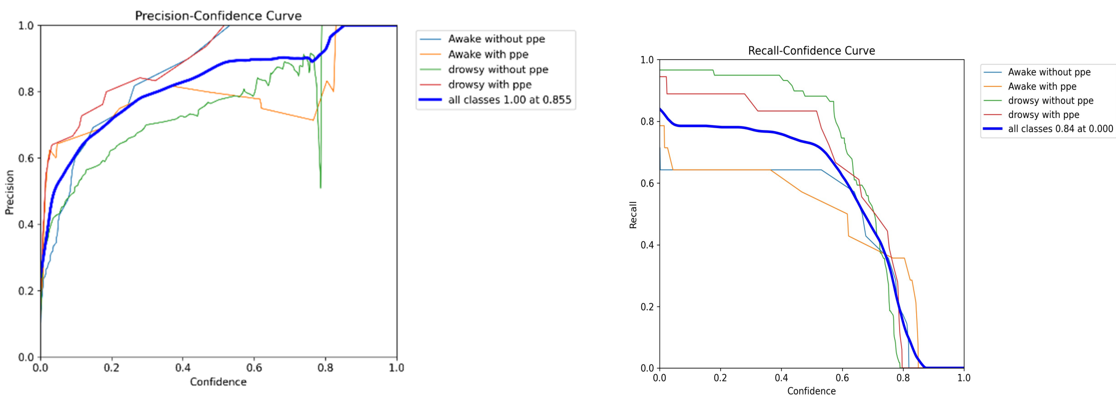
**Figure 5.** Performance of YOLO-v8 on the drowsiness dataset based on (**a**) precision, (**b**) recall and (**c**) mAP at the 50 IoU threshold.

From the evaluation metrics obtained on the validation drowsiness dataset, as summarized in Table 3, we discern that the overall precision approximated 87%, with a recall of 73% and a mAP at the 50 IoU threshold of 78%. When delving into the class-wise performance, we note that the model detected 'Awake without PPE' with 96% precision, 64% recall, and 67% mAP at the 50 IoU threshold. The 'Awake with PPE' category had a precision of 80%, recall of 57%, and 68% mAP at the 50 IoU threshold. For the 'Drowsy without PPE' class, the precision was 77%, a recall was 88%, and the mAP at the 50 IoU threshold was 84%. The 'Drowsy with PPE' class exhibited a precision of 96%, recall of 83%, and 92% mAP at the 50 IoU threshold. The compelling contrast between the model's proficiency in discerning drowsiness from being awake reiterates the significance of a balanced dataset in improving model performance.

**Table 3.** Validation outcomes on the drowsiness dataset.

| | Metrics | | | |
|---|---|---|---|---|
| **Class** | **Precision** | **Recall** | **F1** | **mAP@50** |
| All | 0.87 | 0.73 | 0.79 | 0.78 |
| Awake without PPE | 0.96 | 0.64 | 0.77 | 0.67 |
| Awake with PPE | 0.80 | 0.57 | 0.67 | 0.68 |
| Drowsy without PPE | 0.77 | 0.88 | 0.82 | 0.84 |
| Drowsy with PPE | 0.96 | 0.83 | 0.89 | 0.92 |

The model's performance correlation with respect to the precision of the dataset and corresponding confidence level is encapsulated in the precision–confidence Curve (PCC curve) depicted in Figure 6a. This curve exhibits a gradual ascent until it peaks at 1.00 accuracy and 0.855 confidence, maintaining this level after that. The recall–confidence curve (RCC) in Figure 6b elucidates the inverse relationship between the recall of the dataset and confidence. The distinct behaviors observed in both these curves further underscore the complexity and intricacies involved in achieving high precision and recall in object detection tasks. Both metrics have been shown to have a relationship that is inversely proportional to the another.




(**a**) (**b**)

**Figure 6.** (**a**) YOLOv8 precision–confidence curve (RCC), (**b**) YOLOv8 recall–confidence curve (RCC).

Figures 7 and 8 visually juxtapose actual labels from the validation dataset with the predicted labels post-training, further illuminating the efficacy of our model. According to the outcomes of the tests and validations, drowsiness detection was carried out well. However, the awake with PPE category had a noticeable result, which is to be expected given the small sample size of the dataset.


**Figure 7.** Drowsiness datasets actual labels.


**Figure 8.** Drowsiness datasets predicted labels.

*4.2. Discussion*

This study's objective was to discern the viability of the YOLOv8 model in detecting drowsiness among construction operatives with significant accuracy and in real time. Our findings reveal promising outcomes, with the YOLOv8 model displaying remarkable precision in the images and an inference speed reaching 0.4 ms for preprocessing, 7.5 ms for inference, 0.0 ms for loss calculation, and 1.7 ms for postprocessing per image in the drowsiness dataset. Furthermore, the model achieved a notable mean average precision (mAP) of 92% in the drowsiness detection task.

Despite these encouraging results, examining the model's performance exposes a shortcoming in handling imbalanced classes. The underrepresented class, 'Awake with PPE', was detected with high precision, but comparatively, it demonstrated a lower recall and mAP in the testing dataset. This disparity in performance across various classes reinforces the need for a balanced dataset and well-chosen hyperparameters to ensure optimal performance in deep learning-based object detection tasks [34].

The performance of the YOLOv8 model was also compared with similar works in the field, as indicated in Table 4. Our mAP of YOLOv8 detecting drowsiness was 78%, which compares favorably with other studies employing different methodologies for similar or related object detection tasks. For instance, Wang et al. [43] employed the R-CNN model to detect safety hazards and reported an mAP of 92.55%. On the other hand, Lee et al. [35] utilized the YOLOACT model for detecting construction worker presence, hardhat usage, and safety vest usage, with reported mAPs of 64.3%, 77.2%, and 62.3%, respectively. Our results substantiate the potential of YOLOv8 for real-time detection tasks, with the added advantage of computational efficiency.

**Table 4.** A general comparison between the YOLOv8 model and other related work.

| Reference | Domain | Methodology | mAP (%) |
|---|---|---|---|
| Proposed | Drowsiness | Yolo-v8 | 78 |
| Lee et al. (2023) [35] | Worker | YOLOACT | 64.3 |
| Lee et al. (2023) [35] | Hardhat | YOLOACT | 77.2 |
| Lee et al. (2023) [35] | Safety vest | YOLOACT | 62.3 |

Comparing our YOLOv8 implementation (78% mAP) with YOLOACT's varying performance across different tasks (64.3% for worker detection, 77.2% for hardhat detection, and 62.3% for safety vest detection) demonstrates our model's superior capability in detecting complex human states. The improved performance can be attributed to YOLOv8's enhanced feature extraction capabilities, which are particularly beneficial for detecting subtle facial and postural changes indicative of drowsiness. However, it should be noted the contrast in our aim as the detection tasks and datasets differ significantly as seen in similar studies [47].

## 5. Implications of the Study

### *5.1. Drowsiness as an Indicator of Fatigue*

Given the propensity of most fatigue measurements to be subjective, an algorithm to identify drowsiness helps to easily measure workers' readiness and cognition to be involved in construction tasks. This also helps workers to be aware of the effects of sleep deprivation and what they can do on a personal level to sleep better and be more physically ready for laborious construction tasks. This proactive approach is equally applicable in other sectors, such as transportation, where it could lead to a substantial reduction in accidents, promoting safer travel conditions for all road users. Furthermore, integrating such systems with existing vehicle technology could enhance overall traffic management and safety protocols. The healthcare industry, especially in high-stakes environments like emergency rooms and critical care units, demands high levels of alertness from professionals. By employing drowsiness detection technologies, hospitals can monitor staff fatigue levels, facilitating timely breaks and ensuring optimal staff performance. This not only protects patient safety but also contributes to the mental well-being of healthcare providers, fostering a healthier work environment. In manufacturing environments, where workers often operate heavy machinery or engage in repetitive tasks, drowsiness can lead to accidents that not only endanger workers but also disrupt production lines. Implementing a drowsiness detection system in these settings can enhance safety protocols and reduce the frequency of workplace injuries. Moreover, fostering a culture of safety through regular monitoring can lead to increased employee morale and retention, positively impacting overall productivity. The mining industry operates under inherently dangerous conditions where fatigue can significantly impair worker judgment and reaction times. Utilizing drowsiness detection systems in this sector could mitigate risks associated with fatigue-related accidents, ensuring that workers remain alert during critical tasks. Additionally, these systems can be integrated with existing monitoring technologies to provide comprehensive safety solutions tailored to the unique challenges of mining operations. The implications of drowsiness detection technology extend far beyond the construction industry, with potential applications across various sectors where worker fatigue is a critical concern. By adapting and implementing such systems in diverse environments, industries can enhance safety protocols, improve productivity, and promote overall worker well-being.

### 5.2. Enhanced Construction Health, Safety and Well-Being

With an improved method of identifying drowsiness, risks associated with fatigue are reduced as against using subjective measures which workers can easily manipulate. This helps avoid risk to the worker, the client and the contractor. Although the created computer vision approach cannot identify drowsy workers with 100% accuracy, it offers project managers various advantages in their daily work. To begin with, safety behavior can be observed without disrupting those who are at work. Secondly, a variety of operating areas can be simultaneously observed, which can cut down on the expense and duration of inspections. It provides a way to lessen hazards on site as a system in place to monitor persons with physical fatigue from being a danger to themselves and their teammates. To implement the proposed drowsiness detection methodology in real-world construction environments, we have devised a phased approach. The initial phase involves the initiation of a pilot program at selected construction sites. This will necessitate collaboration with site managers to install the requisite hardware, including strategically positioned cameras designed to capture the facial and eye movements of workers engaged in various tasks. The primary focus during this phase will be on high-risk areas where fatigue-related accidents are most likely to occur. Our drowsiness detection system will be integrated into the existing safety protocols of the construction sites. For instance, upon detecting signs of drowsiness, the system is programmed to trigger real-time alerts for both supervisors and workers, prompting immediate intervention to mitigate risks. This integration process will include comprehensive training for site personnel on the functionalities of the system and the establishment of clear protocols for responding to alerts effectively. Following the pilot implementation, we will establish a feedback loop that facilitates continuous monitoring of the system's effectiveness. Data collected during this phase will undergo thorough analysis to refine algorithms and enhance detection accuracy over time. We recognize that construction sites present diverse challenges, including varying lighting conditions, weather influences, and worker attire (such as personal protective equipment, PPE), all of which may affect the accuracy of facial and eye feature detection. Therefore, developing adaptive algorithms capable of performing reliably under these differing environmental conditions will be critical. Furthermore, we are aware that the use of video surveillance may raise privacy concerns among workers. It is essential to address these concerns proactively by ensuring compliance with relevant legal regulations and establishing clear guidelines regarding data use and worker consent.

The deployment of cameras and other necessary hardware may encounter logistical challenges, such as installation feasibility and ongoing maintenance. To mitigate these issues, we will collaborate closely with construction teams to identify optimal camera placements that maximize coverage while minimizing disruption to ongoing work activities. Although our current focus is on the construction sector, we believe that the methodology can be adapted for application in other high-risk industries, including manufacturing, transportation, and healthcare. This adaptability could contribute significantly to mitigating fatigue-related accidents across a broader range of work environments. Future iterations of the drowsiness detection system may incorporate wearable devices capable of monitoring physiological signals, such as heart rate and sleep patterns, thereby providing a more comprehensive assessment of worker fatigue. Additionally, we plan to develop a real-time analytics dashboard that aggregates data from the drowsiness detection system. This dashboard would serve as a valuable tool for site managers, offering insights into worker fatigue trends over time and facilitating proactive management of worker safety and health.

## 6. Conclusions and Limitation of Study

The findings of this research are particularly significant in two respects.

- Firstly, this pioneering work may pave the way towards safer and smarter construction sites by enabling real-time identification and intervention for drowsiness detection.
- Secondly, because this study was one of the initial deployments of the most recent YOLOv8 model in the construction sector, it provides vital insights into the field of computer vision research, regarding the resilience and usability of this advanced approach.

Implementing effective safety measures, such as real-time drowsiness detection, can significantly reduce the economic costs associated with workplace accidents. Accidents often lead to project delays, increased insurance premiums, and potential legal liabilities, all of which can strain financial resources. By minimizing the likelihood of fatigue-related incidents, construction firms can enhance productivity and operational efficiency, leading to cost savings.

The primary beneficiaries of this study are construction workers, as it will highlight the risks associated with fatigue caused by sleep deprivation and low wages. Addressing these issues could lead to improved working conditions, better policies on rest and breaks, and safer environments, reducing the risk of accidents and injuries. Construction employers and contractors can also benefit from the study's findings by recognizing the importance of worker health and safety. Understanding the links between fatigue, sleep deprivation, and performance can encourage them to implement strategies like better scheduling, adequate rest periods, and higher wages, which could enhance productivity, reduce accidents, and improve job satisfaction. Occupational health and safety professionals can use the study's findings to develop more effective risk management strategies. By focusing on fatigue and its impact on workers' health and performance, they can adjust safety protocols to minimize fatigue-related risks.

The generalizability of the methodology is significantly influenced by the specific characteristics of each work environment. Factors such as the nature of the tasks performed, the physical demands placed on workers, and the typical work schedules can impact the effectiveness of the detection system. To enhance this, prioritizing testing and validating the methodology in diverse settings to assess its robustness and adaptability is crucial. Moreover, construction sites and other working environments can present varying lighting conditions, weather influences, and differences in worker attire that may affect detection accuracy. Although the study has developed adaptive algorithms, their efficacy in handling extreme variations remains an area for subsequent studies. The performance of the model may also be contingent upon the quality and representativeness of the training dataset. If the dataset fails to encompass a wide variety of worker behaviors and environmental conditions, the system may struggle to generalize effectively to novel situations. Additionally, individual variations in fatigue responses pose a challenge. Workers exhibit differing fatigue expressions based on factors such as age, health status, and personal experiences. While the study's methodology accounts for some of these variations, it may not fully capture the complete spectrum of fatigue indicators across diverse worker populations.

Investigating the ethical implications and privacy concerns associated with the deployment of drowsiness detection systems in the workplace is essential. Research could focus on developing guidelines and frameworks for ensuring worker privacy while maintaining the effectiveness of safety monitoring systems. Exploring the use of advanced AI and machine learning techniques to improve the accuracy and efficiency of drowsiness detection systems can be a promising area for future research. This could include the development of predictive models that anticipate fatigue based on work patterns, environmental factors, and individual worker characteristics. The deployment of cameras in construction environments could lead to apprehensions among workers about constant monitoring and potential misuse of recorded data. To address these concerns, stringent privacy protocols will be implemented. This includes ensuring compliance with local and international data protection regulations. This process involves transparently communicating the purpose of the monitoring, the types of data collected, how the data will be used, and the measures taken to protect privacy. Providing workers with the option to opt in or opt out of the monitoring program will further respect their autonomy. Anonymizing collected data to prevent identification of individual workers and ensuring that access to the data is restricted to authorized personnel only must be ensured. Recognizing that attitudes toward surveillance and privacy can vary across different cultural contexts, engagement with workers and stakeholders in each specific environment will be critical. Understanding their perspectives and concerns will foster trust and ensure that the system is perceived as a tool for enhancing safety rather than as an invasive monitoring mechanism. While the primary goal is to enhance safety and prevent accidents, vigilance regarding the ethical implications of this approach is necessary. The possibility of misinterpreting data leading to false positives could create undue pressure on workers. Establishing protocols that differentiate between genuine safety concerns and normal fluctuations in behavior that may not indicate drowsiness is essential. Discussions with ethics boards and stakeholder groups will be necessary to navigate the complexities of implementing this methodology ethically.

## 7. Areas for Further Studies

- The enhancements to the proposed system will primarily revolve around improving drowsiness detection. This can be achieved by augmenting the training datasets with more diverse data, thus enabling the model to learn from a richer variety of instances. Further research could also consider implementing the model on a video-based inspection system and developing a timed alarm system to proactively alert supervisors of potential safety risks.
- Given the supervised learning techniques employed in this study, exploring the possibility of combining supervised and unsupervised learning methods could result in the development of a more intelligent system, heralding the beginning of a new era of safety management in the construction sector.
- As a recommendation for future research, a comprehensive survey or longitudinal study could be conducted to specifically investigate the effects of chronic sleep deprivation—such as sleeping for only two hours daily—on workers' cognitive function, decision-making abilities, physical performance, and safety. Such a study could include variables such as reaction times, error rates, accident occurrences, and overall productivity, along with a demographic breakdown of workers' health, age, and the nature of their job.
- More studies are also needed to examine the integration of drowsiness detection systems with wearable devices that monitor physiological signals such as heart rate variability, skin temperature, and galvanic skin response. This multi-modal approach could enhance the accuracy of fatigue assessments by combining behavioral indicators

with physiological data, providing a more comprehensive understanding of worker fatigue levels. Investigating the development of adaptive algorithms that can adjust to the unique environmental conditions of different workplaces would be valuable.

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## References

1. Luo, H.; Wang, M.; Wong, P.K.Y.; Tang, J.; Cheng, J.C.P. Vision-Based Pose Forecasting of Construction Equipment for Monitoring Construction Site Safety. In Proceedings of the 18th International Conference on Computing in Civil and Building Engineering (ICCCBE 2020), São Paulo, Brazil, 18–20 August 2020; Springer: Cham, Switzerland, 2021; Volume 98, pp. 1127–1138. [CrossRef]
2. Onososen, A.O.; Musonda, I.; Onatayo, D.; Tjebane, M.M.; Saka, A.B.; Fagbenro, R.K. Impediments to Construction Site Digitalisation Using Unmanned Aerial Vehicles (UAVs). *Drones* **2023**, *7*, 45. [CrossRef]
3. Powell, R.; Copping, A. Sleep Deprivation and Its Consequences in Construction Workers. *J. Constr. Eng. Manag.* **2010**, *136*, 1086–1092. [CrossRef]
4. Ansaripour, A.; Heydariaan, M.; Kim, K.; Gnawali, O.; Oyediran, H. Applied Sciences ViPER+: Vehicle Pose Estimation Using Ultra-Wideband Radios for Automated Construction Safety Monitoring. *Appl. Sci.* **2023**, *13*, 1581. [CrossRef]
5. ncs®—National Safety Council. *Fatigue in Safety Critical Industries—Impacts, Risks & Recommendations*; ncs®—National Safety Council: Itasca, IL, USA, 2018.
6. Maman, Z.S.; Yazdi, M.A.A.; Cavuoto, L.A.; Megahed, F.M. A Data-Driven Approach to Modeling Physical Fatigue in the Workplace using Wearable Sensors. *Appl. Ergon.* **2017**, *65*, 515–529. [CrossRef]
7. Zhang, K.; Li, X. Human-Robot Team Coordination That Considers Human Team Fatigue. *Int. J. Adv. Robot. Syst.* **2014**, *11*, 91. [CrossRef]
8. Yu, Y.; Guo, H.; Ding, Q.; Li, H.; Skitmore, M. An Experimental Study of Real-Time Identification of Construction Workers' Unsafe Behaviors. *Autom. Constr.* **2017**, *82*, 193–206. [CrossRef]
9. Ray, S.J.; Teizer, J. Real-Time Construction Worker Posture Analysis for Ergonomics Training. *Adv. Eng. Inform.* **2012**, *26*, 439–455. [CrossRef]
10. Wójcik, B.; Żarski, M.; Książek, K.; Miszczak, J.A.; Skibniewski, M.J. Hard Hat Wearing Detection Based on Head Keypoint Localization. *arXiv* **2021**, arXiv:2106.10944.
11. Mariam, A.T.; Olalusi, O.B.; Haupt, T.C. A Scientometric Review and Meta—Analysis of the Health and Safety of Women in Construction: Structure and Research Trends. *J. Eng. Des. Technol.* **2021**, *19*, 446–466. [CrossRef]
12. Fang, Q.; Li, H.; Luo, X.; Ding, L.; Luo, H.; Li, C. Computer Vision Aided Inspection on Falling Prevention Measures for Steeplejacks in an Aerial Environment. *Autom. Constr.* **2018**, *93*, 148–164. [CrossRef]
13. Gheisari, M.; Rashidi, A.; Esmaeili, B. Using Unmanned Aerial Systems for Automated Fall Hazard Monitoring. In Proceedings of the Construction Research Congress 2018, New Orleans, LA, USA, 2–4 April 2018; ASCE Library: Reston, VA, USA, 2018; pp. 62–72. [CrossRef]

14. Kim, D.; Lee, S.; Kamat, V.R. Proximity Prediction of Mobile Objects to Prevent Contact-Driven Accidents in Co-Robotic Construction. *J. Comput. Civ. Eng.* **2020**, *34*, 04020022. [CrossRef]
15. Aditya, U.S.; Singh, R.; Singh, P.K.; Kalla, A. A Survey on Blockchain in Robotics: Issues, Opportunities, Challenges and Future Directions. *J. Netw. Comput. Appl.* **2021**, *196*, 103245. [CrossRef]
16. Tjebane, M.M.; Musonda, I.; Okoro, C. Organisational Factors of Artificial Intelligence Adoption in the South African Construction Industry. *Front. Built Environ.* **2022**, *8*, 823998. [CrossRef]
17. Bowen, P.; Zhang, R.P.; Edwards, P. An Investigation of Work-Related Strain Effects and Coping Mechanisms among South African Construction Professionals. *Constr. Manag. Econ.* **2021**, *39*, 298–322. [CrossRef]
18. Seo, J.; Han, S.; Lee, S.; Kim, H. Computer Vision Techniques for Construction Safety and Health Monitoring. *Adv. Eng. Inform.* **2015**, *29*, 239–251. [CrossRef]
19. Luo, H.; Wang, M.; Wong, P.K.Y.; Tang, J.; Cheng, J.C.P. Construction Machine Pose Prediction Considering Historical Motions and Activity Attributes Using Gated Recurrent Unit (GRU). *Autom. Constr.* **2021**, *121*, 103444. [CrossRef]
20. Souto Maior, C.B.; Santana, J.M.; Nascimento, L.M.; Macedo, J.B.; Moura, M.C.; Isis, D.L.; Droguett, E.L. Personal Protective Equipment Detection in Industrial Facilities Using Camera Video Streaming. In *Safety and Reliability—Safe Societies in a Changing World*; CRC Press: Boca Raton, FL, USA, 2018; pp. 2863–2868. [CrossRef]
21. Liang, C.J.; Kamat, V.R.; Menassa, C.C. Teaching Robots to Perform Construction Tasks via Learning from Demonstration. In Proceedings of the 36th International Symposium on Automation and Robotics in Construction, ISARC, Banff, AB, Canada, 21–24 May 2019; The International Association for Automation and Robotics in Construction: Frankfurt, Germany, 2019; pp. 1305–1311. [CrossRef]
22. Akinosho, T.D.; Oyedele, L.O.; Bilal, M.; Ajayi, A.O.; Delgado, M.D.; Akinade, O.O.; Ahmed, A.A. Deep Learning in the Construction Industry: A Review of Present Status and Future Innovations. *J. Build. Eng.* **2020**, *32*, 101827. [CrossRef]
23. Ibrahim, A.; Nnaji, C.; Namian, M.; Koh, A.; Techera, U. Investigating the Impact of Physical Fatigue on Construction Workers' Situational Awareness. *Saf. Sci.* **2023**, *163*, 106103. [CrossRef]
24. Malomane, R.; Musonda, I. The Opportunities and Challenges Associated with the Implementation of Fourth Industrial Revolution Technologies to Manage Health and Safety. *Int. J. Environ. Res. Public Health* **2022**, *19*, 846. [CrossRef]
25. Noble, J.; Kerr, S. Qatari World Cup chief says 400 workers killed during construction. *Financial Times*, 29 November 2022.
26. Onososen, A.O.; Musonda, I.; Ramabodu, M.; Tjebane, M.M. Resilience in Construction Robotics and Human-Robot Teams for Industrialised Construction. In Proceedings of the 12th International Conference on Construction in the 21st Century (CITC-12), Amman, Jordan, 16–19 May 2022; pp. 537–546.
27. Nath, N.D.; Behzadan, A.H.; Paal, S.G. Deep Learning for Site Safety: Real-Time Detection of Personal Protective Equipment. *Autom. Constr.* **2020**, *112*, 103085. [CrossRef]
28. *OSHA-1926.28(a)*; Personal Protective Equipment—Safety and Health Regulations for Construction—1926 Subpart C—General Safety and Health Provisions. Occupational Safety and Health Administration: Washington, DC, USA, 2004.
29. Anwer, S.; Li, H.; Antwi-Afari, M.F.; Umer, W.; Mehmood, I.; Al-Hussein, M.; Wong, A.Y. Test-Retest Reliability, Validity, and Responsiveness of a Textile-Based Wearable Sensor for Real-Time Assessment of Physical Fatigue in Construction Barbenders. *J. Build. Eng.* **2021**, *44*, 103348. [CrossRef]
30. Namian, M.; Albert, A.; Feng, J. Effect of Distraction on Hazard Recognition and Safety Risk Perception. *J. Constr. Eng. Manag.* **2018**, *144*, 04018008. [CrossRef]
31. Soltani, M.M.; Zhu, Z.; Hammad, A. Skeleton Estimation of Excavator by Detecting Its Parts. *Autom. Constr.* **2017**, *82*, 1–15. [CrossRef]
32. Cha, Y.-J.; Choi, W.; Büyüköztürk, O. Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks. *Comput. Civ. Infrastruct. Eng.* **2017**, *32*, 361–378. [CrossRef]
33. Yokoyama, S.; Matsumoto, T. Development of an Automatic Detector of Cracks in Concrete Using Machine Learning. *Procedia Eng.* **2017**, *171*, 1250–1255. [CrossRef]
34. Nepal, U.; Eslamiat, H. Comparing YOLOv3, YOLOv4 and YOLOv5 for Autonomous Landing Spot Detection in Faulty UAVs. *Sensors* **2022**, *22*, 464. [CrossRef]
35. Lee, Y.-R.; Jung, S.-H.; Kang, K.-S.; Ryu, H.-C.; Ryu, H.-G. Deep Learning-Based Framework for Monitoring Wearing Personal Protective Equipment on Construction Sites. *J. Comput. Des. Eng.* **2023**, *10*, 905–917. [CrossRef]
36. Onatayo, D.A.; Srinivasan, R.S.; Shah, B. Ultraviolet Radiation Transmission in Building's Fenestration: Part II, Exploring Digital Imaging, UV Photography, Image Processing, and Computer Vision Techniques. *Buildings* **2023**, *13*, 1922. [CrossRef]
37. Karlsson, J.; Strand, F.; Bigun, J.; Alonso-Fernandez, F.; Hernandez-Diaz, K.; Nilsson, F. Visual Detection of Personal Protective Equipment and Safety Gear on Industry Workers. *arXiv* **2023**, arXiv:2212.04794, 395–402. [CrossRef]
38. Aich, S.; Joo, M.; Kim, H.C.; Park, J. Improvisation of Classification Performance Based on Feature Optimization for Differentiation of Parkinson's Disease from Other Neurological Diseases Using Gait Characteristics. *Int. J. Electr. Comput. Eng.* **2019**, *9*, 5176–5184. [CrossRef]

39. Karystianis, G.; Adily, A.; Schofield, P.; Knight, L.; Galdon, C.; Greenberg, D.; Jorm, L.; Nenadic, G.; Butler, T. Automatic Identification of Mental Health Disorders from Domestic Violence Police Narratives. *J. Med. Internet Res* **2018**, *20*, e11548. [CrossRef] [PubMed]
40. Cromsjö, M.; Hallonqvist, L. Detection of Safety Equipment in The Manufacturing Industry Using Image Recognition. Master's Thesis, Linköping University, Linköping, Sweden, 2021.
41. Onatayo, D.A.; Srinivasan, R.S.; Shah, B. Ultraviolet Radiation Transmission in Buildings' Fenestration: Part I, Detection Methods and Approaches Using Spectrophotometer and Radiometer. *Buildings* **2023**, *13*, 1670. [CrossRef]
42. Aboah, A.; Wang, B.; Bagci, U.; Adu-Gyamfi, Y. Real-Time Multi-Class Helmet Violation Detection Using Few-Shot Data Sampling Technique and YOLOv8. In Proceedings of the 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Ancouver, BC, Canada, 17–24 June 2023; pp. 5349–5357.
43. Wang, M.; Wong, P.K.-Y.; Luo, H.; Kumar, S.; Delhi, V.-S.; Cheng, J.C.-P. Predicting Safety Hazards Among Construction Workers and Equipment Using Computer Vision and Deep Learning Techniques. In Proceedings of the 36th International Symposium on Automation and Robotics in Construction, Banff, AB, Canada, 21–24 May 2019; The International Association for Automation and Robotics in Construction: Frankfurt, Germany, 2019. [CrossRef]
44. Moolayil, J. *An Introduction to Deep Learning and Keras: A Fast-Track Approach to Modern Deep Learning with Python*; Apress: Berkeley, CA, USA, 2019. [CrossRef]
45. Ultralytics. *YOLOv8, Version 8.0.0*; Ultralytics: Frederick, MD, USA, 2023.
46. Wang, C.-Y.; Bochkovskiy, A.; Liao, H.-Y.M. YOLOv7: Trainable Bag-of-Freebies Sets New State-of-the-Art for Real-Time Object Detectors. In Proceedings of the 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Vancouver, BC, Canada, 17–24 June 2023. [CrossRef]
47. Duran, B.; Emory, D.; Eftekhar Azam, Y.; Linzell, D.G. A novel CNN architecture for robust structural damage identification via strain measurements and its validation via full-scale experiments. *Measurement* **2025**, *239*, 115393. [CrossRef]